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What Drives German Trend Output Growth? A Sectoral View

Abstract

In this paper, we outline material and capital linkages across sectors to quantify the role of the German production network in amplifying sectoral dynamics on aggregate trend gross domestic product growth. This allows us to study the impact of sectoral labor input and total factor productivity trend growth variation on the persistent decline in long-run output growth. Our estimation reveals that sector-specific developments have historically accounted for half of this long-term decline. Zooming into the reunification period, we find a pronounced decline of total factor productivity growth in Professional and Business Services together with a fall in labor input growth in the Construction sector to drive the sharp decline of German trend output growth over the 1990s. We further document significant changes regarding the sectors' importance as input suppliers to the economy over the past decades. Our analysis identifies the labor-intensive Construction sector as a major input hub in the production network, its long-run amplification effect exceeding four times its share in value added. Given the impending demographic change, the low potential for automation in this sector may significantly reduce future German trend output growth.

JEL-Codes: C320, E220, E230, O410.

Keywords: trend GDP growth, sectoral multiplier, amplification effects, structural change.

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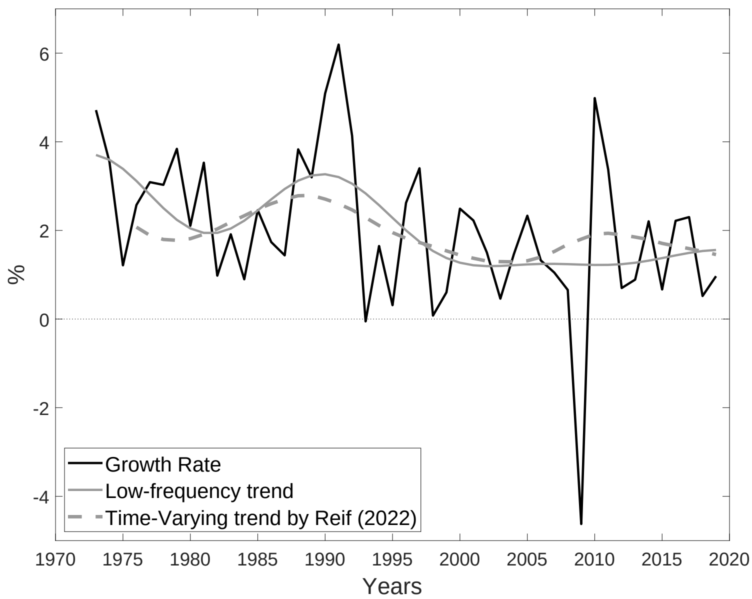
1 Introduction

In the last decades, trend growth of gross domestic product (GDP) has slowed remarkably in most industrialized economies. Rising concerns about the phenomena emerged first in the US due to the sluggish economic recovery in the aftermath of the Great Recession and the following low average GDP growth rate over the 2010s. Fernald *et al.* (2017) document a slowdown in total factor productivity (TFP) growth and a decrease in labor input to be the main reasons for the moderate US GDP growth pace, forces which they underline to have been present long before 2008. Antolin-Diaz *et al.* (2017) underpin these findings. Foerster *et al.* (2022) delve further and document the considerable impact of variations in TFP and labor input growth at the sectoral level on overall long-term economic growth. In contrast to the US, the German labor market was only hit mildly by the Great Recession (Rinne and Zimmermann, 2012; Burda and Hunt, 2011). Overall, Germany recuperated astonishingly fast from the financial crisis. Its economy is, however, no exception regarding decelerating long-term GDP growth rates (Reif, 2022). Despite its unique structural composition, there is a lack of literature on the reasons behind the German slowdown in trend GDP growth. This paper presents an empirical investigation into the decline's sources, situating its analysis within a historical context and drawing comparisons with the slowdown observed in the US.

As Europe's largest economy, Germany provides a unique perspective for examining the complexities of slowing economic growth.The German economy shows some remarkable differences compared to its US counterpart: In terms of its share in total gross value added (GVA), its manufacturing sector still plays a pronounced role and is accompanied by a high degree of trade openness. Further, Germany's economy is currently still undergoing a transformation towards a more service-oriented model and the demographic situation of the country is about to impact its labor market. Additionally, the German economy has undergone enormous structural changes during the last five decades. Next to its integration into the European market, Germany's reunification in 1989 presents a unique structural break in its economic history. A variety of economic consequences following reunification have been studied intensively, for example, labor market effects and migration patterns (Burda and Hunt, 2001; Uhlig, 2006). Apart from the German "labor market miracle" (Jacobi and Kluve, 2007; Krebs and Scheffel, 2013) and the current account imbalances arising around the turn of the century (Sabbatini and Zollino, 2010), trends underlying (unified) Germany's aggregate economic developments have on the contrary not been subject to much empirical investigation. Even less attention has been given to developments at the disaggregated level, Coricelli and Wörgötter (2012) focusing on the gap in productivity growth between manufacturing and services underlying the pronounced German current account surplus being an exception. Intending to change this, our paper focuses on the role of sectoral trends in the evolution of German trend GDP growth.

We closely follow Foerster *et al.* (2022) and estimate low-frequency trends in German GDP growth from 1970 to 2019, capturing movements longer than 15 years. The estimated long-term trend in German GDP growth shown in Figure 1 is fairly in line with the estimation by Reif (2022). Both series correlate by 0.88. Therefore, our low-frequency trend is a suitable starting point for a sectoral analysis. German trend GDP growth has been on a downward path since more than four decades, declining from more than 3% in the 1970s to around 1% in the mid-2000s. Besides the overall trend growth decline, Figure 1 also points towards periods of substantial increases in trend growth, for example, during the late 1980s. In recent years German trend GDP growth has no longer slowed down.

Figure 1: German Trend GDP Growth



Notes: The low-frequency trend captures variability for periodicities longer than 15 years.

The declining German business cycle volatility, one major focus of Reif (2022), has been subject of several studies. A relevant finding from this literature for our purpose is that structural shifts—accelerated by the German reunification—and changing relationships between various GDP components have contributed significantly in reducing volatility (Assmann *et al.*, 2009). We suspect those shifts of sectoral importance to also influence long-run trend growth dynamics. Loosely related to our work is Wolf (2018), who examines German economic growth between the beginning of the twentieth century and 2010. He, however, focuses on regional disparities. In contrast, we contribute to the literature by expanding the analysis to the sectoral level: Disentangling low-frequency trends in labor input and TFP for 15 sectors constituting the German private-sector economy, we are able to identify key sectors contributing to the declining in German trend GDP growth during the past five decades. We further examine the amplifying effects of sectoral changes on aggregate trend growth in labor input, TFP, and GDP. In doing so, we rely on a multi-sector economic growth model that captures the amplifying effects as multipliers arising from sectoral interactions in the German production network characterized by material inputs and investment goods. Our analysis adopts the methodology of Foerster *et al.* (2022), who investigate aggregate implications of changing sectoral trends for the US. Amongst other results, they find sector-specific factors having accounted historically for around 3/4 of the variations in US trend GDP growth. As the German economy fundamentally differs from the US, one of our major interest is the comparison of the German application to the results from Foerster *et al.* (2022). For Germany, we find sector-specific forces accounting historically for about 1/2 of the variation in long-run GDP growth. This lower importance of sector-specific forces for output growth in Germany might root in the major shock represented by reunification as well as the delayed and still ongoing shift from an industry-oriented towards a service-oriented economy. German trend GDP growth declined by 2.1 percentage points over our sample. We find the Durables sector alone to have contributed 0.5 percentage points to that decline, mainly driven by a slowdown in the sector's TFP trend growth. Zooming into the reunification period, we find that a 1.4 percentage point decline of TFP growth in Professional and Business Services combined with a fall of 0.6 percentage points in trend labor input growth in the Construction sector having driven the sharp decline of German trend GDP growth over the 1990s. Interestingly, regardless the structural change towards a service-orientated economy, we find no major positive contributions of the service sectors.

Our paper further enriches the German data landscape by providing the first capital-flow matrices for the German private-sector economy, spanning from 1990 to 2018. These matrices allow an annual approximation of the German investment network. Starting in 1995, the capital-flow matrices further account for investments in intangibles. The evolution of the sectoral multipliers over time denote the importance of a specific sector as input supplier to the economy and hence its amplification effects. Not surprisingly, we document a rise for the majority of the labor multipliers of service sectors, with Professional and Business Services quadrupling over the sample period. Concurrently, we register a significant decline of the Durables sector's labor multiplier (most likely due to automation processes) while the labor multiplier of the Construction sector remains rather high. Due to the Construction sector's pronounced labor intensity, it's overall high importance as input supplier in the production network and the looming demographic change, we find the Construction sector to have the potential to significantly influence future German trend GDP growth.

The paper is organized as follows. Section 2 introduces the data and presents some descriptive facts on German long-run growth dynamics. In Section 3, we present the methodology to estimate the trends together with the decomposition in sector-specific and common forces. The German production network and the sectoral multipliers are discussed in Section 4. Some robustness checks and implications for future growth perspectives are illustrated in Section 5. The last section concludes. The Supplementary Material complements the main paper and delves into the data issues, estimation algorithms, model specifications, robustness checks, and additional results.

2 Long-run Growth Dynamics in Germany

We start by presenting selected descriptive facts on Germany's long-term economic development. Along those lines we discuss its economic structure and point out several reasons for the German economy differing from that of the US. We further introduce our data set constructed from official sources and data transformations that puts us in a position to examine our empirical questions. We further debate the long-term growth dynamics of GDP, labour input and TFP at both the aggregate and the sectoral level.

2.1 Data Set

Construction of historical series. Studying the evolution of economic trends in Germany is due to historical reasons challenging: Reunification took place only about 30 years ago and included the integration of the centrally planned economy of the German Democratic Republic (GDR) into the market-traded economy of the former Federal Republic of Germany (FRG). Time series for macroeconomic aggregates of unified Germany are therefore available only since 1991. As we are interested in growth trends over a longer period, resorting to the period of reunified Germany only would leave us with an insufficient number of observations to formulate meaningful results. To extend our sample, we rely on data retrieved in the former FRG for the period from 1970 to 1990. As a result, our sample describes the evolution of key German macroeconomic variables as a combination of their respective evolution in the FRG until 1990 and their further development in unified Germany from 1991 to 2019. The year 2020 is excluded to avoid distorting effects of the COVID-19 pandemic.

For the two periods prior and after German reunification, the Federal Statistical Office of Germany has published detailed national accounts figures on a two-digit level, comprising 63 sectors. These figures include GVA, the total number of employees representing labor input, the capital stock, and labor compensation. The two periods both include the year 1991, theoretically allowing for the combination of both data sources. Unfortunately, the raw data sets do, however, not adhere to the same classification standards of economic activities. Although the systematization is comparable, there is one notable difference given by the Information and Communication sector. Data on this sector was specifically sampled only after the change in classification standards and is hence only included for the post-reunification period. For the former FRG, we need to calculate it from the raw data. To do so, we start by dividing the "old" sectors (according to the classification of the sub-period covering the FRG data) based on employment shares. Second, we either add up the values to the newly created sector (e.g., nominal value added) or apply share-weighted Divisia indices. To ensure conformity with classification standards in both data sources, we combine the 1991 post-reunification levels with the pre-reunification growth rates. This procedure preserves the historical dynamics while updating the levels. We end up with macroeconomic information for Germany and its sectors from 1970 to 2019.

One of our main objectives is to compare the results for Germany to those of Foerster *et al.* (2022) for the US. This comparison is ensured by collapsing the German raw data to their sectoral definitions. We end up with 15 sectors constituting the German private-sector economy, excluding all government and non-market-traded activities. Unlike Foerster *et al.* (2022), we do not possess data to construct a housing sector, hence the German FIRE aggregate (financial, insurance and real estate) includes it. This difference is important to keep in mind when comparing our quantitative results with the US case.

Calculation of Total Factor Productivity. Sectoral TFP growth is defined as the Solow residual of a Cobb-Douglas-type production function, where all firms operate under constant returns to scale and perfect competition. According to Hulten (1978), the aggregate private-sector economy TFP is then simply the sum of sectoral TFP weighted by the means of their value added shares. The availability of a long time series for Germany comes at the price that TFP can only be extracted from a much smaller pool of data. Compared to the EU KLEMS data we cannot distinguish between labor services (e.g., different qualification levels) and capital services (e.g., different types of assets) but have to use the sheer number of employees and a standard measure for capital instead.[1] However, both aggregate TFP series are highly correlated for the period from 1996 to 2019 (correlation coefficient: 0.95).

A more recent strand of literature is concerned with the (mis-)measurement of TFP, for example, due to business cycle fluctuations. Existing studies mostly argue that standard TFP measures not only capture technological improvements but are also influenced by the degree of factor utilization. More recent measures—either called factor-utilized or purified TFP—extent standard TFP estimates to include a variable that captures the degree of factor utilization. In the case of Basu *et al.* (2006) and Fernald (2014) this variable is growth in hours per worker. Other studies use survey-based capacity utilization measures instead (Christofzik *et al.*, 2021; Comin *et al.*, 2023). The common feature of the German measures is that the series only begin in the mid-1990s, thus, making them too short for our purposes. However, we argue that TFP (mis-)measurement is not a major issue in our case for two reasons. First, we adjust our TFP estimates for short-run fluctuations, which is described in the next paragraph. Secondly, as our focus is on the long-term trends of the series, they should not be significantly affected by fluctuations in the business cycle, as long as we consider enough periods of economic growth and decline. For this reason, we apply an 11-year moving average to both our TFP growth estimates and those of Comin *et al.* (2023). If we interpret this moving average as the slow-moving component or trend of the series, then both series exhibit a downward-sloping behavior from the early 2000s to the mid-2010s. This observation gives us confidence that our approach captures the underlying long-run dynamics of the German economy quite well.

[1] Unfortunately, the calculation or estimation of total hours worked is only available for Germany since 1991. Before 1991, only the number of persons employed is available from the national accounts. Thus, our approach captures only the extensive margin of labor supply and leaves the intensive margin aside.

Cyclical adjustment. The raw annual growth rates of GDP, labor input and TFP are quite volatile over time. A significant part of this variation can be attributed to rather short-lived business cycle fluctuations. To focus on the long-run variability of our time series, we eliminate these short-run fluctuations by using an Okun's Law-type regression following Fernald *et al.* (2017) and Foerster *et al.* (2022). The cyclically adjusted series are defined as the residuals after regressing the series' annual growth rates on contemporary changes in the unemployment rate as well as both one lag and one lead. Because Germany implemented significant labor market reforms in the mid-2000s and has a more regulated job market compared to the US, one could argue that the unemployment rate is not sufficient to capture the variability associated with the overall German business cycle. To address these concerns, we conducted a full additional analysis using one of the most important survey-based leading indicators for the German economy, the ifo Business Climate Index, as instrument.[2] The results are discussed in the robustness section.

2.2 Facts on German Long-run Economic Development since 1970

The dynamics of cyclically adjusted German GDP growth from 1971 to 2019 are shown in Figure 2. GDP is measured as the share-weighted (chain-weighting) value added growth from the 15 sectors comprising the German private-sector economy. To visually analyze the potential impact of structural changes in the German economy on GDP growth, we calculate hypothetical growth rates using three sets of fixed sectoral shares: the average from 1970 to 1979, the average from 2010 to 2019, and the average over the full sample period. We apply a similar procedure to labor input and TFP growth. Based on the raw but cyclically adjusted data (left column in Figure 2), it appears that structural shifts have primarily impacted labor growth, as the differences for GDP and TFP are not very pronounced. Structural changes tend to occur gradually, and their effects become more apparent in long-term fluctuations.

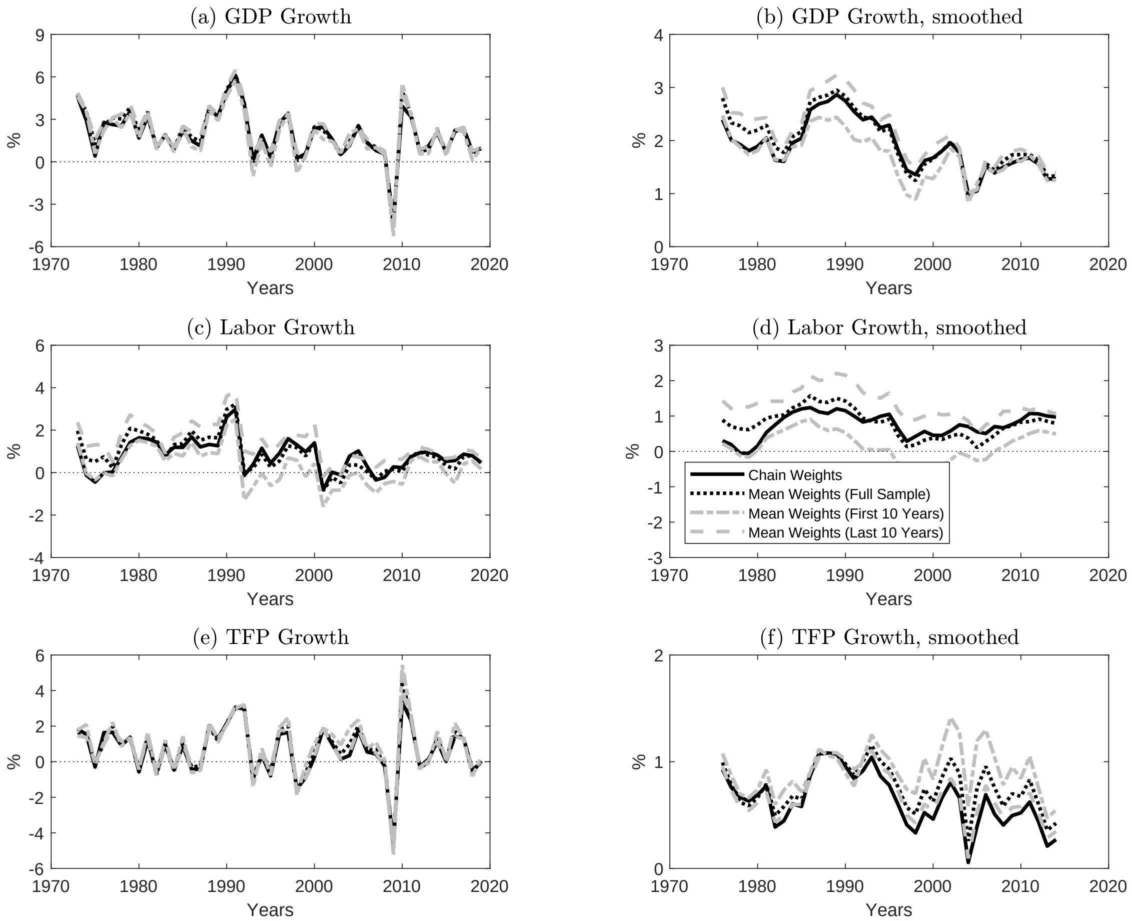
The right column of Figure 2 therefore shows smoothed annual growth rates using an 11-year centered moving average. It is evident that the long-term growth patterns of all three aggregates are shaped not only by inter-sectoral changes but also, to a large extent, by shifts between sectors reflecting structural change. This is a remarkable difference to the US case as argued by Foerster *et al.* (2022). They claim that it is mainly changes within sectors that affect aggregate growth trajectories. For now, we apply mean weights over the full sample. However, we discuss the influences of different weights in the robustness section.

Panel (b) clearly indicates the slowdown of GDP growth in the long run as also reported by Reif (2022). This picture is also reflected in the growth rates of cyclically adjusted GDP averaged over different sub-periods. Smoothed GDP growth fell to two percent in the late 1970s and early 1980s before rising to approximately three percent around German

[2]The ifo Business Climate is regarded as one of the most important leading indicators for German GDP growth, is listed on Bloomberg's "12 Global Economic Indicators to Watch", and has proven to be useful in business cycle dating as well as in nowcasting economic aggregates (Lehmann, 2023).

reunification. After the brief reunification boom, long-term GDP growth fell rapidly over the 1990s, reaching a trough shortly before the new century. After recovering in the early 2000s, smoothed GDP growth declined sharply in the mid-2000s, most likely as a result of the financial crisis. Over the past decade, long-term growth rates have stabilized at around one and a half percent.

Figure 2: Annual Growth Rates of GDP and Input Factors



Notes: The figure shows cyclically adjusted annual growth rates which are share-weighted averages from 15 sectors making up private-sector economic activity in Germany. Smoothed values represent 11-year centered moving averages. The weighting scheme is either based on official national accounting standards (chain-weighting) or on constant share-averages of three different (sub-)periods. *Source:* Federal Statistical Office of Germany; own calculations.

Unraveling long-term GDP development into both labor input and TFP growth reveals interesting patterns in the German economy. Panels (d) and (f) spotlight the 11-year centered moving averages for these two input factors. After the low levels of labor input growth rates in the late 1990s and the early 2000s, the mid-2000s marked the reversal of declining labor input growth. In Panel (d), the long-term growth trend can be observed to increase after the turn of the twenty-first century. As Burda and Seele (2020) elucidate, labor input in the 15 years between 2003 and 2018 grew sustainably by 19.3% (or 7.3 million employees), resulting in employment levels last seen before reunification.[3] This development, often referred to as the "German labor market miracle", was however accompanied by unspectacular GDP growth. Further, TFP growth over the same period unfolded only disappointingly and volatile. This slowdown in TFP growth is not a German-specific issue, but rather a global phenomena since the mid-2000s. In contrast to the labor market miracle, Hutter and Weber (2021) refer to it as the "productivity debacle". The German TFP slowdown is a particularly interesting case, which, as Christofzik *et al.* (2021) state, does not only reflect the US slowdown in productivity. They identify two domestic factors explaining the decline. First, they find the structural shift from the highly productive manufacturing to the service sector to have a restraining effect on productivity. Second, they underline that technology advancements in Information and Communications Technologies (ICT) have lead to higher output and employment. Elstner *et al.* (2022), however, find persistent technology spillovers from ICT producers to intensive users of these inputs in the mid-2000s, thus, enhancing TFP.

To comprehend these advancements, we follow the methodology of Foerster *et al.* (2022) and trace the aggregate declines back to sectoral factors, thereby expanding on the existing research for Germany (for example, Reif, 2022). Additionally, we aim to compare our findings to the results of Foerster *et al.* (2022) for the US while attempting to link significant sectoral developments to key events in Germany's recent economic history. Due to significant structural differences between the two economies, we suspect sectoral drivers to differ prominently, particularly in terms of their intensity. The German economy is characterized by its above-average share in manufacturing compared to many other industrialized countries. In 2021, service activities accounted for almost 70% of market-traded nominal gross value added in Germany, while manufacturing accounted for more than 22%. Constituting 80% of the US private economy, services dominate the sectoral mix in the US even more while manufacturing only contributes by 12%. German manufacturing is characterized by medium- and high-level sectors such as automotive production, chemicals and machinery and equipment. It has a high degree of trade specialization ("export champion").[4] Most of the firms are owner-managed small- and medium-sized enterprises (SME), defining the group of the German "Mittelstand". This group is widely recognized as a primary driver of innovation and is considered to be quite crisis-resistant (Berlemann *et al.*, 2022). A significant number of those firms are "Hidden Champions", world leaders in small product niches. The US economy instead specializes in knowledge-intensive services and high-tech manufacturing, such as biotechnology. Although the share of total manufacturing is smaller than in Germany, high-tech manufacturing is considerably bigger in the US. An important contributor to US growth and competitiveness is the significant start-up and spin-off scene, mainly operating in

[3] German employment growth is unique compared to any other OECD country over that period, which, on average, grew by about 5% (Burda and Seele, 2020).

[4] The degree of trade openness is quite different between the German and the US economy. Whereas the sum of exports and imports expressed in terms of GDP was approximately 89% in Germany in 2021, the US, instead, exhibits a foreign trade quota of 25%.

the information and software business. These firms are primarily responsible for innovations in the US. The Global Innovation Index of the World Intellectual Property Organization ranks the United States on the second place among 48 high-income economies in 2022, while Germany is ranked on the eighth place. According to the German Ministry for Education and Research, however, Germany has almost twice as many global market-relevant patents per million inhabitants compared to the US. Investments in future technologies are conducted by different actors in the two countries, mirroring the respective economic structure. In Germany, most spending on research and development (R&D) activities is conducted in the medium high-technology sectors (automobiles, machinery, chemicals), while R&D expenditures for cutting-edge technologies such as in the ICT sector, where most of the US R&D spending takes place, are rather small. Further, the R&D share of the service sector is considerably higher in the US than in Germany (Hommes *et al.*, 2011; Gehrke and Schasse, 2011). Finally, European economies are in general considerably less digitized than the US economy. It follows that US firms show a superior use of IT (than German firms) in many industries according to Bloom *et al.* (2012).

The future development of labor input and innovation capacities, and therefore TFP growth, is heavily influenced by demographic trends. Currently, the German population is significantly older than the US population. In 2021, 22.2% of Germans were older than 65 years, compared to 16.8% in the US. The effects of an aging labor force will therefore manifest themselves earlier in the German economy than on the other side of the Atlantic. Further, the German labor market is still in the process of structural change, shifting from manufacturing to services. For instance, the sectoral choice of new labor market participants differs compared to previous generations and reentering employment often coincides with a change in sectors (Dauth *et al.*, 2017).

The shift from manufacturing to services is not only reflected in labor input, but also in GVA dynamics. Comparing the average historical growth rates, we observe large variations across the 15 sectors, which are ultimately suppressed when looking at aggregates (see Table 1). Labor input growth varied greatly, ranging from -4.7% in Mining to 3.9% in Professional & Business Services (PBS). In line with the structural shift, the service sector experienced growth in labor input above the average rate, while negative average labor input growth can be observed for Non-Durable Goods, Construction, and Durable Goods. Overall, TFP and labor input growth do not seem to be highly connected. Variation in TFP growth across sectors is considerably lower, ranging from -1.2% in Arts, Entertainment & Accommodation to 3.6% in Information & Communication. Similar to the US, we notice negative TFP growth rates in the disaggregated data for Germany. As Foerster *et al.* (2022) explain, this well-known issue is likely due to measurement errors in output. Average real GVA growth ranges from a strong average decline in Mining (-2.7%) to a strong increase in Information & Communication (5.5%). Total GDP growth was primarily driven by service sectors growing above average rates.

Table 1: Average Annual Growth and Sector Shares in Germany

Sector	Average Growth (in %)			Average Share (in %)	
	GVA	L	TFP	L	TFP
Agriculture	0.7	-2.6	2.9	3.5	1.6
Mining	-2.7	-4.7	1.7	0.7	0.8
Utilities	2.0	0.4	0.5	1.5	3.1
Construction	-0.4	-0.3	-0.1	8.1	6.4
Durable Goods	1.9	-0.3	1.7	17.0	19.0
Non-Durable Goods	1.2	-1.0	1.7	8.4	8.7
Wholesale Trade	2.5	0.2	1.9	5.4	4.8
Retail Trade	2.1	0.9	0.8	10.0	6.0
Transp. & Wareh.	2.1	0.8	0.7	5.6	4.9
Inform. & Commun.	5.5	1.5	3.6	2.8	4.1
FIRE†	2.3	1.0	0.2	4.1	14.9
PBS	3.6	3.9	0.1	8.5	9.2
Educ. & Health	2.0	2.6	-0.6	14.9	10.8
Arts, Entert. & Accom.	1.1	2.4	-1.2	4.6	2.8
Misc.	1.3	1.8	-0.8	5.0	2.8
Aggregate	2.0	0.9	0.8	100	100

Notes: The table shows average annual growth rates for each of the 15 sectors considered and three macroeconomic indicators: gross value added (GVA), labor input (L) and total factor productivity (TFP). The row labeled 'Aggregate' is the chain-weighted average of the 15 sectors representing private-sector economic activity in Germany. The averages are calculated for the period from 1973 to 2019. FIRE includes housing (†). FIRE: Financial, Insurance & Real Estate; PBS: Professional & Business Services. *Source:* Federal Statistical Office of Germany; own calculations.

In contrast to the US, where according to Foerster *et al.* (2022) labor as an input factor for production has on average declined only in Agriculture over the years, in Germany it has also lost importance as an input factor in Construction and Durable Goods. Additionally, it is noteworthy that the average labor shares of the service sectors are mostly higher in Germany than in the United States.

3 Sectoral Trend Growth in TFP and Labor Input

We start by introducing the methodology to extract a series' low-frequency movements and apply it to both sectoral labor input and TFP growth in Germany. Together with the description of sectoral trends since the 1970s, we classify remarkable developments into German economic history and compare them to the US. The trends for Germany are then plugged into a factor model to decompose trend growth rates into common factors affecting all sectors and idiosyncratic forces that can be interpreted as sector-specific developments.

3.1 Low-frequency Movements by Sector

Trend extraction. For the extraction of low-frequency movements in GDP, labor input and TFP, we follow the empirical framework of Foerster *et al.* (2022), who apply a method formerly introduced by Müller and Watson (2008). Their method produces smooth trend estimates that are fitted values from OLS-based regressions for each aggregate separately.[5] In these OLS regressions, the slow moving components in the time series are approximated by a constant term and q low-frequency cosine functions, $\Psi_k(s) = \sqrt{2}\cos(ks\pi)$, with a period equalling $2/k$. With $s = (t - 1/2)/T$, $k = 1, \ldots, q$ and $t = 1, \ldots, T$, the fitted values from the regression represent the time series' slow moving components longer than $2T/q$. Our sample for Germany runs—after the cyclical adjustment—from 1973 to 2019, thus, the total number of observations is $T = 47$. With $q = 6$ we capture long-run movements with periodicities longer than 15.7 ($= 2 \times 47/6$) years. As the filtering of trends is also influenced by the preceding adjustment of short- and medium-run fluctuations, the cyclical adjustment becomes even more valuable. We work with these smooth trends in the following and answer the question how sectoral developments have influenced the aggregate GDP trend.

Trend growth in Germany. Over the last five decades, Germany has undergone several economic policy and structural changes. Our sample starts with a new episode in German economic history: In March 1973, Germany left the Bretton-Woods system and allowed the German Mark to float freely. Additionally, the prosperous years of the German economic miracle after World War II ended with the first oil crisis in October 1973. This crisis revealed the inadequacy of Keynesian demand management as an economic policy. In shaping the future of German economic development, fiscal policy had been the central instrument of the government. However, following the oil crisis and the resulting economic downturn, unemployment rose sharply and immigrant working schemes were abruptly stopped. To evaluate the impact of such major events, Figure 3 highlights both the sector-specific labor input (gray line) and TFP (black line) trend growth rates over the last five decades. The two trend growth rates appear to be negatively correlated within sectors.

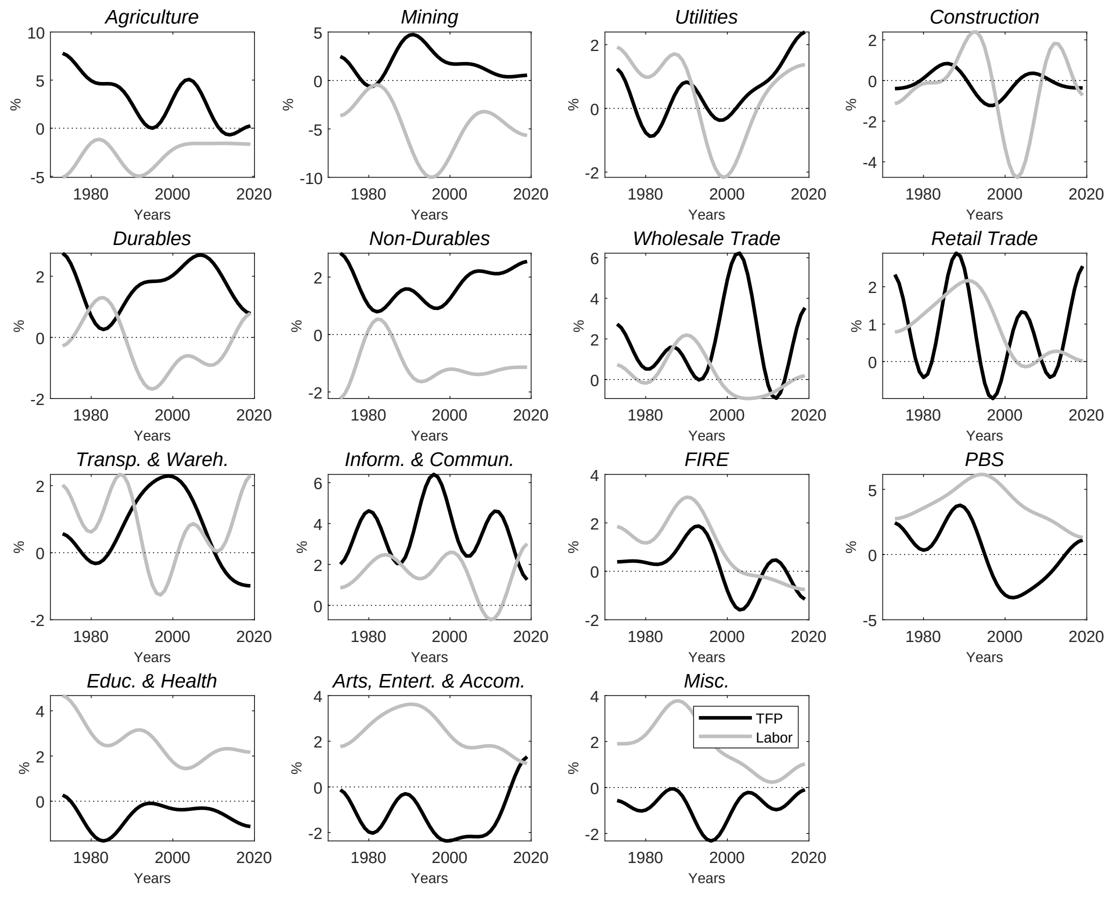
We note that labor input in Agriculture and Mining has constantly been decreasing, while the majority of the service sectors, such as PBS and Education & Health, recorded only increases. This development coincides with Germany's late start of the shift from an industrial towards a service economy, also underlined by the steady declines observed in both the Durables and the Non-Durables sector. With a majority of employees working in services rather than in manufacturing only in 1975, structural change evolved only slowly.[6]

[5] Müller and Watson (2020) provide a very detailed discussion on the low-frequency extraction method applied here. We refer the reader to this important contribution. Some methodological details are presented in the Supplementary Material.

[6] In the US, the share of employees in the service sector was already higher than the share of employees in manufacturing in 1950, in 1970 only around 30% of employees worked in the industrial sector—in Germany this share concurrently amounted to 45% according to the Federal Agency for Civic Education.

Interpreted as a timeline, we can infer episodes of German economic history from the sectoral trends plotted in Figure 3: The rise in labor input trends from the 1970s to the early 1980s can be interpreted as structural recovery after the oil crises. Interestingly, we also note that the rise in the long-term trend growth of labor as an input factor peaked in many service sectors in the beginning of the 1990s. This might be attributable to reunification acting like a supply shock to the German labor market, as the German workforce increased by several million people overnight: Due to run-down production facilities, firms in the former GDR were operating under non-competitive productivity levels. This resulted in a substantial wave of firm and plant closures after reunification, leading to the migration of many workers from East to West. Around the turn of the millennium, a labor market malaise due to high unit labor costs lead to Germany being identified as the "sick man of Europe". In response, the Social-Democrat lead government reformed the labor market with the so called "Agenda 2010". The following "German labor market miracle" can be deduced by noting the recoveries of labor input trend growth rates following the early 2000s in several sectors, for example, in Transportation & Warehouse. Notably, the labor input trend growth rates do not appear to be heavily impacted by the Great Recession.

Figure 3: Sectoral Labor Input and TFP Trend Growth in Germany



Notes: Each sectoral panel shows the low-frequency movements in labor input (gray) and TFP (black) growth. FIRE: Financial, Insurance & Real Estate; PBS: Professional & Business Services.

Comparing the sectors' labor input growth trends, we note their uniqueness. While, for example, Arts, Entertainment & Accommodation shows a rather stable development of labor input trend growth, Construction exhibits a very lively trend development instead. This heterogeneous evolution of the sectors' labor trends observed in Figure 3 suggest that next to common factors affecting all sectors without exception, sector-specific developments dominate labor input trend growth. Characterizing the two forces, common factors are represented by historic events such as the oil crisis mentioned above. Sector-specific factors are, for example, represented by the introduction of sectoral labor-augmenting technologies.

Large sectoral differences are observed in the evolution of TFP trend growth rates. Over the last few decades, the Durables and Non-Durables sectors have registered steady positive TFP increases. However, in Construction and Retail Trade, TFP trend growth fluctuated around zero. It is interesting to note that trend TFP growth decreased in the second half of our sample in both FIRE and PBS, whereas we observe a steady and large increase in Information & Communication, as well as in Durables. The observed changes in the cyclically adjusted TFP growth rates across sectors may reflect the adoption of new technologies, such as the internet, and the shift towards business models relying on E-commerce. Additionally, the advancing digitization of the German economy may also play a role. Overall, we observe more variation in the cyclically adjusted sectoral TFP growth rates than for labor input.

Comparison to US developments. We again put the spotlight on the comparison between Germany and the US. Table 2 introduces the coefficients of variation in labor input and TFP trend growth, defined as the ratio between the standard deviation and the mean of a series. Some remarkable differences stand out. The trends in construction appear to differ significantly between the two countries, with higher volatility in Germany. This might be attributable to the huge construction crises between 1995 and 2005: The short construction boom due to housing construction and huge infrastructure renovation projects after reunification led to large over-capacities, which, as governmental support stopped in 1995, resulted in numerous bankruptcies among construction firms. The consequences were severe structural problems until the beginning of the 2000s. The year 2005 is generally recognized as the year in which German construction returned back on a rather stable growth path.

Another major difference is observed for Mining, which can be explained by structural changes in the Ruhr and Lausitz areas due to several closures of mines over the past decades (for example, hard coal). Further, the declining long-term labor input growth trends in Durables and Non-Durables compared to the increases in the sectors constituting the tertiary sector again emphasize the ongoing "late" structural shift from an industrial towards a service economy. For Non-Durables and Durables, the volatility of TFP trend growth is found to be considerably lower in Germany than in the US. Further, TFP trend growth in PBS is shown to have performed highly volatile in Germany over our sample period. In the following, we aim to study the effects of sectoral differences on aggregate trend GDP growth.

Table 2: Coefficient of Variation for Sectoral Trends in Labor Input and TFP

Sector	**Labor**		**TFP**	
	Germany	US	Germany	US
Agriculture	-0.5	-1.4	0.8	0.6
Mining	-0.6	9.3	0.9	13.7
Utilities	3.2	1.1	1.8	-3.6
Construction	-5.6	0.9	-4.3	-8.7
Durable Goods	-3.4	3.8	0.5	1.0
Non-Durable Goods	-0.6	15.6	0.4	2.2
Wholesale Trade	4.0	0.5	1.0	0.6
Retail Trade	0.9	0.7	1.4	1.3
Transp. & Wareh.	1.3	1.3	1.6	0.9
Inform. & Commun.	0.6	1.1	0.4	1.2
FIRE†	1.3	0.5	5.3	-26.7
PBS	0.4	0.4	20.7	3.7
Educ. & Health	0.3	0.2	-0.8	-3.5
Arts, Entert. & Accom.	0.3	0.5	-0.8	2.2
Misc.	0.6	2.6	-0.7	1.8

Notes: The table compares the coefficients of variation for sectoral trends in labor input and TFP across Germany and the US. FIRE includes housing in the German case, but not for the US (†). Furthermore, the time period under investigation for Germany runs from 1973 to 2019 and for the US from 1950 to 2018. A comparison of equal time periods across both states can be found in the Supplementary Material. The coefficients of variation for the US are calculated from Foerster *et al.* (2022). FIRE: Financial, Insurance & Real Estate; PBS: Professional & Business Services.

3.2 Common and Sector-specific Trend Components

Factor model. Although the trend variation across sectors highlights several sector-specific developments over the past decades, studying the trend variations closely also reveals time periods when sectoral trend movements did not significantly diverge. In addition, labor input and TFP trend growth appear to be (mostly negatively) correlated in sectors as, for example, PBS or Non-Durable Goods. To adequately capture these features, we apply the factor model from Foerster *et al.* (2022),

$$\begin{bmatrix} \Delta \ln l_{j,t} \\ \Delta \ln z_{j,t} \end{bmatrix} = \begin{bmatrix} \lambda_j^l & 0 \\ 0 & \lambda_j^z \end{bmatrix} \begin{bmatrix} f_t^l \\ f_t^z \end{bmatrix} + \begin{bmatrix} u_{j,t}^l \\ u_{j,t}^z \end{bmatrix}, \tag{1}$$

with which we aspire to separate the sector-specific disturbances $(u_{j,t}^l, u_{j,t}^z)$ as well as the unobserved factors (f_t^l, f_t^z) together with the factor loadings $(\lambda_j^l, \lambda_j^z)$ from observed labor input and TFP growth $(\Delta \ln l_{j,t}, \Delta \ln z_{j,t})$. Following Foerster *et al.* (2022), we apply a factor model representation in terms of the estimated low-frequency trends. This representation can then be estimated to uncover the common components $(g_{f,t}^l, g_{f,t}^z)$ and the sector-specific components $(g_{u,j,t}^l, g_{u,j,t}^z)$ from the labor input and TFP trend growth rates.

The term "common component" hereby denotes a broad development affecting all sectors, although possibly to varying degrees. To illustrate the characteristics of both components, consider again the case of labor input: Common factors here might—next to historic events—include changes in labor force participation among women and older generations or changes in the education level of the workforce. Sector-specific factors instead only affect the given sector, possibly including the shifting needs of worker characteristics and skills. For the TFP trends, common factors could materialize due to the introduction of general purpose technologies (GPT) such as computers or other ICT. A main advantage of the factor model is its representation to include lags of one or more decades. Thus, it captures the time delay needed for GPTs to affect productivity growth (Basu *et al.*, 2003). In the German case, Elstner *et al.* (2022) find pronounced TFP spillovers arising from the ICT producing industry that need time to materialize. The factor model—particularly the common factors—is suitable to detect such a form of technology diffusion. As argued previously, the trend extraction is based on $q = 6$ observations, thus, the estimation is a 'small sample' problem. We apply Bayesian methods for estimation. The prior for the factor loadings is chosen according to Foerster *et al.* (2022) who follow a normal distribution with mean one and a time-constant variance. The variance is scaled by the parameter η, which defines the loadings' degree of shrinkage against unity. In the discussion section, we elaborate more on the robustness of our results against changes to this prior.

Component decomposition. Table 3 summarizes the factor decomposition for labor input and TFP in Germany, together with a comparison to their US equivalents.[7] The fraction in trend variability that is described by common factors is marked by R_l^2 for labor input and R_z^2 for TFP, respectively. The correlation between sector-specific trends in labor input and TFP is labeled by $\rho(l, z)$; for the aggregate, this correlation represents the connection between the common trends of both inputs. What stands out is the similarity in aggregate trend growth explained by common factors across Germany and the US. Two-thirds of aggregate trend labor input growth (0.68) and one-third of aggregate trend TFP growth (0.30) can be explained by common trend movements.

Looking more closely at the sectoral level, we yet observe significant differences across industries and countries which are suppressed when looking at aggregates: We find that in Germany, particularly the service sectors' labor input trend growth rates are to a large extent explained by common factors (for example, $R_l^2 = 0.84$ for Arts, Entertainment & Accommodation). Again, this presents an illustration of the ongoing shift towards a service-oriented economy. While this pattern is also present in the US, it is considerably less pronounced compared to the German case (see, for example, the differences in trade or the remaining service sectors). On the opposite, labor input trend growth in the German secondary sec-

[7]The German trends apply to the period between 1973 and 2019 while the US trends are estimated for the time period between 1950 and 2018. Further, the German trends describe low-frequency movements for more than 15 years compared to more than 17 years in the US case. Comparisons with US trends estimated for a more comparable time period (1973 to 2018) and hence an almost identical frequency as the German ones reveal only small differences.

tor is driven by sector-specific rather than common movements. For the German Durable Goods sector, the common trend explains 9% of historical labor input trend growth. Another pronounced difference between the two countries is remarked by the extent of the common trend explaining labor input trend growth in the Construction sector. Turning to TFP, the industrial influence of common trends is rather low. However, we observe some exceptions, for example, Construction (40%) or the Non-Durable Goods sector (27%). For exactly those two sectors we also find remarkable differences to the US, where common trends do not seem to play any role at all (2% and 4%).

Table 3: Factor Decomposition of Trend Labor Input and TFP Growth

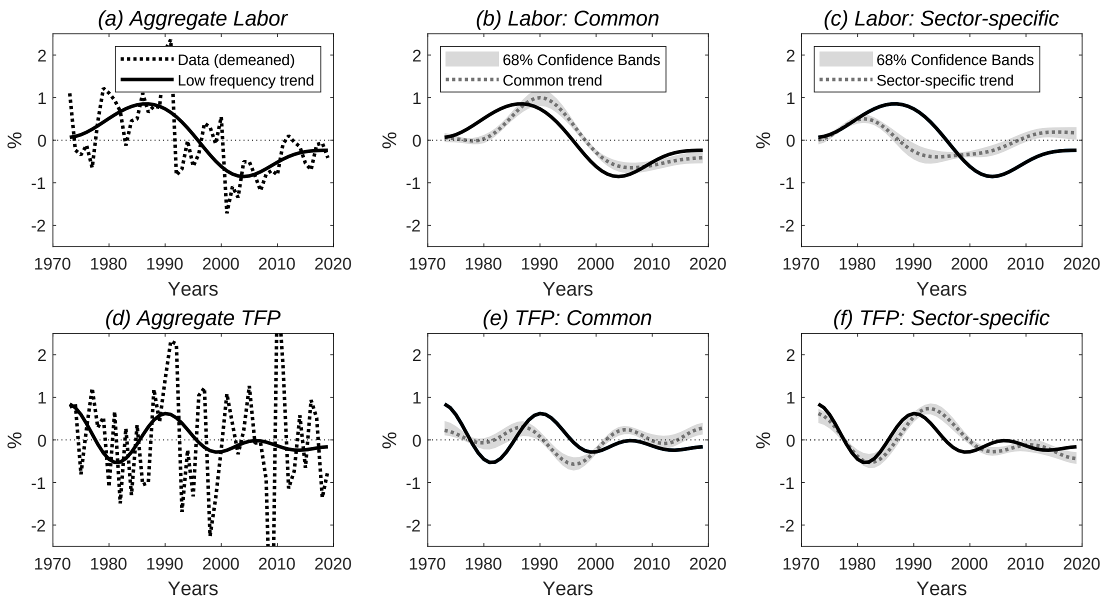
Sector	**Germany**			**US**		
	R_l^2	R_z^2	$\rho(l,z)$	R_l^2	R_z^2	$\rho(l,z)$
Agriculture	0.05	0.02	0.04	0.21	0.02	-0.32
Mining	0.03	0.05	-0.65	0.01	0.01	-0.35
Utilities	0.10	0.07	0.24	0.24	0.05	0.22
Construction	0.18	0.40	0.09	0.33	0.02	-0.25
Durable Goods	0.09	0.15	-0.73	0.03	0.03	-0.35
Non-Durable Goods	0.04	0.27	-0.66	0.06	0.04	-0.36
Wholesale Trade	0.88	0.02	-0.09	0.53	0.04	0.20
Retail Trade	0.94	0.21	-0.84	0.26	0.05	0.06
Transp. & Wareh.	0.13	0.06	-0.36	0.05	0.06	0.06
Inform. & Commun.	0.14	0.02	-0.18	0.22	0.03	-0.25
FIRE[†]	0.75	0.02	0.23	0.76	0.08	0.01
PBS	0.56	0.01	-0.88	0.64	0.06	-0.92
Educ. & Health	0.25	0.04	0.31	0.16	0.10	-0.63
Arts, Entert. & Accom.	0.84	0.03	-0.77	0.37	0.05	-0.18
Misc.	0.80	0.80	0.32	0.06	0.02	-0.07
Housing	–	–	–	0.01	0.10	0.07
Aggregate	0.68	0.30	-0.08	0.67	0.30	-0.29

Notes: The table presents the fraction in trend variation explained by common factors for both labor input (R_l^2) and TFP (R_z^2) as well as the correlation between sector-specific trends in labor and TFP, $\rho(l,z)$. For the aggregate, $\rho(l,z)$ corresponds to the correlation between common trends. FIRE includes housing in the German case, but not for the US (†). Furthermore, the time period under investigation for Germany runs from 1973 to 2019 and for the US from 1950 to 2018. A comparison of equal time periods reveals only small differences. The values for the US are extracted from Foerster *et al.* (2022). FIRE: Financial, Insurance & Real Estate; PBS: Professional & Business Services.

Moving on to the correlations between sector-specific labor input and TFP trend growth, we can partially confirm the pattern of negative connections as observed across the Atlantic. Overall, we find a slightly negative correlation between aggregate input factors for Germany (-0.08), however it is found to be more pronounced in the US (-0.29). Again, the heterogeneity across sectors and countries is remarkable. We find the largest negative correlations for PBS (-0.88) and Retail Trade (-0.84). The correlation between sector-specific labor input and TFP trend growth does not seem to hold true for US Retail Trade (0.06), although this pattern is observed for PBS in the US. Conversely, Construction shows a slightly positive correlation for Germany (0.09) and a negative one for the US (-0.25).

The previous figures are averages for the total sample. Given the degree in low-frequency variability over time, we proceed to analyze how strong the influence of common trends varied over the last five decades. For aggregate labor input and TFP, Figure 4 shows the low-frequency trends and their historical decomposition into common and sector-specific components. We observe—comparable to the US—that the aggregate labor input trend is well explained by common factors, peculiarly since the mid-2000s. Sector-specific movements continuously played a supporting role. The picture for TFP is not that unambiguous: Until the 1990s, its trend is well explained by sector-specific movements and supported by common factors. Between the mid-1990s and the new century, we observe a clear divergence of the sector-specific and the common trend. Since the beginning of the twenty-first century, the aggregate TFP trend appears to be dominated by the movement of common forces—increasingly so in the recent years.

Figure 4: Historical Decomposition of Aggregate Labor Input and TFP Trend Growth for Germany



Notes: Panels (a) and (d) show the raw labor input and TFP growth rates as deviations from their sample means (demeaned, dotted black lines), together with the estimated low-frequency trends (black lines). The other panels show the trends' decomposition into common and sector-specific components, separately shown as gray dotted lines. While the dotted lines denote the posterior median, the shaded areas are equally-tailed 68% credible intervals.

In comparison to the US, the low-frequency aggregate labor input trend has been catching up in Germany since the mid-2000s. Although the growth rates of the German labor input trend are still weak, they slightly exceed their current low-frequency counterpart in the US, which had also been catching up until the financial crisis but then worsened. Regarding TFP trend growth, it is worth noting that the US experienced a significant decline in the respective aggregate low-frequency trend during the 2000s, followed by a slow recovery after 2010. In contrast, the decrease of TFP trend growth in Germany evolved more gradually. German TFP trend growth rates expanded already in the 1990s, with rates only below average. In the two subsequent decades, German TFP trend growth has remained relatively stable. In both countries, the trend growth rate of TFP is increasing. When comparing similar periods and model specifications for both countries, it is observed that while labor is mostly determined by common movements, the role of sector-important factors in TFP has historically been more significant than common factors.

Going deeper, we proceed by analyzing the trend growth rates jointly with the sector-specific part of the trend for each of the sectors. In line with our results for the sectoral R^2 values from Table 3, we observe that sector-specific variation in TFP trends is, on average, less aligned with the total trend in Germany than this is the case in the US. Further, labor input trends are also in Germany more determined by common forces: Particularly for service-orientated sectors, the sector-specific trend behaves very different from the aggregate trend. A good example underlining the latter is Retail Trade. While the sector's overall trend is almost equal to the US one, its sector-specific component diverges considerably from the overall trend. Notably, in Germany the long-term labor input trends in the secondary sector of the economy, especially in Durables and Non-Durables, are even more explained by the respective sector-specific trends than in the US. In both countries, we observe a strict divergence of the sector-specific and the overall labor input trend after 2000 for FIRE and PBS. We further highlight that particularly in the sectors in which the labor input trends are well explained by sector-specific forces—which is the case for the industrial sector (Durables and Non-Durables)—TFP trend growth is mainly driven by common forces. In this context we again also point to the high negative correlation between the input factors in several sectors, such as in Durables and Non-Durables as well as in Wholesale Trade.

As explained by Foerster *et al.* (2022), we cannot trace a sectors' influence on the overall trend growth rate of GDP by simply comparing shares in value added or labor. Instead, aggregate importance depends on the type of goods or services supplied by the specific sector and its position in the inter-sectoral production network. Sectors acting as crucial suppliers for other sectors (for example, investment goods) can have a large influence on aggregate trends, even if their share in value added or labor is rather small. In the following, we discuss the production network of the German economy and quantify sectoral multipliers depending on the production linkages across sectors.

4 Production Linkages and Sectoral Multipliers

The differences in sectoral growth rates have implications for trend GDP growth. Sectors are highly interconnected due to production linkages and capital investments, which amplifies sector-specific growth for the aggregate. This implies that a change in, for example, the growth rate of TFP in Durable Goods does not only affect the sector's own value added growth but also the value added growth of other sectors through capital investment. Such amplification effects for aggregate growth can be quantified by sectoral multipliers composed of the direct effect (the sector's share in value added) as well as the indirect effect (the multiplier arising from the production network). The magnitude of the multiplier is governed by the importance of a given sector as a supplier of capital and/or material inputs. An extensive description of the derivation of the sectoral multipliers central to the following analysis of our quantitative findings can be found in Foerster *et al.* (2022). Referring the reader to the latter and its useful appendix for details, we limit the characterization of the multi-sectoral growth model to the essential mechanisms. We, however, closely describe the construction of a capital flow table for Germany, which is not available from official sources.

4.1 Theoretical Considerations

Multi-sector growth model. To adequately account for production linkages and their meaning for long-run growth dynamics, we adopt the multi-sector growth model from Foerster *et al.* (2022). The model is characterized by two sources of inter-sectoral connections: linkages via (i) material inputs and (ii) investment goods. Gross output of sector j at time t, $y_{j,t}$, is—according to standard national accounts identities—composed by gross value added, $\upsilon_{j,t}$, and aggregated materials used for production, $m_{j,t}$. Both inputs are used according to the following technology:

$$y_{j,t} = \left(\frac{\upsilon_{j,t}}{\gamma_j}\right)^{\gamma_j} \left(\frac{m_{j,t}}{1-\gamma_j}\right)^{(1-\gamma_j)}, \text{ with } \gamma_j \in [0,1]\,. \tag{2}$$

The aggregate material input of each sector captures material purchased by sector j from all sectors n representing the economy (including its own intra-sectoral linkages). The technology behind the material aggregate is given by:

$$m_{j,t} = \prod_{i=1}^{n} \left(\frac{m_{ij,t}}{\phi_{ij}}\right)^{\phi_{ij}}, \text{ with } \sum_{i=1}^{n} \phi_{ij} = 1 \text{ and } \phi_{ij} \geq 0\,. \tag{3}$$

Material linkages across sectors are captured by a standard $n \times n$ Input-Output (IO) matrix, Φ, with ϕ_{ij} being the typical output coefficient. We introduce the German IO data in Section 4.2.

Sectoral gross value added, $\upsilon_{j,t}$, is produced with labor input, $l_{j,t}$, and capital, $k_{j,t}$, following a Cobb-Douglas-type production function of the form:

$$\upsilon_{j,t} = z_{j,t} \left(\frac{k_{j,t}}{\alpha_j}\right)^{\alpha_j} \left(\frac{l_{j,t}}{1-\alpha_j}\right)^{(1-\alpha_j)}, \text{ with } \alpha_j \in [0,1]\,. \tag{4}$$

Capital accumulation is captured by the standard Perpetual Inventory Method: Tomorrow's capital stock, $k_{j,t+1}$, equals the sum of today's capital stock after depreciation, $(1-\delta_j)k_{j,t}$, and today's investment in new capital, $x_{j,t}$. With $x_{ij,t}$ denoting the quantity of investment or capital goods from sector i, the investment aggregate mirrors the technology of the material aggregate:

$$x_{j,t} = \prod_{i=1}^{n} \left(\frac{x_{ij,t}}{\omega_{ij}} \right)^{\omega_{ij}}, \text{ with } \sum_{i=1}^{n} \omega_{ij} = 1 \text{ and } \omega_{ij} \geq 0 \,. \tag{5}$$

Capital goods originating in external sectors can be of central importance for a sector's production. Hence, in addition to materials, capital embodies a second source of intersectoral linkages. As it has been demonstrated by vom Lehn and Winberry (2022), capital linkages across sectors constitute a main mechanism of business cycle movement propagation in the US. This idea is adopted and transferred to long-run dynamics in Foerster *et al.* (2022). The capital linkages are captured in the $n \times n$ capital flow matrix, Ω, with ω_{ij} referring to the coefficient capturing each sector's importance as capital good supplier. We again refer to Section 4.2, where we present new data to approximate the German capital flow matrix.

Market clearing takes place under the resource constraint $y_{j,t} = c_{j,t} + \sum_{i=1}^{n} m_{ji,t} + \sum_{i=1}^{n} x_{ji,t}$ with $c_{j,t}$ denoting the quantity of a representative household's consumption expenditure for a good produced in sector j. The household's aggregate consumption bundle is defined as $C_t = \prod_{j=1}^{n} \left(\frac{c_{j,t}}{\theta_j} \right)^{\theta_j}$. Sectoral labor input and TFP are assumed to be exogenous, thus, we can reformulate gross value added as $\upsilon_{j,t} = A_{j,t} \left(k_{j,t}/\alpha_j \right)^{\alpha_j}$, where $A_{j,t} = z_{j,t} \left(l_{j,t}/(1-\alpha_j) \right)^{(1-\alpha_j)}$ represents a composite variable capturing both inputs. Sectoral change is approximated by the development of this composite variable over time:

$$\Delta \ln A_{j,t} = \Delta \ln z_{j,t} + (1-\alpha_j) \Delta \ln l_{j,t} \,. \tag{6}$$

Using the theoretical foundations laid out above to account for sectoral linkages, we proceed by examining how the sectoral changes in labor input and TFP observed in Section 3 have impacted German aggregate trend GDP growth. Here, it is important to remember that a change in one sector does not only affect that sector's contribution to aggregate growth but via its position in the production network also the output of all remaining sectors.

Balanced growth path and sectoral multipliers. We now derive the steady-state behavior of the economy's variables. Along a balanced growth path (BGP), labor input and TFP grow with constant and exogenous rates, g_j^l and g_j^z, respectively. According to Equation (6), the composite variable, $A_{j,t}$, therefore evolves according to:

$$\Delta \ln A_{j,t} = g_j^a = g_j^z + (1-\alpha_j) g_j^l \,. \tag{7}$$

As suggested before, changes in a sectoral input growth rate of labor input or TFP result not only in output changes in the respective sector: Due to the production network a change in one sector indirectly also influences value added in other sectors. Depending on its importance as material or investment goods supplier to others, a sector's multiplier can further exceed its share in value added.

To pin down the sectoral multipliers, we need to focus on the development of the economic variables along the BGP. Given the exogenous growth rates for labor input and TFP, sectoral gross output, $y_{j,t}$, and its usages ($c_{j,t}, m_{ji,t},$ and $x_{ji,t}$) will grow by the same sector-specific rate defined as g_j^y. According to Equation (3), sectoral material input growth then reads as $g_j^m = \sum_i \phi_{ij} g_i^y$, such that $g^m = \Phi' g^y$ holds. For sectoral capital accumulation and investment a similar outcome emerges: $g_j^k = g_j^x = \sum_i \omega_{ij} g_i^y$ and $g^k = \Omega' g^y$. The gross output rate—according to Equation (2) with $\Gamma_d = diag\{\gamma_j\}$—has the following form: $g^y = \Gamma_d g^v + (I - \Gamma_d) g^m$, with gross value added evolving as $g^v = g^a + \alpha_d g^k$ and $\alpha_d = diag\{\alpha_j\}$. Reducing all terms to gross output yields $g^y = \Gamma_d g^a + \Gamma_d \alpha_d \Omega' g^y + (I - \Gamma_d) \Phi' g^y$, hence gross output can be expressed in the compact form:

$$g^y = \Xi' g^a \,. \tag{8}$$

In this equation, $\Xi' = \left[I - \Gamma_d \alpha_d \Omega' - (I - \Gamma_d)\Phi'\right]^{-1} \Gamma_d$ represents what Foerster *et al.* (2022) call the "generalized Leontieff inverse" capturing both material and capital linkages. Finally, gross value added growth, g^v, can be expressed as:

$$g^v = g^a + \alpha_d g^k = g^a + \alpha_d \Omega' g^y = g^a + \alpha_d \Omega' \Xi' g^a = \left[I + \alpha_d \Omega' \Xi'\right] g^a \,. \tag{9}$$

The value added expression is divided into a direct and an indirect effect. The first term, Ig^a, denotes the direct effect and it entails how sectoral gross value added is affected by own changes in labor input and TFP. The indirect effect is given by the second term, $\alpha_d \Omega' \Xi' g^a$, which captures all network effects within the economy, stemming either from material or capital linkages.

As a last step, we want to quantify the influence of the sectoral linkages on total GDP growth. To do so, we rely on the Divisia index for GDP, which is according to accounting standards simply given by the product of sectoral gross value added, g^v, and constant sectoral shares in GDP, s^v:

$$g^V = s^{v'} g^v = s^{v'} \left[I + \alpha_d \Omega' \Xi'\right] g^a \,. \tag{10}$$

As in Foerster *et al.* (2022), the vector of *sectoral multiplier* is the first derivation of g^V with respect to the composite variable g^a: $\partial g^V / \partial g^a = s^v + \Xi \Omega \alpha_d s^v$. Thus, a sectoral change in the composite variable *directly* effects GDP growth by a sector's value added share and *indirectly* via production linkages across the economy.

4.2 German Production Network

Data source. The data underlying our estimated sectoral multipliers stem from both official (material linkages) and non-official (capital flows) sources. Material linkages are extracted from the IO tables provided by the Federal Statistical Office of Germany. Tables for unified Germany are currently available for the years 1991 to 2020. For the baseline estimation, the results of which are compared to those of Foerster *et al.* (2022), we apply the IO coefficients of 2018, $\left\{\phi_{ij}^{2018}\right\}$. They entail the share of materials flowing from sector j to sector i for production and can easily be extracted from the IO table published by official sources. The German IO tables also capture data on gross output and labor compensation. For consistency reasons, we hence use this information to calculate both the sectoral value added share in total sectoral expenditures (γ_j) and the sectoral labor income share ($1-\alpha_j$). The value added shares to calculate the sectoral multiplier for GDP growth, s^v, are extracted from national accounts.

Quantifying the German investment network and the corresponding coefficients, $\{\omega_{ij}\}$, is challenging, as—to the best of our knowledge—no capital flow table is published by the Federal Statistical Office of Germany. We therefore combine two non-official sources to estimate the first German capital flow matrix: the ifo Investment Database and the INTAN-Invest Database. The ifo Investment Database (IIDB) provides annual investment data for 12 investment assets in 50 German sectors from 1991 to 2018; the data can be accessed via the LMU-ifo Economics & Business Data Center (IIDB, 2018). A detailed description of the IIDB can be found in Strobel *et al.* (2013). It is consistent with national accounts' investment figures published by the Federal Statistical Office of Germany and provides estimates of the volume that companies in a certain sector invest in the respective investment assets. To comply with the 15 sectors defined earlier to constitute the German private-sector economy, we aggregate the IIDB sectors to match them accordingly. Further, except for intangible assets, we assign the investment assets to their corresponding sectors, namely Durables, Construction, and the Information & Communication sector.

An issue arising from the category of intangible assets is that we are not able to deduct from the IIDB in which sector the investment good has been produced. We solve this issue by relying on the INTAN-Invest Database, a research collaboration dedicated to improve the measurement and analysis of intangible assets. It provides data on intangible investment by sector beginning in 1995 and allows us to distribute a sector's intangible capital expenditures onto sectors producing intangible assets. We use data from the latest release, covering the years up to 2018. Again using the INTAN-Invest data, we first aggregate sectors to obtain data on intangible asset investment and production for the 15 sectors previously defined. The database allows us to differentiate intangible assets into 10 subcategories, which we assign to sectors producing that type of intangible capital. An initial analysis of the data reveals that intangible investment has doubled in Information & Communication and the Durables sectors over the past thirty years, and even tripled in the case of PBS.

We end up with time-varying IO coefficients for the years 1991 to 2020 and capital flow matrices between 1995 and 2018. Particularly the latter is an additional source of information compared to Foerster *et al.* (2022), who can only rely on a capital flow table for 1997. Our year-specific capital tables allow us to deepen the analysis of German sectoral multipliers by observing dynamic developments following significant changes within the German production network. Before discussing those dynamics in Section 5, we first compare our baseline results to Foerster *et al.* (2022) by fixing the coefficients to the year 2018 in the baseline case.

Investment network. Panel (a) of Figure 5 shows the German investment network for the year 2018. It highlights the importance of the German Construction sector as an investment good supplier to the German economy: On average, all sectors receive the largest share of their capital goods from Construction, which is indicated by the size of its node. Compared to the 1997 investment network of the US in panel (b), the Durable Goods sector is only the second largest capital hub in the German economy. Overall, as in the US, the production of investment goods in Germany is concentrated in relatively few sectors. Furthermore, a significant fraction of intangible capital is developed in firms directly and hence used by the producing sector itself. This is indicated by the circles surrounding the nodes. The circle for the German Durable Goods sector is much thicker than its US counterpart, which we explain by the high specialization of German manufacturing in automotive production. Vehicles are used by most other (manufacturing) sectors as investment goods. Interesting is the significant role of the Information & Communication sector, which also produces a lot of intangible capital that it then uses itself. Further, the edge between Construction and FIRE stands out, which can traced back to the housing sector. We also observe a similar linkage between Construction and housing in the US.

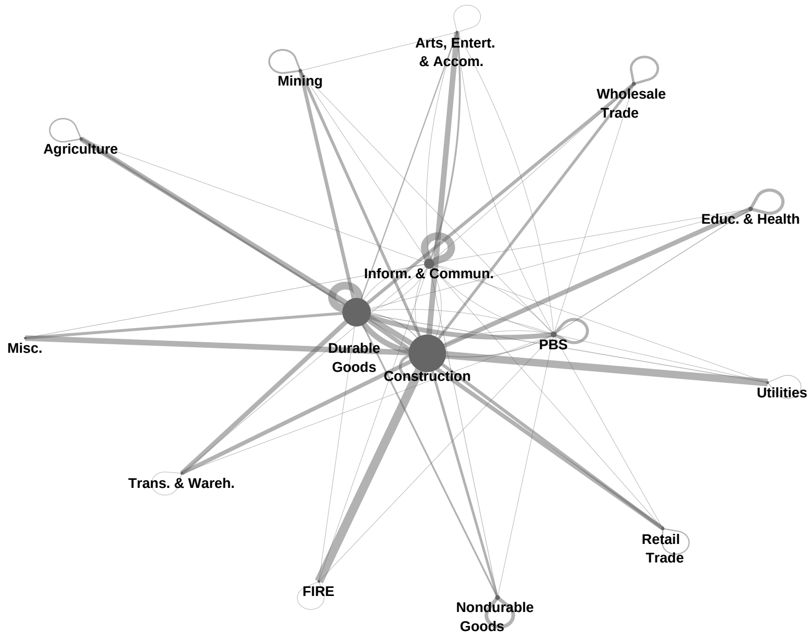
4.3 Sectoral Multipliers

As mentioned before, for our baseline setup we fix the year 2018 as a representative for both the IO and the capital matrix. This allows us to compare the sectoral multipliers for Germany with those of the US as found by Foerster *et al.* (2022). To be more precise: we apply constant matrices for the year 2018 and constant mean value added shares over the entire sample period. In case of the US, the IO table applied is from 2015 and the capital flow matrix from 1997; the value added shares are, as in our case, average shares over the entire sample period. Table 4 compares resulting sectoral multipliers for TFP.[8] Overall, we observe three main sectoral differences between both economies. First, and probably the most pronounced difference, is that the German Construction sector reveals to have a much larger multiplier (0.26) than the US Construction sector (0.17). This is mainly driven by the indirect effects (0.20 vs. 0.12), that is, the sector's importance as capital goods supplier within the economy. The multiplier for Construction is four (three) times higher than its value added share in Germany (the US) and therefore heavily influences overall trend GDP growth, given the negative trend rates in labor input and TFP growth from Figure 3.

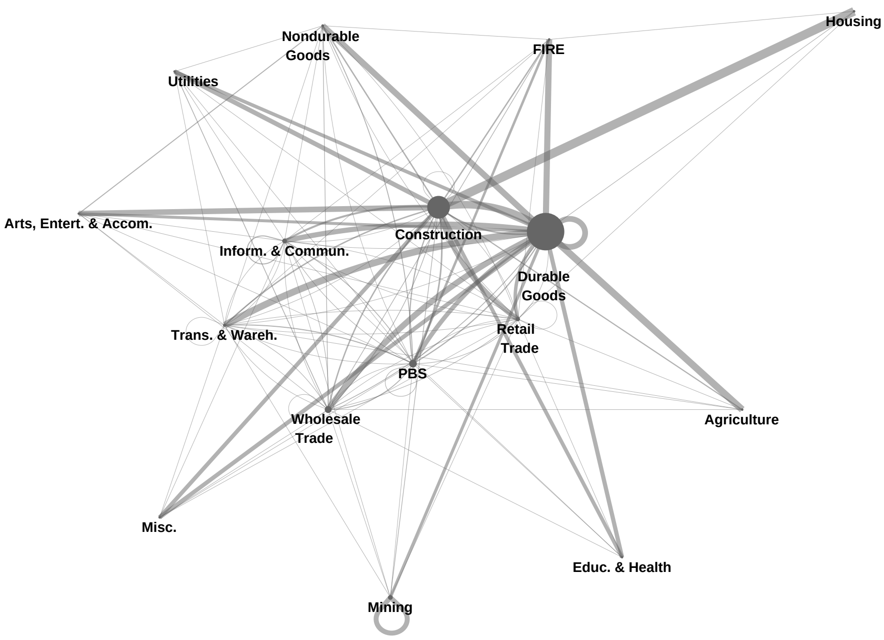
[8]The Supplementary Material holds the comparison of the sectoral multipliers for labor input.

Figure 5: Investment Networks for Germany and the United States

(a) German Investment Network 2018



(b) US Investment Network 1997



Notes: The figures show the investment networks for both the German and the US economy based on its corresponding capital flow matrix. Nodes represent sectors and edges express the strength of capital flows between sectors. The larger a node is, the more important is a sector as capital producer for other sectors. The thickness of an edge marks the strength of bi-directional capital flows between or within sectors compared to all other sectors. The US values are taken from Foerster *et al.* (2022). FIRE: Financial, Insurance & Real Estate; PBS: Professional & Business Services.

Second, the Durable Goods sector exhibits a sectoral multiplier that is almost equal for both economies. However, the composition varies heavily. Whereas the sector's value added share is—with almost one fifth—higher in Germany than in the US, the opposite holds true for the indirect effect. This might be an expression for the heterogeneity in the economies' specialization. The Durable Goods' multipliers exceed two (Germany) to three (US) times their value added share in total GDP. Overall, the Durable Goods sector has positive effects on German trend GDP growth as we have observed positive but diminishing rates in TFP.

Table 4: Sectoral TFP Multipliers for Germany and the United States

Sector	**Germany**			**United States**		
	direct	indirect	total	direct	indirect	total
Agriculture	0.02	0.01	0.02	0.03	0.01	0.03
Mining	0.01	0.01	0.02	0.02	0.03	0.05
Utilities	0.03	0.01	0.04	0.02	0.01	0.03
Construction	0.06	0.20	0.26	0.05	0.12	0.17
Durable Goods	0.19	0.21	0.40	0.13	0.28	0.41
Non-Durable Goods	0.09	0.03	0.12	0.09	0.03	0.13
Wholesale Trade	0.05	0.05	0.09	0.07	0.08	0.15
Retail Trade	0.06	0.01	0.07	0.08	0.02	0.10
Transp. & Wareh.	0.05	0.02	0.07	0.04	0.03	0.07
Inform & Commun.	0.04	0.04	0.08	0.05	0.03	0.08
FIRE†	0.15	0.06	0.20	0.10	0.04	0.14
PBS	0.09	0.09	0.19	0.09	0.15	0.24
Educ. & Health	0.11	0.01	0.11	0.06	0.00	0.06
Arts, Entert. & Accom.	0.03	0.01	0.03	0.04	0.01	0.04
Misc.	0.03	0.00	0.03	0.03	0.01	0.04
Housing	–	–	–	0.09	0.00	0.09

Notes: The table presents the sectoral TFP multipliers for Germany and the United States. The direct effect equals the sectors' value added shares (s^v). The indirect effect captures both the sector's importance as material supplier in the IO environment and as capital goods supplier in the investment network ($\Xi\Omega\alpha_d s^v$). For Germany, both the IO table and the capital flow matrix from the year 2018 are applied. In case of the US, the IO table is from 2015 and the capital flow matrix from 1997. FIRE includes housing in the German case, but not for the US (†). Furthermore, the time period under investigation for Germany runs from 1973 to 2019 and for the US from 1950 to 2018. The values for the US are extracted from Foerster *et al.* (2022). FIRE: Financial, Insurance & Real Estate; PBS: Professional & Business Services.

Third, the influence of PBS is much more pronounced in the US. Especially the indirect effect of the sectoral multiplier is higher. This might again indicate that the structural change of the German economy towards a service-oriented one is still ongoing whereas it has already further progressed and is almost completed in the US economy. Still, the multiplier for German PBS is two times higher than its overall value added share. According to Figure 3, PBS should hence also have contributed positively to trend GDP growth.

We find further minor differences. The multipliers for Mining and Wholesale Trade are higher in the US. Underlying the former might be the diminishing importance of mining activities especially in the German Ruhr and Lausitz area where numerous mines have been closed during the last decades. Today, Germany imports the majority of its required raw materials (for example, natural gas and rare-earth metals). The US, instead, is the second largest producer of rare-earth metals after China and also an exporter of many other raw materials. Furthermore, the multiplier for the German Education & Health sector is twice as high as in the US, which is mainly driven by the raw value added share. Internationally compared, the German health sector is rather large in size. This is attributable to a high density of both doctors and hospital beds as well as the demographics of the German population. Given the negative employment trend growth in Education & Health since the turn of the millennium, this sector has most likely contributed negatively to trend GDP growth over the last decades.

4.4 Contributions to Trend GDP Growth

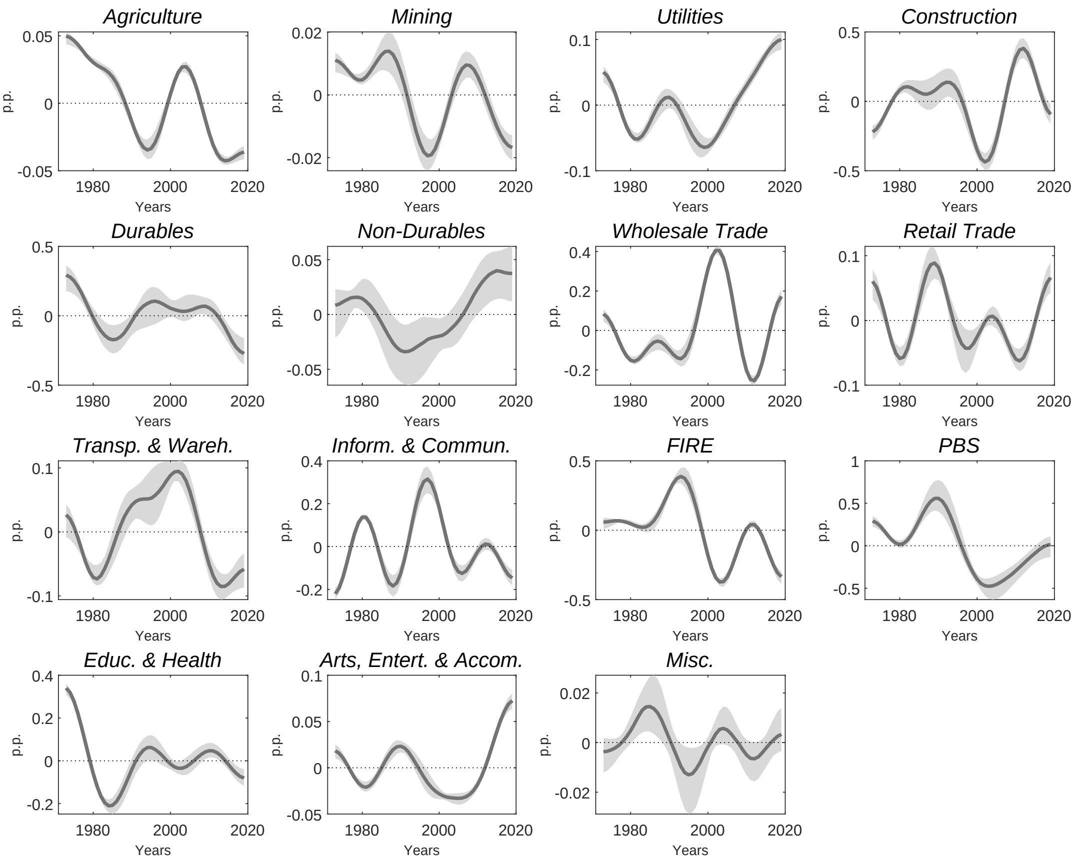
Having estimated the common and sector-specific trend components and derived the sectoral multipliers, we continue by combining the two. Bringing together trend components and multipliers allows us to calculate a decomposition of trend GDP growth by means of sectoral trend labor input and TFP growth. Recall that along the BGP value added growth evolves as: $g^v = [I + \alpha_d \Omega' \Xi'] \, g^a$. As we are exclusively interested in long-run movements, we approximate them by our sectoral trend estimates for labor input ($g^l_{j,t}$) and TFP growth ($g^z_{j,t}$). Value added can hence be expressed as: $g^v_t = [I + \alpha_d \Omega' \Xi'] \left(g^z_t + (I - \alpha_d) g^l_t \right)$. Our aim is to quantify the contribution of both common factors and sector-specific developments to the long-run movements. To do so, we restate sectoral value added using the factor model introduced in Section 3.2 as:

$$g^v_t = [I + \alpha_d \Omega' \Xi'] \left(\lambda^z g^z_{f,t} + g^z_{u,t} + (I - \alpha_d) \left(\lambda^l g^l_{f,t} + g^l_{u,t} \right) \right) . \tag{11}$$

The BGP of value added is characterized by the common components in labor input and TFP growth ($g^l_{f,t}, g^z_{f,t}$), the vectors of factor loadings (λ^l, λ^z), and the sector-specific components ($g^l_{u,t}, g^z_{u,t}$). Model-implied GDP growth can then be written as: $g^V_t = s^{v\prime} g^v_t$. We first show the sector-specific components, followed by a discussion on average sectoral contributions for two sample periods. Third, we present model-implied trend GDP growth. Finally, we discuss the decomposition of trend GDP growth by means of common factors and sector-specific developments. All following results are based on constant multipliers from the year 2018. The impact of time-varying multipliers is discussed in Section 5.

Figure 6 shows the year-by-year sector-specific trend contributions to aggregate GDP growth. In short, it shows the combination of labor input and TFP trend growth according to the respective sectoral multipliers. Obviously, no sector steadily contributed with a positive or negative sign to trend GDP growth. However, there is a tendency towards negative contributions of Durables, FIRE, PBS, and Education & Health. Rather positive contributions can be observed for Non-Durables, Information & Communication, Utilities, Wholesale, and Construction. Given the sectoral value added shares, the heterogeneity in the contributions' magnitude is very interesting. Small sectors such as Construction, Wholesale Trade and Information & Communication contributed in a similar way to trend GDP growth—expressed by the y-axes' magnitudes—as large sectors. Further, although we have referred to the ongoing structural shift in the German economy, we do not observe major positive contributions of the service sectors to trend GDP growth.

Figure 6: Sector-Specific Contributions to Trend Growth in GDP



Notes: Each panel shows the contributions (in percentage points) of sector-specific trends for trend GDP growth using the model-implied multipliers along the balanced growth path. The solid lines denote the posterior median and the shaded areas are equally-tailed 68% credible intervals. FIRE: Financial, Insurance & Real Estate; PBS: Professional & Business Services.

In the next step, we evaluate how much the sectors contribute to the change in trend GDP growth between 1973 and 2019. German trend GDP growth decreased by 2.1 percentage points in the last five decades. The Durables sector is responsible for the largest negative contribution of 0.72 percentage points due to the decline in trend TFP growth (see Table 5). Another -0.30 percentage points stem from the negative TFP development in FIRE and PBS. Also the TFP decline in Education & Health contributed negatively (-0.19 percentage points) to the decline in total trend GDP growth between 1973 and 2019; a negative contribution of trend labor input (-0.27 percentage points) further increases the overall negative impact of Education & Health. Remarkable positive contributions only stem from increases in labor input. The negative TFP effect observed for Durables is, on average, reduced by a positive contribution of labor input growth (0.25 percentage points). The same holds true for the sector Information & Communication with a positive contribution in trend labor input growth of 0.13 percentage points.

Table 5: Sectoral Contributions to the Decline in German Trend GDP Growth

Sector	**1973–2019**		**1991–2000**	
	Labor	TFP	Labor	TFP
Agriculture	0.01	-0.10	0.01	0.02
Mining	-0.01	-0.02	0.00	0.03
Utilities	-0.01	0.05	-0.05	-0.05
Construction	0.05	0.01	-0.63	-0.14
Durable Goods	0.25	-0.72	0.01	0.15
Non-Durable Goods	0.06	-0.02	0.02	-0.02
Wholesale Trade	-0.03	0.08	-0.16	0.44
Retail Trade	-0.04	0.01	-0.08	-0.13
Transp. & Wareh.	0.01	-0.11	-0.07	0.05
Inform. & Commun.	0.13	-0.08	0.07	0.11
FIRE†	-0.10	-0.31	-0.10	-0.51
PBS	-0.20	-0.29	-0.11	-1.40
Educ. & Health	-0.27	-0.19	-0.15	0.00
Arts, Entert. & Accom.	-0.02	0.06	-0.04	-0.07
Misc.	-0.01	0.01	-0.02	-0.01

Notes: The table shows the sector-specific contributions (in percentage points) of trend labor input and TFP growth to the decline of trend GDP growth for two separate time periods. The calculation of contributions are based on constant sectoral multipliers for the year 2018. FIRE includes housing (†). FIRE: Financial, Insurance & Real Estate; PBS: Professional & Business Services.

The decade following reunification marks a special period for Germany. Trend GDP growth faced a strong decline in the 1990s (-1.7 percentage points), which is especially characterized by a far-reaching transformation of the Construction sector. In the following, we zoom into this period. Table 5 lists both the labor input and TFP contributions of all sectors to that decline. What stands out is the large impact from PBS: With a contribution of -1.40 percentage points from its decline in TFP growth, it accounts for more than half of the decline in German trend GDP growth over that decade. FIRE added another half percentage point to the 1990s decline. Notably is further the impact of the decline in labor input in the Construction sector (-0.63 percentage points). Between 1991 and 2000, only the Durables and the Wholesale Trade sector acted as stabilizers: Their individual TFP trend growth as well as their importance in the production network resulted in the two sectors contributing positively to aggregate GDP trend growth. While the differences resulting from the multipliers used in the model—baseline year 2018 or the average multiplier over the decade—are small overall, they are pronounced for the impact of the Construction sector's labor trend growth. Its negative contribution to the overall decline is significantly higher using the average multipliers, which indicates the decline of the sector's importance as capital and materials provider over the decades. The opposite is true for PBS: Using the average multiplier results in a smaller contribution than applying the baseline multiplier.

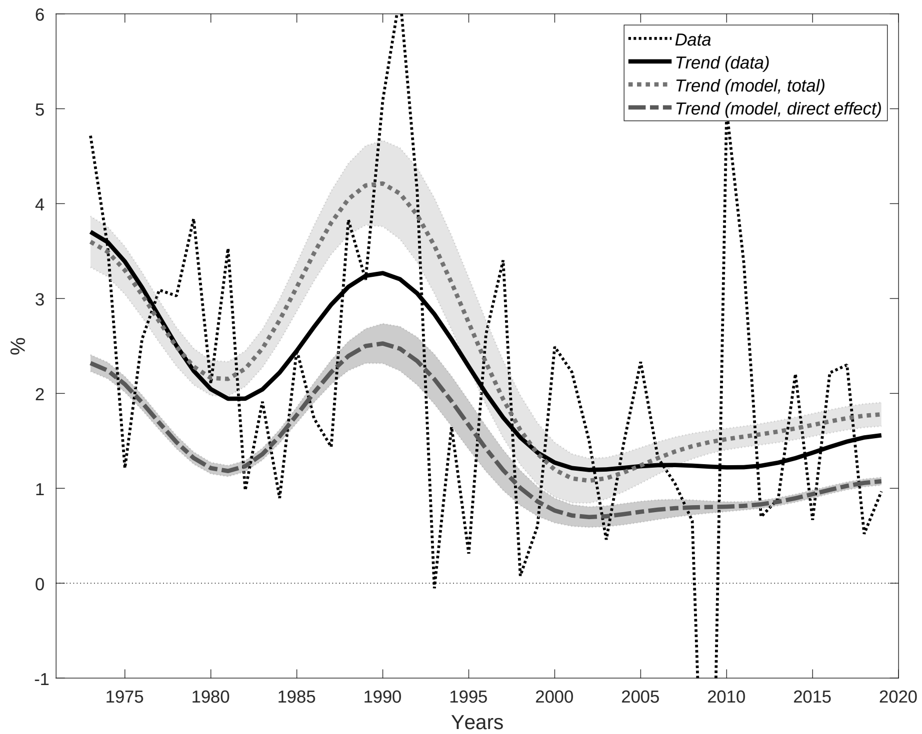
This might hence indicate that the importance of PBS as an investment good supplier has grown over the years. Using specific annual multipliers therefore seems to be of overall importance, particularly when focusing on a specific time period. We discuss this issue in the next section.

Figure 7 compares the low-frequency movement in German GDP growth (black line), calculated in Section 3, with the trend implied from the balanced growth multipliers (dotted gray line) and the direct effect's contribution to the trend (dashed gray line), which is based on the sectoral value added shares. The bands around both model-implied trend components mark the estimations' standard deviations resulting from time-varying IO as well as capital matrices and value added shares. As the total multipliers' bands are significantly more pronounced, we suspect the additional indirect effects stemming from sectoral inter-linkages to be the major contributor to the variation in the total multipliers over the years. Overall, long-term GDP trend growth declined by about 2 percentage points over the entire period. The significant difference between the trend estimated using the direct multiplier and the trend calculated using the BGP multiplier highlights the importance of considering inter-sectoral linkages to avoid underestimating the long-term trend growth rate. Our model including indirect effects tends to estimate higher trend growth rates than the ones retrieved directly from the data in the period around reunification. We suggest that a periodicity of 15 years might not perfectly grab the special dynamics in capital accumulation and the renewal of the Eastern German capital stock in the 1990s. Similarly, accounting for network effects results in slightly higher long-term GDP growth rates from 2005 onwards. If we apply time-varying weights and thus account for structural change over the years, the model-implied trend growth rate comes even closer to the estimated low-frequency movement.

Finally, we discuss the decomposition of the model-implied trend GDP growth rate into its components derived from common factors and sector-specific developments (see Figure 8). The model indicates that sector-specific or unique factors in trend labor input and TFP growth have historically accounted for roughly 1/2 of the long-run changes in German trend GDP growth. Hence, the remaining half of the variation of trend GDP growth since 1973 has been arising from common factors of input growth. Panel (c) shows the posterior for the fraction of the variance explained by common factors. This finding contrasts with the information of common factors explaining roughly 2/3 of the variation in the trend growth rate of total labor input, as presented in Section 3. The primary reason behind is that sectors with high multipliers, such as Construction or PBS, experience significant variation in trend growth over the period. These trends are almost exclusively driven by idiosyncratic factors.

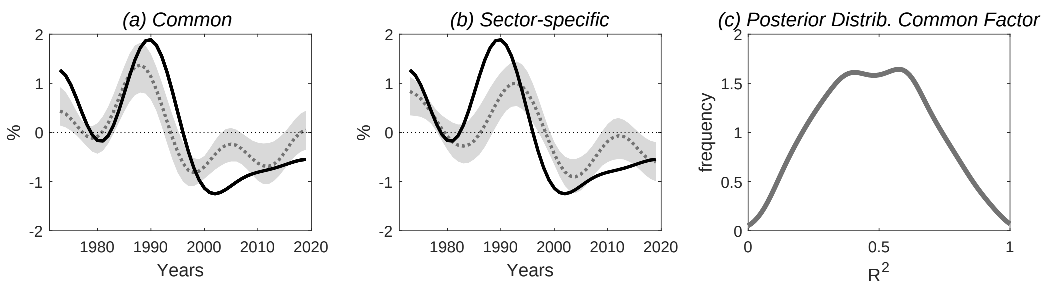
Our results for Germany are quite different to the finding of Foerster *et al.* (2022) which states that 3/4 of US trend variation is explained by sector-specific developments. We suggest that German trend variation being explained to a significantly larger extent by common forces can be attributed to the delayed structural change of the German economy, as well as the overall impact of reunification. From a historical perspective, we note that the common factor can almost entirely explain the rise of German trend GDP growth over the 1980s. Further, the slowdown of German trend GDP growth since the mid-1990s is driven by two opposite forces: While sector-specific developments contributed positively to aggregate trend GDP growth until the turn of the century, common factors have been driving the decline. For the subsequent decades, we observe that the contributions by common factors and sector-specific developments have been moving in opposite directions. In the next section, we elaborate more on the robustness of these results.

Figure 7: Estimated and Model-implied Trend Growth in GDP



Notes: The figure shows the cyclically adjusted GDP growth rate (thin dotted black line) and its estimated low-frequency trend (thick black line). The dotted gray line marks the model-implied trend growth rate along the balanced growth path. The dashed gray line, instead, presents the trend growth rate based on the value added shares, or direct effects, only. These lines represent the baseline case and are calculated from the 2018 IO as well as capital flow matrices and constant value added shares, respectively. The shaded areas mark the one standard deviation bands from estimates based on either time-varying IO and capital flow matrices or non-constant value added shares.

Figure 8: Decomposition of Trend Growth in GDP



Notes: Panels (a) and (b) show the demeaned model-implied trend GDP growth (black line) together with the changes stemming from common factors and sector-specific developments (gray lines), respectively. Panel (c) shows the posterior distribution for the fraction of the total variance explained by common factors.

5 Discussion

In this section, we present the outcome of a bunch of robustness checks that underpin our baseline results. We will only briefly describe the outcomes of these checks and refer the reader to the Supplementary Material for more details. Furthermore, we discuss the impact of structural change on the sectoral multipliers as our new data sources allow for time-varying analyses. The section closes with some implications of our results for future German trend GDP growth, which is heavily influenced by changing demographic conditions.

5.1 Robustness Checks

Cyclical adjustment. The extraction of a time series' low-frequency movements might depend on the cleaning step beforehand, switching off business cycle dynamics in the data. Instead of applying an Okun's Law-relationship by linking sectoral outcomes to leads and lags of the unemployment rate, we cyclically adjust our data by the ifo Business Climate. The latter counts as one of the most important business cycle indicators for the German economy. Overall, the application of the ifo Business Climate confirms our baseline findings, albeit exhibiting some minor differences in the magnitudes. We interpret the results obtained from the unemployment rate-adjusted data as the upper bound and the results obtained from the ifo Business Climate-adjusted data as the lower bound of estimates. The unemployment rate might capture not all business cycle-related dynamics as Germany has underwent some huge labor market reforms and its labor market is much more regulated compared with the US. The ifo Business Climate, on the opposite, might account for too much business cycle variation as cyclical signals vary across sectors.

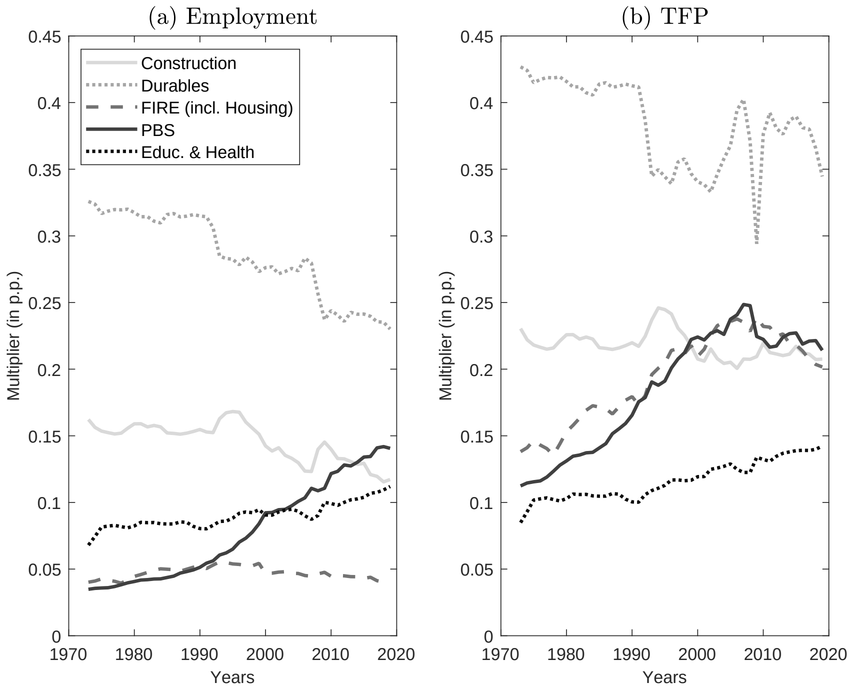
Parameter and prior. In the following, we discuss the sensitivity of our baseline results with respect to the crucial parameter defining the length of long-term movements (q) and the prior on the strength of the factor loading's shrinkage towards unity (η). We set $q = 6$ and $\eta = 1$ in the baseline case. For the robustness checks, we assume q to take values $q = 5$ and $q = 7$, which corresponds to long-run movements longer than 13.4 or 18.8 years, respectively. Furthermore we vary the degree of shrinkage with η taking values of $\eta = 0.5$ and $\eta = 2$. The former value tightens the constraint of shrinkage and the latter one loosens it. Our baseline results are again very robust to various parameter and prior combinations. Furthermore, we observe an even better fit of the multi-sector growth model-implied trend rate to the extracted low-frequency movement.

Aggregation weights. The aggregation to private-sector GDP might crucially depend on the sectoral weights applied. In the baseline case, we use mean weights over the entire sample for each sector. As robustness check we apply chain-weighting instead, which is in line with current standards in national accounting. Again, our baseline results do not change.

5.2 Structural Change in the German Economy

Over the last decades, we observed a large increase in the service sector's share in total German gross value added. This structural change is also reflected in the smoothed labor input and TFP growth patterns from Figure 2, for which we apply different sectoral weights to calculate the aggregates. Below, we examine how time-varying sectoral multipliers affect our baseline evaluation. In contrast to Foerster *et al.* (2022), we note large differences in the German sectoral multipliers depending on which capital matrices and IO tables we use. The evolution of the sectoral multipliers in labor input and TFP over our estimation period is depicted in Figure 9 for the five sectors with the overall largest multipliers. Both figures show the value of the respective sectoral multipliers for each year, given annual capital flow tables, IO tables and shares in value added.[9]

Figure 9: Evolution of Sectoral Multipliers



Notes: The figure shows the timely evolution of the sectoral multipliers, constructed from the overall sectoral multiplier of the composite variable g^a: $s^v + \Xi\Omega\alpha_d s^v$. FIRE: Financial, Insurance & Real Estate; PBS: Professional & Business Services.

For both input factors we observe ambivalent trends in the multipliers' evolution. Examining panel (a) of Figure 9, we note three interesting facts in the evolution of the sectoral labor multipliers. First, the labor multiplier for the Durables sector—the largest multiplier across all sectors—declines over the entire period and significantly dropped from around 0.33 at the start of our sample to 0.24 in 2019. Overall, this decline is mainly driven by a drop in the direct effect of the multiplier, but gets also amplified by a decline in the indirect effect at the end of the sample. Second, the labor multiplier for the Construction sector

[9] All variation in the multipliers before 1991 results uniquely from the sectoral shares in value added.

significantly dropped from around 0.18 after reunification and stood at 0.12 in 2019. Until the beginning of the 2000s the direct effect mainly drives the decline, followed by a large drop of the indirect effect until the end of the sample. Third, the labor multiplier for PBS quadrupled in the last five decades and surpassed the labor multiplier for Construction in 2017. Here, both the direct and the indirect effect caused the overall increase in the PBS labor multiplier. All remaining sectors display rather constant labor multipliers.

Focusing on the TFP multipliers next, we note an overall increasing trend in the multipliers of many service sectors (see panel (b) of Figure 9). The TFP multiplier for PBS steadily increased until 2008, sparked at around 0.25 and then dropped to 0.21 in 2019. This evolution is mainly driven by the indirect effect of the TFP multiplier. For the TFP multiplier in the Construction sector we observe a stable evolution around 0.22 since the 2000s. Both the direct and indirect effect of the multiplier show a rather constant development. The TFP multiplier for the Durables sector heavily fluctuates around 0.37 since reunification. Again, both the direct and indirect effect drive this evolution. Overall, the changes in the multipliers for TFP are more pronounced than for labor, indicating that changes in the sectoral long-run TFP trends might have influenced aggregate trend variation more than changes in the sectoral labor supply.

Given the possibility to apply time-varying multipliers, we re-estimate the contributions of common and sector-specific components in sectoral trends, the model-implied GDP growth rates and the aggregate density on how much the common factors explain the variation in trend GDP growth. Instead of using the 2018 values of the sectoral multipliers as in the baseline scenario, we either apply averaged multipliers (mean over the entire period) or year-specific multipliers. Overall, the estimates back up our baseline results by confirming the sector-specific trend contributions and the fraction of trend GDP growth that is explained by common factors (approximately 50%). What we can improve, however, is the degree of coincidence of the model-implied trend GDP growth rate and the low-frequency movement. Using time-varying or average multipliers brings us much closer to the low-frequency movement, as seen in Figure 7, compared to the baseline estimation. Thus, the BGP from the multi-sector growth model can be a good approximation also for conclusions about future developments or evaluations.

5.3 Implications for Future German Trend GDP Growth

The German population is aging, and compared to other industrialized countries, demographic change is progressing very fast. The comparison of its old age dependency ratio with the US reveals no surprise: In 2019, the German ratio of people older than 64 to its working-age population (aged between 15 and 64 years) was considerably higher (33.6%) than it was in the US (24.2%). It is further estimated that by 2035, one out of four Germans will have reached the legal retirement age of 67 years. In that regard, the German working-age population is anticipated to undergo a discernible contraction in the foreseeable future, a consequence of the impending retirement of the baby boomer generation until 2035. According to the Berlin Institute for Population and Development a demographic imbalance is projected from 2030 onwards, wherein the influx of new entrants into the labor market will be outnumbered by a twofold surge in retirements.

In a recent study, Ochsner *et al.* (2024) show that German potential output growth will remain on a low pace, mainly driven by the diminishing labor volume. In other words, labor input will be the bottleneck in the future that prevents—everything else equal—the German economy to grow faster. Gründler and Potrafke (2023) further show that a boost of the pensioner-worker ratio has a negative effect on TFP. In detail, they find that a 10 percentage point increase in the pensioner-worker ratio results in an up to 6% decline in TFP. The effect is found to be stronger when production is labor-intensive and has a low potential for automation—an accurate description of the Construction sector. Indeed, Construction was the most labor-intensive sector (total number of employees per gross fixed assets in mill. Euros) in 2019 (20.9), followed by the miscellaneous category (20.0) and Retail Trade (15.0). Given the demographic perspectives, a drop in the Construction sector's labor input might not only weight on aggregate GDP due to its labor multiplier, but might have an additional damping effect on aggregate growth via its TFP multiplier. Examining the impact of modeling each sector separately and considering the sectoral multipliers from our analysis on potential output or trend growth estimates would be an interesting exercise. We hypothesize that German trend GDP growth will slow down to a much higher degree as labor-intensive sectors, such as Construction, exhibit large multipliers. However, we leave such considerations for future research.

6 Conclusion

Over the last five decades, German trend GDP growth has fallen by more than two percentage points. This paper aims to decompose this decrease into trend labor input and TFP growth of the 15 major German sectors and to compare its findings to those for the US economy. Our results show that both sector-specific and common forces in labor input and TFP growth account for half of the overall trend growth variation each. This stands in contrast to the US, where three-fourth of long-term GDP development is accounted for by sector-specific factors and one-fourth by common forces (Foerster *et al.*, 2022).

The differences between the two economies can be attributed to sectoral differences and their specializations. The sectors' multipliers in both economies' production networks exhibit significant heterogeneity. Professional and Business Services have a greater impact on the US economy than on the German economy, which reflects the ongoing structural change in Germany towards a service-oriented model. However, the multiplier for German Professional and Business Services remains significantly higher than its overall value added share, contributing positively to trend GDP growth. The Construction sector also holds significant economic importance in both economies, with its share in value added being almost identical. Whereas the multiplier in Germany is more than four times higher than the Construction sector's value added share, the factor is around three for the US. However, the sector's multiplier and thus its importance in the local production network is much more pronounced in Germany. The Durable Goods sector exhibits a sectoral multiplier that is nearly equal for both the German and US economies, yet the composition of this sector varies significantly between the two economies. While Germany exhibits a higher value added share in Durable Goods, the US surpasses in the indirect (or network) effect. This underscores the heterogeneity in the economies' specialization. Despite positive effects on German trend GDP growth from the Durable Goods sector, challenges arise, particularly in the diminishing rates of TFP.

Constructing the to our knowledge unique capital tables for Germany allows us to construct year-specific production networks and therefore annually differing multipliers. Employing a specific multiplier for each year allows for a more nuanced understanding of the non-stationary nature of the production network. Further, it enables us to calculate total average contributions over different time periods taking into account the specific shape of the production network at that time. We these time-varying information we can even increase the model performance to trace long-term economic development in Germany.

Our results may have also implications for the modeling and conclusions drawn from projecting the German future economic trajectory. Demographic changes, particularly an aging workforce, pose potential challenges and will lead to a much slower pace of future potential output growth (Ochsner *et al.*, 2024). As labor input will likely be the bottleneck for future growth perspectives, especially labor-intensive sectors like Construction as well as Professional and Business Services will suffer. The declining labor input in these sectors not only exerts pressure on aggregate GDP due to their labor multipliers but may also dampen aggregate growth via their TFP multipliers. Thus, Germany faces rather unfavorable future conditions as sectors with large multipliers are the most labor-intensive ones. Recognizing the intricate interplay between sector-specific and common factors is crucial for policymakers seeking to navigate the challenges and opportunities in the evolving economic landscape.

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What Drives German Trend Output Growth? A Sectoral View*

– Supplementary Material –

Robert Lehmann Lara Zarges

Abstract

This is the Supplementary Material to the article "What Drives German Trend Output Growth? A Sectoral View". It contains additional information complementing the results from the main paper. In particular, it includes further details on the applied data, additional results, some methodological issues, the robustness checks, and some further explanations on the structural change of the German economy.

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1 Data and Additional Results

1.1 Sector Classification

The raw German data on gross value added (GVA), the total number of employees representing labor input (L), the capital stock (K) and labor compensation are available from the Federal Statistical Office of Germany at the two-digit level.[1] The 63 single sectors are classified according to the German Classification of Economic Activities, Edition 2008, which is perfectly comparable to the European classification NACE Rev. 2.[2] One of our main purposes is the comparability of the German results to those for the US documented by Foerster *et al.* (2022). Consequently, it is imperative to establish uniform sectoral definitions. This process yields 15 distinct sectors that collectively represent the German private-sector economy, excluding all government and non-market traded activities. Regrettably, comprehensive data for the housing sector is not available, which necessitates the inclusion of housing within the Financial, Insurance, and Real Estate (FIRE) aggregate, whereas it does not in Foerster *et al.* (2022). All remaining sectors are identical. Table 1 shows the sector aggregates.

Table 1: Sector Aggregation and Classification

Sector Aggregate	**NACE Rev. 2 Code**
Agriculture	A
Mining	B
Utilities	D, E
Construction	F
Durable Goods	C19, C24-25, C26-C27, C26, C29-C30, C31-C33
Non-Durable Goods	C10-C12, C13-C15, C16-C18, C20-C21, C20, C22-C23
Wholesale Trade	G46
Retail Trade	G45, G47
Transportation & Warehouse	H
Information & Communication	J
FIRE (incl. Housing)	K, L
Professional & Business Services	M, N
Education & Health	P, Q
Arts, Entertainment & Accommodation	I, R
Miscellaneous	S, T

Notes: The table shows the applied setor aggregates and the corresponding sector codes according to the NACE Rev. 2. FIRE: Financial, Insurance & Real Estate.

[1] The long series for unified Germany can be accessed at the website of the Federal Statistical Office of Germany. The corresponding publication is entitled "National Accounts, Calculation of Gross Domestic Product, Detailed Annual Results, Series 18, Issue 1.4" and available here: `https://www.destatis.de/EN/Themes/Economy/National-Accounts-Domestic-Product/_node.html`.

[2] The acronym NACE has been derived from the French term "Nomenclature générale des Activités économiques dans les Communautés Européennes".

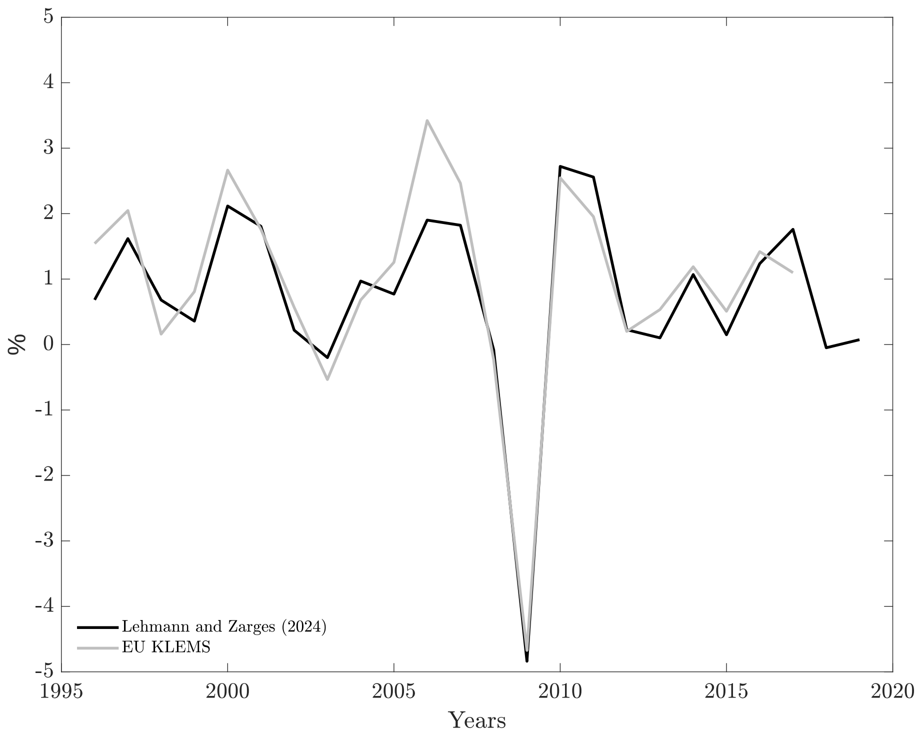
1.2 Calculation of Total Factor Productivity

Sectoral total factor productivity (TFP) for Germany is available from the EU KLEMS database. However, these series only commence in 1991 and are insufficiently long for our purposes. Consequently, we must calculate sectoral TFP independently. This entails the limitation that we can only access a smaller number of variables. To be more precise, our estimates can only be based on the sheer number of employees and the sectoral capital stock. It follows that it is not possible to control for the quality of labor (e.g., qualification levels) and capital (e.g., asset types) as well as the intensive margin of labor supply. TFP in sector j at time t, $z_{j,t}$, is defined as the Solow residual from a standard Cobb-Douglas-type production function, where firms operate under constant returns to scale and perfect competition:

$$\upsilon_{j,t} = z_{j,t} k_{j,t}^{\alpha_j} l_{j,t}^{(1-\alpha_j)}, \text{ with } \alpha_j \in [0,1], \tag{1}$$

with $\upsilon_{j,t}$ representing sectoral gross value added, $l_{j,t}$ defining labor input, $k_{j,t}$ the capital stock, and α_j the labor income share. According to Hulten (1978), aggregate TFP is then simply the weighted sum of sectoral TFP. The weights equal the sectoral shares in total gross value added. Figure 1 compares our estimate for aggregate TFP growth with the estimates from EU KLEMS. Both series show a synchronous movement and correlate by 0.95, which gives us confidence in our estimates.

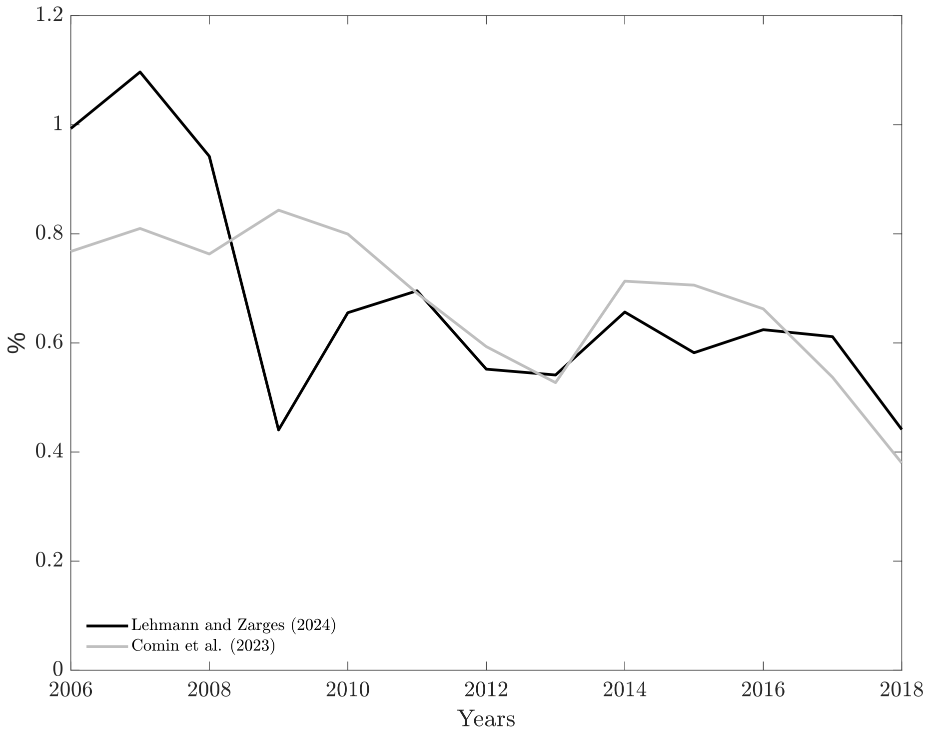
Figure 1: Comparison of Aggregate TFP Growth



Notes: The figure compares our estimated aggregate TFP growth with the estimate from EU KLEMS.

Another issue is TFP (mis-)measurement due to business cycle fluctuations or the degree of factor utilization. Newer measures for factor-utilized or purified TFP apply capacity utilization measures from business survey results to augment standard TFP measures (see Christofzik *et al.*, 2021; Comin *et al.*, 2023). As previously argued in the main paper, we believe that TFP (mis-)measurement is not a significant concern in our case for two reasons. First, we employ a cyclical adjustment of our raw data through the use of an Okun's Law-type regression. Second, we are primarily interested in the low-frequency movements of the series, which is why we apply an 11-year moving average to both our aggregate TFP growth measure and the one by Comin *et al.* (2023), which we interpret as the slow moving component in total TFP growth. Figure 2 depicts the two adjusted series, which correlate with a correlation coefficient of 0.52 and exhibit a downward-sloping behavior. It is once again evident that our measures, particularly those pertaining to trend components, are capable of accurately capturing the underlying trends.

Figure 2: Comparison of Long-run TFP Growth



Notes: The figure compares the long-run movements of both our estimated aggregate TFP growth measure and the estimate by Comin *et al.* (2023). The long-run movements are approximated by an 11-year moving average.

1.3 Capital-flow Matrices

Official statistics in Germany do not provide—to the best of our knowledge—capital-flow matrices, that is, the connection between capital goods producing sectors and those that use them for production. Therefore, we rely on two non-official sources for approximation: the ifo

Investment Database (IIDB, 2018) and the INTAN-Invest Database. With the IIDB we can access sectoral investment data in a variety of asset types. The advantage of the INTAN-Invest Database is its detailed data on intangible assets. By combining both databases, we can approximate full-fledged capital-flow matrices for Germany between 1995 and 2018. The IIDB consists of 12 investment assets: "metal products", "machinery", "computers and office equipment", "electrical generation and distribution", "communication equipment", "instruments, optics and watches", "furniture, music and sports equipment", "other machines and equipment", "automobiles", "other vehicles", "intangible assets", and "buildings and structures". According to the INTAN-Invest Database, intangible investment can broadly be distinguished into three main categories, capturing several (intangible) assets: "digitized information", "innovative property", and "economic competencies".

The main challenge lies in the distribution of intangible assets to the sectors providing them. Overall, the assignment is not unambiguous: In many cases it is hard to state a sector uniquely responsible to create a specific asset. Hence, our approach represents a first step towards the "true" connection across sectors with respect to investments in intangible assets. Table 2 shows the classification of intangible investment assets and their assignment to the producing sector. To be more precise, we distribute the sectoral investment into intangibles as stated by the IIDB onto the producing sectors using the shares in total intangible investment retrieved from the INTAN-Invest Database. Summing up, we add the fraction of total intangible investment going to a specific producing sector as given by the INTAN-Invest Database to the capital a sector receives within the production network for providing investment goods.

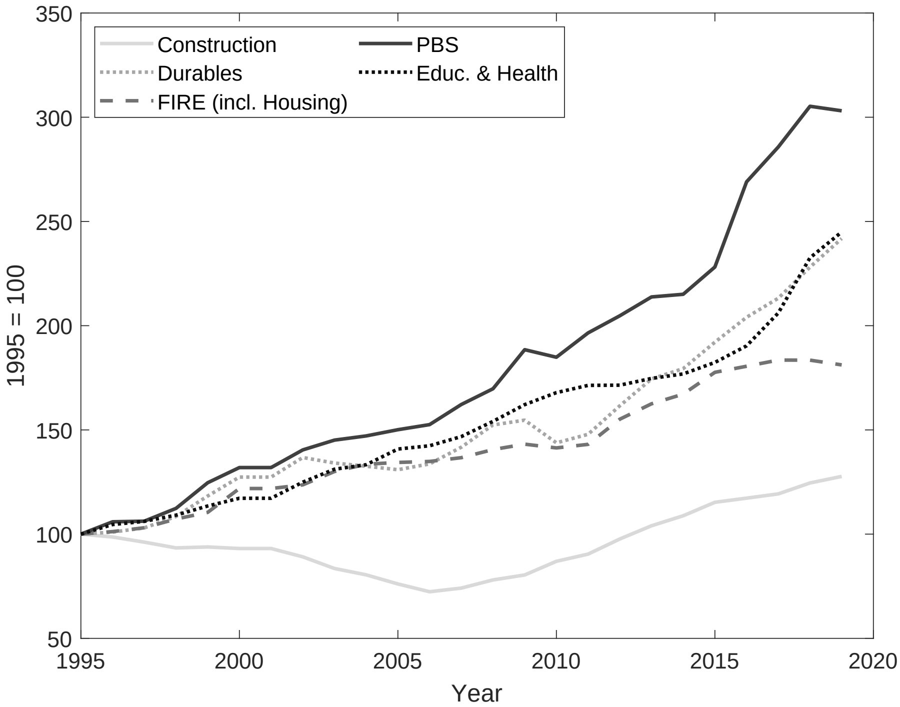
Table 2: Intangible Asset Classification and Producing Sector

Category	**Intangible Asset**	**Producing Sector**
Digitized Information	Software and databases	Inform. & Communic.
Innovative Property	Entertainment, artistic originals	Arts, Accommodation etc.
	Research and development	each sector for itself
	Industrial design	each sector for itself
	Financial product development	FIRE
Economic Competencies	Brand and market research	each sector for itself
	Organisational capital	each sector for itself
	Training	each sector for itself

Notes: The table shows the assignment of intangible assets from the INTAN-Invest Database to its producing sector.

To get an impression how sectoral investment in intangible assets have evolved, Figure 3 presents their development since 1995 for the five sectors with the overall largest sectoral multipliers. All values are normalized by their 1995 values. The sectors demonstrate a consistent and gradual increase in intangible investment, with the exception of the construction sector. However, we observe a reversal of this sector's intangible trend in the mid-2000s. The strongest increase since 1995 shows the sector Professional & Business Services (PBS), whose investments in intangible assets tripled in the last three decades. Also the sector Education & Health shows remarkable increases.

Figure 3: Intangible Investment by Sector



Notes: The sector-specific investments in intangible assets are normalized by their 1995 values. FIRE: Financial, Insurance & Real Estate; PBS: Professional & Business Services.

After merging the IIDB and the INTAN-Invest Database, we can quantify the 2018 capital-flow coefficients, $\left\{\omega_{ij}^{2018}\right\}$, that represent the importance of sector j as investment good supplier for sector i. Table 3 shows the capital-flow table, Ω^{2018}, used in our baseline estimation.

1.4 Input-Output Matrices

Material linkages across the German sectors are calculated from the Input-Output (IO) tables of the Federal Statistical Office of Germany.[3] The IO tables for unified Germany are available for the years 1991 to 2020. In the baseline case, we apply the 2018 IO output coefficients, $\left\{\phi_{ij}^{2018}\right\}$, that measure the share of materials flowing from sector j to sector i. Table 4 shows the IO table, Φ^{2018}, used in our baseline estimation.

[3]The latest IO tables as well as older publications can be accessed via the Statistical Library: `https://www.statistischebibliothek.de/mir/receive/DESerie_mods_00000191`.

Table 3: German Capital-flow Table Ω^{2018}

	A	M	U	C	DG	NDG	WT	RT	TW	IC	F†	PBS	EH	AEA	MC
A	0.16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
M	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
U	0.00	0.00	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C	0.60	0.33	0.83	0.32	0.10	0.29	0.31	0.36	0.45	0.05	0.97	0.11	0.51	0.62	0.62
DG	0.23	0.39	0.08	0.63	0.86	0.20	0.37	0.46	0.51	0.05	0.01	0.54	0.03	0.14	0.32
NDG	0.00	0.00	0.00	0.00	0.00	0.41	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
WT	0.00	0.00	0.00	0.00	0.00	0.00	0.27	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
RT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.13	0.00	0.00	0.00	0.00	0.00	0.00	0.00
TW	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00
IC	0.01	0.05	0.01	0.03	0.02	0.07	0.04	0.03	0.01	0.82	0.00	0.02	0.02	0.20	0.06
F†	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00
PBS	0.00	0.01	0.00	0.02	0.02	0.05	0.01	0.02	0.00	0.02	0.00	0.33	0.09	0.03	0.00
EH	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.35	0.00	0.00
AEA	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.00	0.00	0.00	0.01	0.00
MC	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Notes: The table presents the German capital-flow matrix for the year 2018, Ω^{2018}. Each row represents the importance of sector j as investment good supplier for sector i, ω_{ij}^{2018}. FIRE includes housing (†). A: Agriculture; M: Mining; U: Utilities; C: Construction; DG: Durable Goods; NDG: Non-Durable Goods; WT: Wholesale Trade; RT: Retail Trade; TW: Transportation & Warehouse; IC: Information & Communication; F: Financial, Insurance & Real Estate (FIRE); PBS: Professional & Business Services; EH: Education & Health; AEA: Arts, Entertainment & Accommodation; MC: Miscellaneous.

Table 4: German Input-Output Table Φ^{2018}

	A	M	U	C	DG	NDG	WT	RT	TW	IC	F†	PBS	EH	AEA	MC
A	0.26	0.01	0.00	0.00	0.00	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00
M	0.00	0.22	0.12	0.01	0.01	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
U	0.05	0.11	0.35	0.01	0.03	0.05	0.03	0.06	0.02	0.01	0.01	0.02	0.04	0.06	0.08
C	0.02	0.03	0.06	0.14	0.01	0.01	0.01	0.02	0.02	0.02	0.17	0.02	0.05	0.04	0.02
DG	0.06	0.16	0.07	0.31	0.62	0.03	0.06	0.01	0.03	0.02	0.00	0.03	0.05	0.02	0.09
NDG	0.18	0.09	0.03	0.11	0.05	0.47	0.06	0.06	0.07	0.03	0.00	0.03	0.10	0.18	0.06
WT	0.10	0.05	0.04	0.10	0.08	0.05	0.08	0.06	0.06	0.01	0.00	0.03	0.07	0.07	0.05
RT	0.04	0.01	0.01	0.02	0.02	0.02	0.01	0.01	0.00	0.01	0.00	0.01	0.09	0.07	0.03
TW	0.01	0.05	0.02	0.01	0.03	0.05	0.38	0.20	0.55	0.03	0.01	0.06	0.03	0.03	0.01
IC	0.00	0.03	0.03	0.01	0.02	0.01	0.04	0.06	0.05	0.63	0.05	0.11	0.07	0.08	0.05
F†	0.04	0.03	0.04	0.14	0.02	0.02	0.12	0.26	0.05	0.06	0.45	0.11	0.08	0.13	0.10
PBS	0.19	0.15	0.13	0.10	0.08	0.10	0.18	0.21	0.10	0.13	0.22	0.47	0.10	0.11	0.16
EH	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.18	0.01	0.00
AEA	0.00	0.01	0.00	0.01	0.00	0.00	0.01	0.02	0.02	0.03	0.01	0.05	0.01	0.11	0.01
MC	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.31

Notes: The table presents the German Input-Output matrix for the year 2018, Φ^{2018}. Each row represents the importance of sector j as material supplier for sector i, ϕ_{ij}^{2018}. FIRE includes housing (†). A: Agriculture; M: Mining; U: Utilities; C: Construction; DG: Durable Goods; NDG: Non-Durable Goods; WT: Wholesale Trade; RT: Retail Trade; TW: Transportation & Warehouse; IC: Information & Communication; F: Financial, Insurance & Real Estate (FIRE); PBS: Professional & Business Services; EH: Education & Health; AEA: Arts, Entertainment & Accommodation; MC: Miscellaneous.

1.5 Average Output Growth since 1970

Table 5 shows averaged GDP growth rates for both different periods and aggregation schemes. The weights for aggregation are either mean weights over the entire period, chaining, or the first (last) 10 years. Average growth rates are either calculated from the raw data (GR) or from cyclically adjusted values (CA). The table reveals two noteworthy insights. First, average GDP growth exhibits a decline over time, irrespective of the weighting scheme or the presence or absence of cyclical adjustments. This phenomenon mirrors the observed decrease in trend German GDP growth over time. Second, as average growth rates vary across weighting schemes, shifts across sectors representing structural change have occurred.

Table 5: Average GDP Growth Rates for Different Time Periods

Period	**Full (Mean)**		**Chain**		**First 10**		**Last 10**	
	GR	CA	GR	CA	GR	CA	GR	CA
1973-2019	2.0	2.0	1.9	1.9	1.8	1.8	2.2	2.2
1973-1980	2.9	3.0	2.5	2.6	2.6	2.7	3.2	3.2
1981-1990	2.4	2.5	2.3	2.4	2.1	2.3	2.6	2.7
1991-2000	2.0	2.1	2.0	2.2	1.6	1.7	2.3	2.4
2001-2010	1.1	1.1	1.1	1.1	1.1	1.1	1.2	1.2
2011-2018	1.7	1.5	1.7	1.6	1.6	1.4	1.8	1.6

Notes: The table presents average GDP growth rates for different periods. The growth rates are either based on non-adjusted data (GR) or on cyclically adjusted values (CA). GDP aggregation is either based on sectoral full sample mean weights, chaining, or on weights representing the first (last) 10 years.

1.6 Sectoral Multipliers for Labor Input

Table 6 presents the baseline sectoral multipliers for labor input. The five largest multipliers can be observed for Construction, Durable Goods, PBS, and Education & Health. The labor input multiplier for construction is identical in both dimensions (direct and indirect effect) between Germany and the United States. However, significant differences emerge for the other three sectors. The total multiplier for Durable Goods is equivalent in the two countries. Nevertheless, the indirect effect is larger in the United States (0.16) than in Germany (0.12), with the opposite being true for the direct effect. The labor multiplier for PBS is smaller in Germany (0.13) than in the US (0.18), which may be indicative of the ongoing transformation of the German economy towards a service-oriented one. For Education & Health, we observe a larger total multiplier for Germany (0.11 vs. 0.05). In both states, the total multiplier of this sector is exclusively described by the direct effect.

Table 6: Sectoral Labor Input Multipliers for Germany and the United States

Sector	Germany			United States		
	direct	indirect	total	direct	indirect	total
Agriculture	0.00	0.00	0.00	0.01	0.00	0.01
Mining	0.00	0.01	0.01	0.01	0.01	0.02
Utilities	0.01	0.00	0.02	0.01	0.00	0.01
Construction	0.03	0.09	0.12	0.03	0.08	0.11
Durable Goods	0.11	0.12	0.24	0.07	0.16	0.23
Non-Durable Goods	0.04	0.02	0.06	0.03	0.01	0.04
Wholesale Trade	0.03	0.03	0.06	0.04	0.04	0.08
Retail Trade	0.04	0.01	0.05	0.05	0.01	0.07
Transp. & Wareh.	0.03	0.02	0.05	0.03	0.02	0.04
Inform & Commun.	0.03	0.03	0.06	0.05	0.01	0.03
FIRE†	0.03	0.01	0.04	0.04	0.02	0.07
PBS	0.08	0.06	0.13	0.14	0.11	0.18
Educ. & Health	0.10	0.01	0.11	0.05	0.00	0.05
Arts, Entert. & Accom.	0.02	0.01	0.03	0.01	0.01	0.03
Misc.	0.01	0.00	0.01	0.00	0.00	0.00
Housing	–	–	–	0.00	0.00	0.00

Notes: The table presents the sectoral labor input multipliers for Germany and the US. The direct effect equals the sectors' value added shares (s^v). The indirect effect captures both the sector's importance as material supplier in the IO environment and as capital goods supplier in the investment network ($\Xi\Omega\alpha_d s^v$). For Germany, both the IO table and the capital-flow matrix from the year 2018 are applied. In case of the US, the IO table is from 2015 and the capital-flow matrix from 1997. FIRE includes housing in the German case, but not for the US (†). Furthermore, the time period under investigation for Germany runs from 1973 to 2019 and for the US from 1950 to 2018. The US values are extracted from Foerster *et al.* (2022). FIRE: Financial, Insurance & Real Estate; PBS: Professional & Business Services.

1.7 Sectoral Labor Intensity

Table 7 presents the sectoral labor intensity as of the year 2019. Labor intensity is defined as the ratio between the number of employees and gross fixed assets (in mill. Euros). The most labor-intensive sectors are Construction (20.9), the Miscellaneous category (20.0), and Retail Trade (15.0). The least labor-intensive sectors are FIRE (0.2), Utilities (0.5), and Mining (1.5). The German average (private-sector economy) is 2.2, which is surprising at first site as nearly all sectors show higher intensities. The main reason is that FIRE alone holds approximately 55% of total gross fixed assets, thus, heavily lowering the average.

Table 7: Sectoral Labor Intensity, 2019

Sector	**Labor Intensity**
Agriculture	1.7
Mining	1.5
Utilities	0.5
Construction	20.9
Durable Goods	4.6
Non-Durable Goods	4.9
Wholesale Trade	8.1
Retail Trade	15.0
Transp. & Wareh.	2.6
Inform. & Commun.	3.9
FIRE†	0.2
PBS	6.6
Educ. & Health	5.0
Arts, Entert. & Accom.	5.4
Misc.	20.0
Average	2.2

Notes: The table presents the sectoral labor intensity as of 2019, defined as the ratio between the number of employees and gross fixed assets (in mill. Euros). FIRE includes housing (†). FIRE: Financial, Insurance & Real Estate; PBS: Professional & Business Services.

2 Methodology

2.1 Cyclical adjustment

Business cycle movements disturb the exact filtering of low-frequency signals from the time series. We therefore follow Foerster *et al.* (2022) and adjust our raw annual growth rates for either labor input or TFP in sector j at time t, summarized in the variable $\Delta\tilde{x}_{j,t}$, by the following Okun's Law-type regression:

$$\Delta\tilde{x}_{j,t} = \mu_j + \beta_j(L)\Delta u_t + \epsilon_{j,t}\,. \tag{2}$$

In this regression, the change in the unemployment rate, Δu_t, is the variable that approximates the economy-wide degree of factor utilization. To capture business cycle movements across the years, we introduce, next to the contemporaneous value, both one lag and one lead to the regression: $\beta_j(L) = \beta_{j,1}L + \beta_{j,0} + \beta_{j,-1}L^{-1}$. The cyclically adjusted sectoral growth rates, $\Delta x_{j,t} = \{l_{j,t}, z_{j,t}\}$, are used throughout the paper and represented by the following difference: $\Delta x_{j,t} = \Delta\tilde{x}_{j,t} - \hat{\beta}_j(L)\Delta u_t$. The coefficients, $\hat{\mu}_j$ and $\hat{\beta}_j(L)$, are estimated via OLS. Section 4 of this Supplementary Material, discusses the robustness of the application of a survey-based business cycle indicator in lieu of the unemployment rate.

2.2 Extraction of Low-frequency Movements

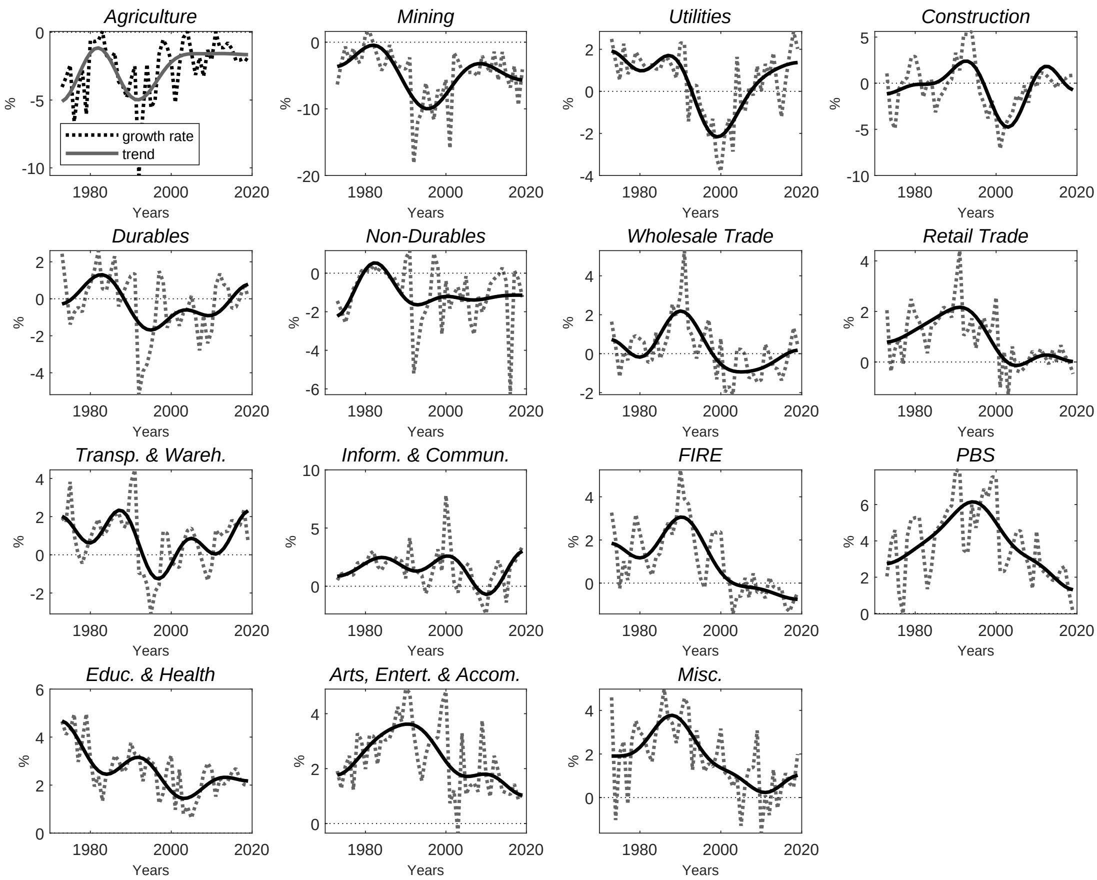
We apply a similar trend extraction method as Foerster *et al.* (2022). In a nutshell, the method, presented by Müller and Watson (2008), is very much related to standard spectral analyses based on low-frequency Fourier transforms (see, for an intensive discussion, Müller and Watson, 2020). To extract the low-frequency movements, we regress our cyclically adjusted variables, $\Delta x_{j,t}$, onto a constant and a set of cosine functions, denoted as $\Psi_k(s) = \sqrt{2}\cos(ks\pi)$ with period $2/k$ and $s \in [0,1]$. Hence, the low-frequency movements are the fitted values from this OLS regression with $\Psi_k((t-1/2)/T)$ for $k = 1, \ldots, q$ representing the single periodicities and $t = 1, \ldots, T$ as the number of observations. Overall, the regression captures periodicities longer than $2T/q$. The crucial parameter for the length of the low-frequency movements is q. We set a value $q = 6$ for the German application. With $T = 47$ observations, our regression captures periodicities longer than $2 \times 47/6 = 15.7$ years. Please note, the first cosine function has a period of $2 \times 47/1 = 94$ years, the second function a period of $2 \times 47/2 = 47$ years and so forth. The OLS regressors are captured in the following $T \times q$ matrix:

$$\mathbf{\Psi}_T^0 = \begin{bmatrix} 1 & \sqrt{2}\cos\left(\left(\frac{1-1/2}{47}\right)\pi\right) & \cdots & \sqrt{2}\cos\left(\left(\frac{1-1/2}{47}\right)6\pi\right) \\ \cdots & \cdots & \cdots & \cdots \\ 1 & \sqrt{2}\cos\left(\left(\frac{t-1/2}{47}\right)\pi\right) & \cdots & \sqrt{2}\cos\left(\left(\frac{t-1/2}{47}\right)6\pi\right) \\ \cdots & \cdots & \cdots & \cdots \\ 1 & \sqrt{2}\cos\left(\left(\frac{T-1/2}{47}\right)\pi\right) & \cdots & \sqrt{2}\cos\left(\left(\frac{T-1/2}{47}\right)6\pi\right) \end{bmatrix}. \tag{3}$$

In all applications of the paper, we utilize the fitted values to represent the smooth trends in labor input, TFP, or private-sector GDP growth. As robustness check, we additionally discuss two separate values for the periodicity length in the Supplementary Material: $q = 5$ and $q = 7$. Furthermore, we compare our results for Germany to the US by adjusting the Foerster *et al.* (2022) estimation to match our parameters: equal sample length, time span, and the length of the low-frequency movements.

Figure 4 shows the cyclically adjusted labor input growth rates for each sector, along with the extracted low-frequency movements, that is, the fitted values from the previously introduced OLS regression. We observe large heterogeneities in the trends across sectors and over time. In contrast to the consistently negative labor input trend growth observed in Agriculture and Mining, a subset of service sectors exhibits a positive trend growth rate (for example, Professional & Business Services and Education & Health).

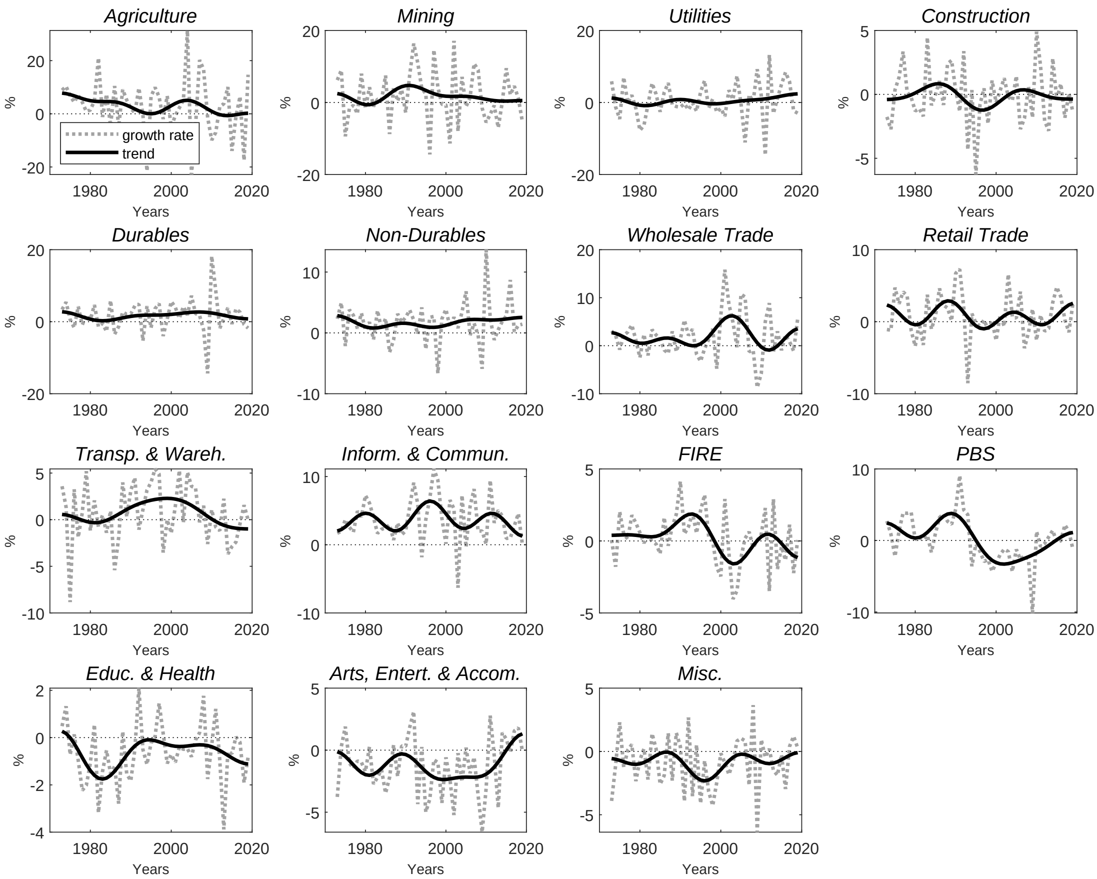
Figure 4: Sectoral Labor Input Trend Growth in Germany



Notes: Each sectoral panel shows the cyclically adjusted growth rate of labor input (dotted line), along with its trend (solid line). FIRE includes housing. FIRE: Financial, Insurance & Real Estate; PBS: Professional & Business Services.

Figure 5 presents the cyclically adjusted and trend growth rates for sectoral TFP. Again, sectoral heterogeneities are pronounced. For both the Durables and the Non-Durables sector we observe positive TFP trend growth rates over the entire period. The same holds true for Information & Communication. However, trend TFP growth in this sector slowed down remarkably in the last two decades. This is a phenomenon that we also observe for other service sectors such as FIRE or Professional & Business Services, for which trend TFP growth becomes even negative.

Figure 5: Sectoral TFP Trend Growth in Germany



Notes: Each sectoral panel shows the cyclically adjusted growth rate of TFP (dotted line), along with its trend (solid line). FIRE includes housing. FIRE: Financial, Insurance & Real Estate; PBS: Professional & Business Services.

2.3 Factor Model

General outline. The sectoral trends previously discussed show both some remarkable similarities as well as sector-specific peculiarities. To disentangle common and sector-specific movements in the data, we apply the following factor model by Foerster *et al.* (2022):

$$\begin{bmatrix} \Delta \ln l_{j,t} \\ \Delta \ln z_{j,t} \end{bmatrix} = \begin{bmatrix} \lambda_j^l & 0 \\ 0 & \lambda_j^z \end{bmatrix} \begin{bmatrix} f_t^l \\ f_t^z \end{bmatrix} + \begin{bmatrix} u_{j,t}^l \\ u_{j,t}^z \end{bmatrix}, \tag{4}$$

with $\Delta \ln l_{j,t}$ and $\Delta \ln z_{j,t}$ as labor input and TFP growth of sector j at time t, λ_j^l and λ_j^z as the factor loadings, f_t^l and f_t^z as the common factors for labor input and TFP, and $u_{j,t} = \left\{u_{j,t}^l, u_{j,t}^z\right\}$ as sector-specific disturbances. The trend growth rates of all components are defined as $g_t = \left\{g_{j,t}^l, g_{j,t}^z, g_{f,t}^l, g_{f,t}^z, g_{u,j,t}^l, g_{u,j,t}^z\right\}$. Assume that the OLS coefficients from the regression of, for example, labor input growth ($\Delta \ln l_{j,t}$) onto a constant and the q low-frequency periodic functions are captured by $\mathbf{X}_j^l$; similar matrices for the other components are $\mathbf{X}_j^z$, $\mathbf{F}^l$, $\mathbf{F}^z$, $\mathbf{U}_j^l$, and $\mathbf{U}_j^z$. The factor model, written in terms of the cosine transforms and approximating the low-frequency variation in the series, takes the following form:

$$\begin{bmatrix} \mathbf{X}_j^l \\ \mathbf{X}_j^z \end{bmatrix} = \begin{bmatrix} \lambda_j^l I_q & 0 \\ 0 & \lambda_j^z I_q \end{bmatrix} \begin{bmatrix} \mathbf{F}^l \\ \mathbf{F}^z \end{bmatrix} + \begin{bmatrix} \mathbf{U}_j^l \\ \mathbf{U}_j^z \end{bmatrix}. \tag{5}$$

We estimate this factor model according to Foerster *et al.* (2022), decomposing the observed long-term growth rates into common factors, $(g_{f,t}^l, g_{f,t}^z)$, and sector-specific forces, $(g_{u,j,t}^l, g_{u,j,t}^z)$.

Estimation. We estimate the factor model expressed in cosine transforms with Bayesian methods. The priors for the factor loadings are: $\lambda^l \sim N(\mathbf{1}, \mathbf{P}_l)$, $\lambda^z \sim N(\mathbf{1}, P_z)$. The variance-covariance matrices take the following form: $\mathbf{P}_l = \eta^2(I_{15} - s_l(s_l' s_l)^{-1} s_l')$, $\mathbf{P}_z = \eta^2(I_{15} - s_z(s_z' s_z)^{-1} s_z')$, with s_l and s_z as the sectoral shares in labor input and TFP, respectively. η governs the tightness of the prior. In the baseline estimation we set $\eta = 1$, but additionally discuss the robustness of our results to $\eta = 0.5$ and $\eta = 2$ in this Supplementary Material. For the remaining parameters, we follow Foerster *et al.* (2022) and set similar uninformative prior. Additionally, an analogous MCMC algorithm was employed, with a total of 550,000 draws. Of these, 50,000 were designated as burn-ins, from the remaining 500,000 draws we save each 200th draw.

3 US Estimates for the Period 1973 to 2018

To ensure that the differences across the results for Germany and the US are not driven by a specific time period or the length of the low-frequency movements, we re-estimated the US model of Foerster *et al.* (2022) in a similar setting. Hence, we restrict the US data to the period from 1973 to 2018 and also consider periods longer than 15 years by applying $q = 6$. Table 8 compares the sectoral factor decompositions for both labor input and TFP growth in this similar setting; the values for Germany equal those presented in the main paper. Some differences emerge compared to the original results of Foerster *et al.* (2022). For aggregate TFP, the fraction that is explained by common factors, R_z^2, increases from 0.30 and amounts to 0.41. The correlation between aggregate input factors also becomes more negative (-0.37 vs. -0.29). Furthermore, we observe some sectoral differences that are exclusive to the services sector.

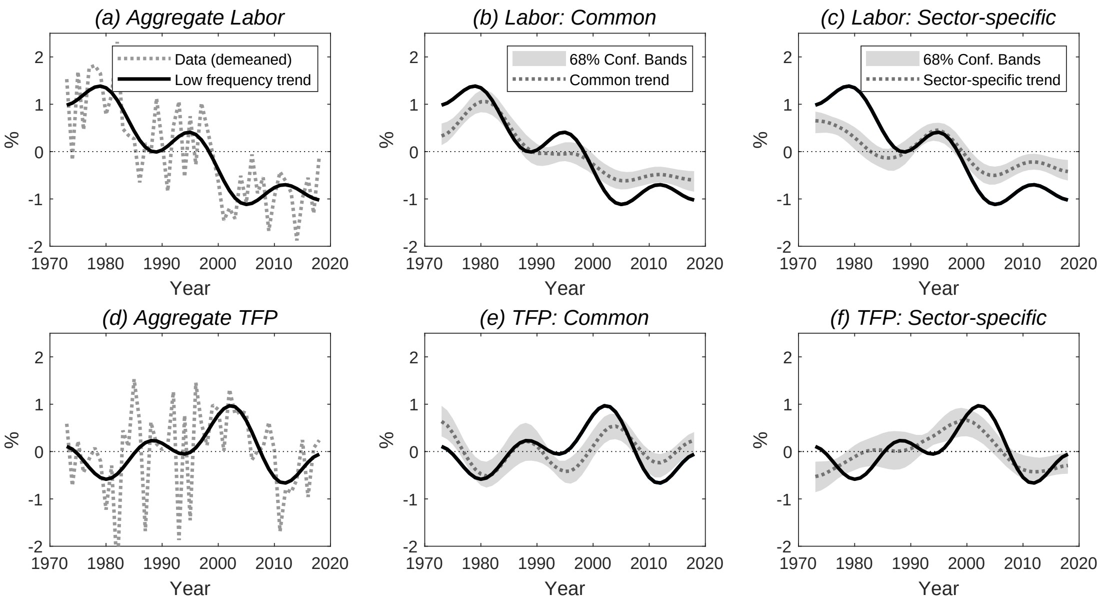
Table 8: Factor Decomposition, 1973 to 2018

Sector	**Germany**			**US**		
	R^2_l	R^2_z	$\rho(l,z)$	R^2_l	R^2_z	$\rho(l,z)$
Agriculture	0.05	0.02	0.04	0.16	0.02	-0.35
Mining	0.03	0.05	-0.65	0.01	0.01	-0.24
Utilities	0.10	0.07	0.24	0.36	0.05	0.30
Construction	0.18	0.40	0.09	0.11	0.10	-0.26
Durable Goods	0.09	0.15	-0.73	0.07	0.06	-0.33
Non-Durable Goods	0.04	0.27	-0.66	0.07	0.06	-0.44
Wholesale Trade	0.88	0.02	-0.09	0.44	0.04	0.02
Retail Trade	0.94	0.21	-0.84	0.12	0.03	0.15
Transp. & Wareh.	0.13	0.06	-0.36	0.04	0.30	0.36
Inform. & Commun.	0.14	0.02	-0.18	0.12	0.21	-0.27
FIRE†	0.75	0.02	0.23	0.47	0.04	-0.01
PBS	0.56	0.01	-0.88	0.65	0.36	-0.81
Educ. & Health	0.25	0.04	0.31	0.16	0.59	-0.78
Arts, Entert. & Accom.	0.84	0.03	-0.77	0.74	0.23	-0.67
Misc.	0.80	0.80	0.32	0.08	0.02	-0.07
Housing	–	–	–	0.01	0.07	-0.01
Aggregate	0.68	0.30	-0.08	0.65	0.41	-0.37

Notes: The table presents the fraction in trend variation explained by common factors for both labor input (R^2_l) and TFP (R^2_z) as well as the correlation between sector-specific trends in labor and TFP, $\rho(l,z)$. For the aggregate, $\rho(l,z)$ corresponds to the correlation between common trends. FIRE includes housing in the German case, but not for the US (†). The time period under investigation runs from 1973 to 2018 and the trends represent periodicities longer than 15 years for both states. The values for the US are calculated from the raw data of Foerster *et al.* (2022). FIRE: Financial, Insurance & Real Estate; PBS: Professional & Business Services.

By looking at the aggregate movements in Figure 6, we observe that the trends of labor input and TFP growth are not completely altered by restricting the sample to the period from 1973 to 2018. In general, the low-frequency movements for both labor input and TFP growth appear to be quite similar to the original ones. With regard to the share of the aggregate trends explained by common and sector-specific factors, we do not observe a significant change for labor input. It is still mainly dominated by common factors and supported by sector-specific trends. However, for TFP growth, we note a less important role of sector-specific factors compared with the original results. It is noteworthy that the decomposition into common factors and sector-specific components at the disaggregated level reveals only minor differences compared to the full sample. We only observe that for Transportation & Warehouse and Information & Communication the fraction of common forces increases slightly (see Figure 7).

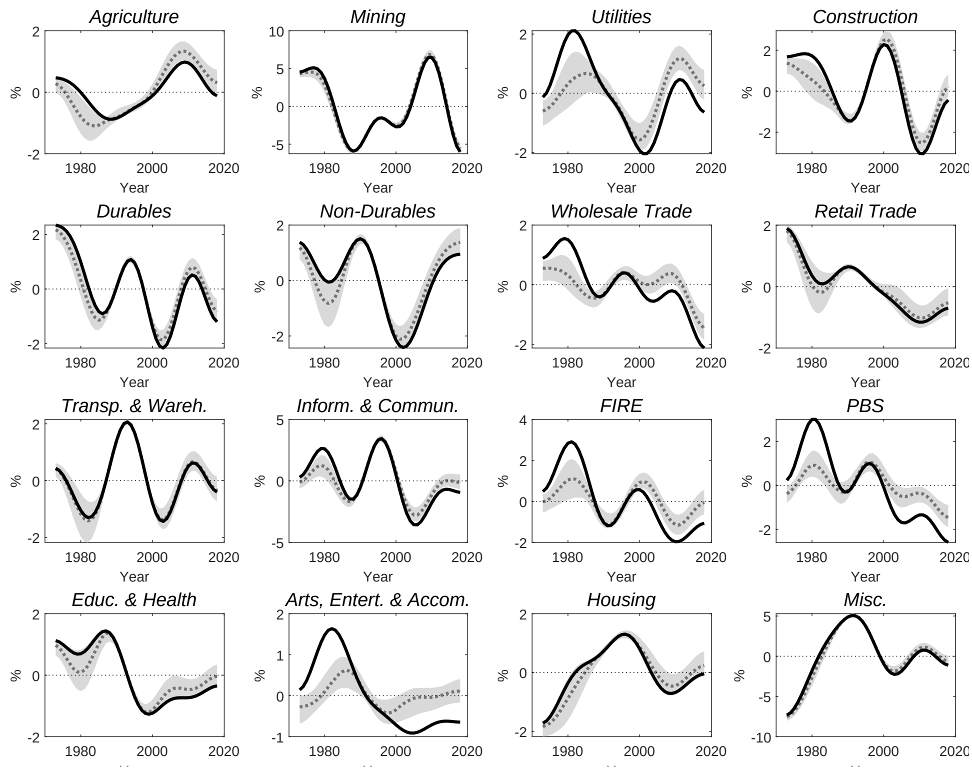
Figure 6: Historical Decomposition for the US, 1973 to 2018



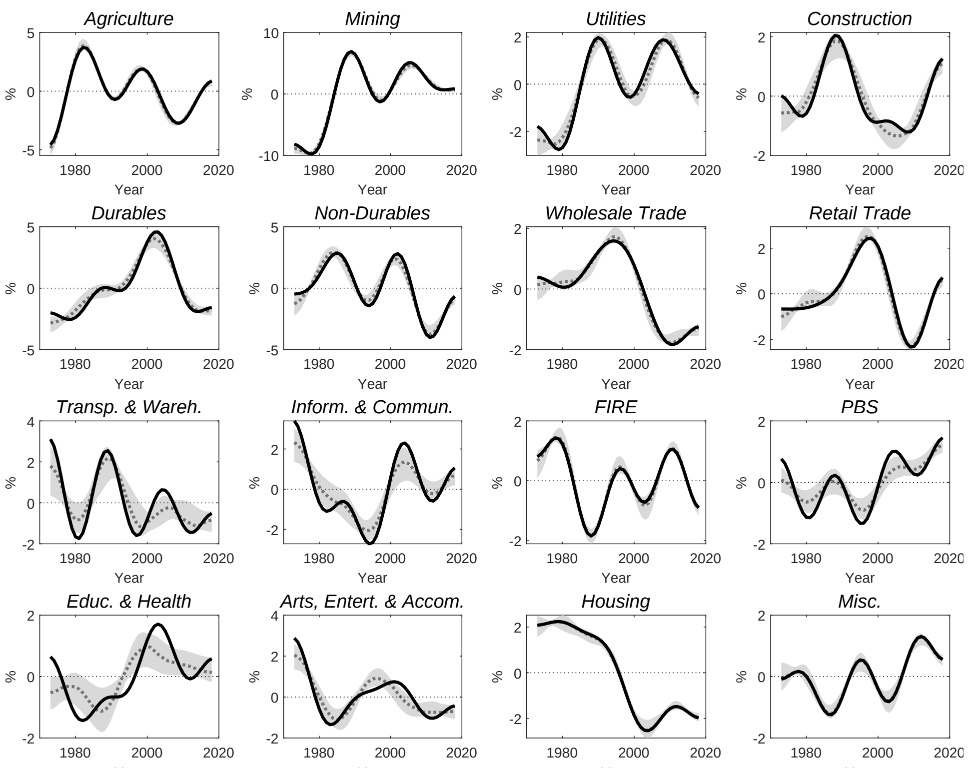
Notes: Panels (a) and (d) show the raw labor input and TFP growth rates as deviations from their sample means (demeaned, dotted black lines), together with the estimated low-frequency trends (black lines). The other panels show the trends' decomposition into common and sector-specific components, separately shown as gray dotted lines. While the dotted lines denote the posterior median, the shaded areas are equally-tailed 68% credible intervals. The models are re-estimated for the US from the raw data of Foerster *et al.* (2022) with equal parameters as for Germany. The period runs from 1973 to 2018 and the trends represent periodicities longer than 15 years.

Figure 7: US Sectoral Trends and Sector-specific Components, 1973 to 2018

(a) Employment



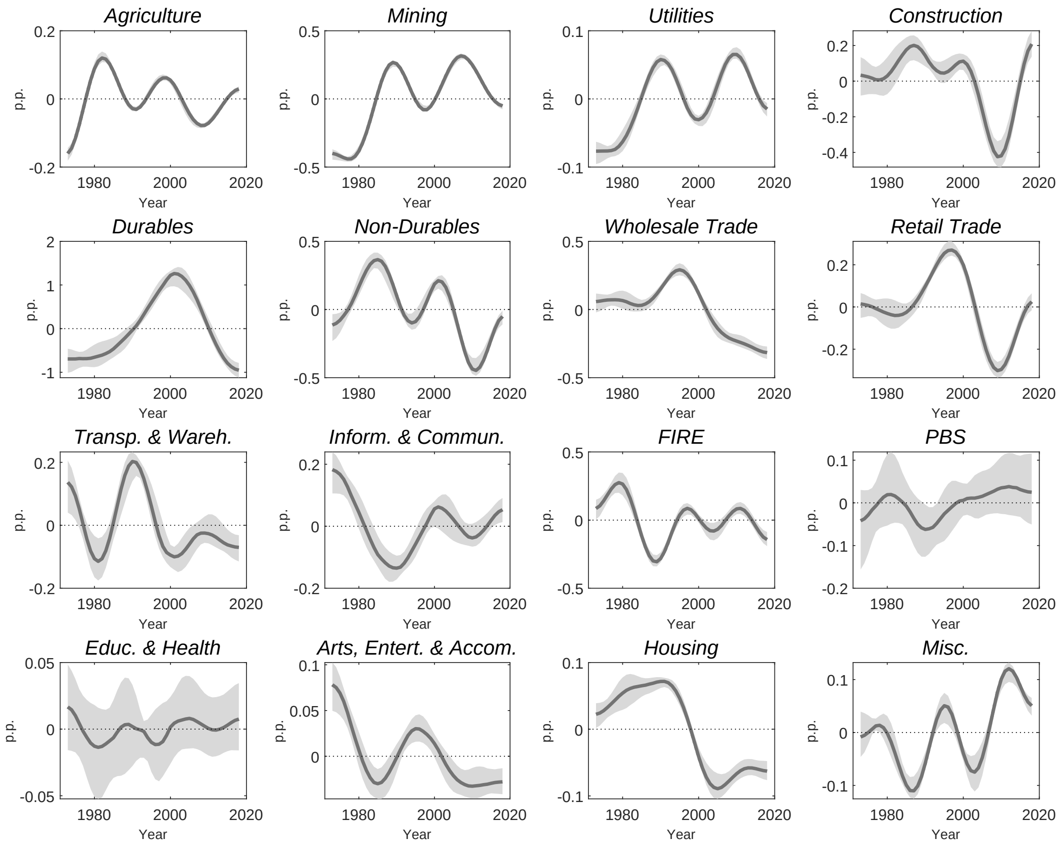
(b) TFP



Notes: Each sectoral panel shows the low-frequency trends (solid black lines) together with its sector-specific component (dotted gray lines). The sector-specific components denote the posterior median and the shaded areas are equally-tailed 68% credible intervals. FIRE includes housing. FIRE: Financial, Insurance & Real Estate; PBS: Professional & Business Services.

As argued by Foerster *et al.* (2022) one cannot infer from the explained fractions how large the influence of a single sector is for overall trend GDP growth due to the inter-sectoral linkages. The sector-specific contributions for the shorter US sample are shown in Figure 8. In comparison to the original findings, we have identified only minor discrepancies. Consequently, we propose that all comparisons presented in our primary study remain valid and are not influenced by the specific period under investigation.

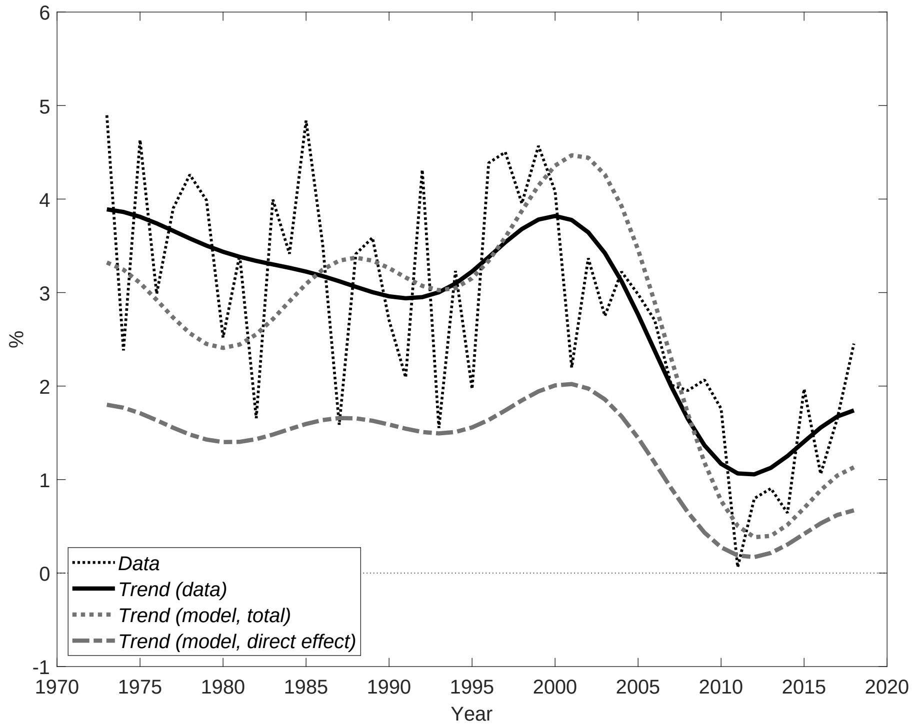
Figure 8: Sector-Specific Contributions to Trend Growth in US GDP, 1973 to 2018



Notes: Each sectoral panel shows the contributions (in percentage points) of sector-specific trends for trend GDP growth using the model-implied multipliers along the balanced growth path. The solid lines denote the posterior median and the shaded areas are equally-tailed 68% credible intervals. The models are re-estimated for the US from the raw data of Foerster *et al.* (2022) with equal parameters as for Germany. The period runs from 1973 to 2018 and the trends represent periodicities longer than 15 years. FIRE: Financial, Insurance & Real Estate; PBS: Professional & Business Services.

Trend GDP growth derived from the multi-sector growth model looks almost identical to the original findings from Foerster *et al.* (2022). Figure 9 illustrates the estimates for the period from 1973 to 2018. We observe that model-implied GDP growth exceeds the low-frequency trend in the 2000s. This turns around in the 2010s. Also at the beginning of the sample, the model-implied GDP growth undershoots the low-frequency trend, which is a finding analogous to the original article by Foerster *et al.* (2022).

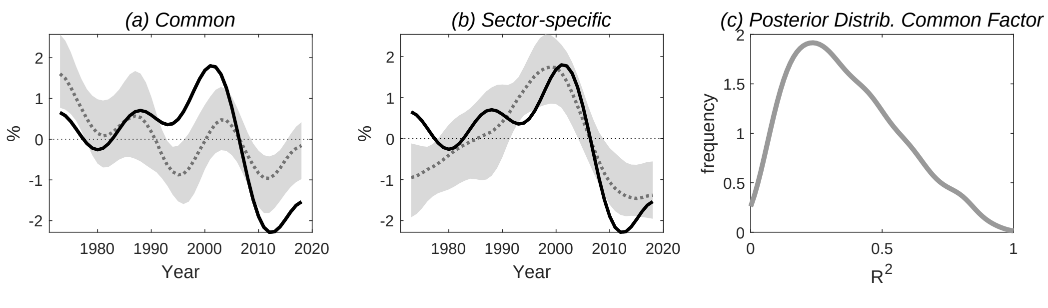
Figure 9: Estimated and Model-implied US Trend Growth in GDP, 1973 to 2018



Notes: The figure shows the cyclically adjusted GDP growth rate (thin dotted black line) and its estimated low-frequency trend (thick black line). The dotted gray line marks the model-implied trend growth rate along the balanced growth path. The dashed gray line, instead, presents the trend growth rate based on the value added shares, or direct effects, only. The models are re-estimated for the US from the raw data of Foerster *et al.* (2022) with equal parameters as for Germany. The period runs from 1973 to 2018 and the trends represent periodicities longer than 15 years.

Unsurprisingly, the fraction explained by common factors for the shorter sample is also almost identical to the original findings (see Figure 10). The re-estimation for the US underpin our conclusion from the main paper that common factors influence GDP growth much stronger in Germany than in the US.

Figure 10: Decomposition of US Trend Growth in GDP, 1973 to 2018



Notes: Panels (a) and (b) show the demeaned model-implied trend GDP growth (black line) together with the changes stemming from common factors and sector-specific developments (gray lines), respectively. Panel (c) shows the posterior distribution for the fraction of the total variance explained by common factors. The models are re-estimated for the US from the raw data of Foerster *et al.* (2022) with equal parameters as for Germany. The period runs from 1973 to 2018 and the trends represent periodicities longer than 15 years.

4 Robustness Checks

4.1 Survey-based Cyclical Adjustment

Germany has implemented significant labor market reforms throughout its recent history, and its labor market regulation is considerably more restrictive than that of the United States. Additionally, Germany offers stronger protection against dismissal. Both countries exhibit notable differences in their social security systems. Germany provides an extensive and prolonged unemployment compensation scheme, and it has been demonstrated that GDP and employment growth have become decoupled over the past two decades (Klinger and Weber, 2020). Because of these reasons, the unemployment rate might not be a sufficient indicator to adequately capture the German business cycle.

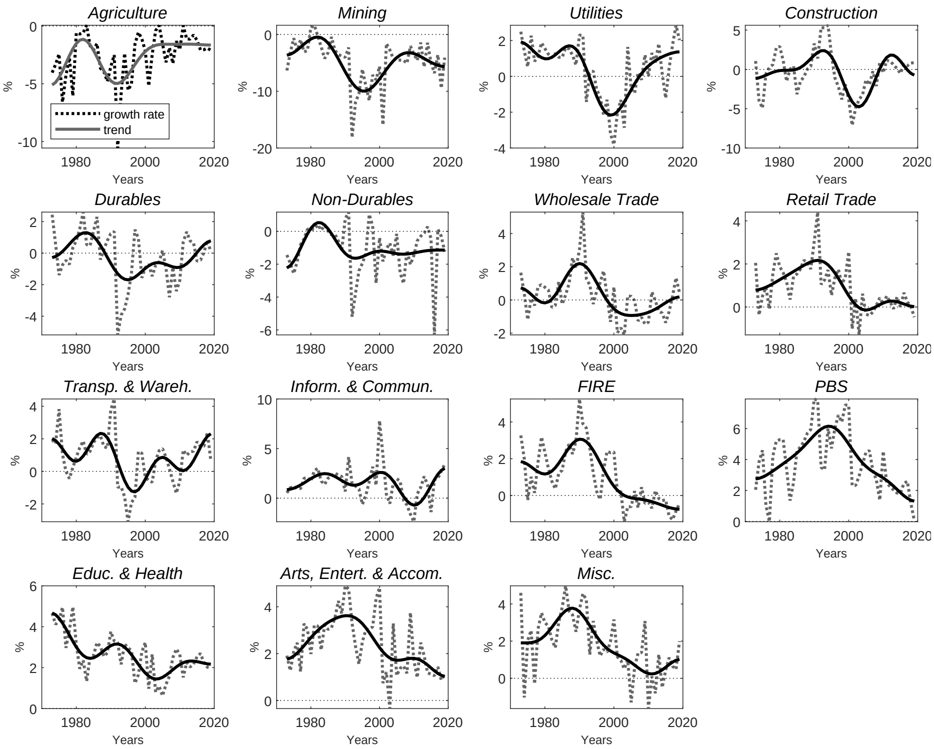
A prominent source for business cycle indicators are surveys at the firm level. We repeat all our estimations from the main paper by applying a German survey-based business cycle indicator. One of the most crucial leading indicators for the German economy is the ifo Business Climate (IBC), which has been demonstrated to be highly useful in the field of business cycle dating and nowcasting economic aggregates (Lehmann, 2023).[4] The results from this robustness check for the cyclical adjustment are presented in the following and comprise the sectoral trend estimates for both labor input and TFP growth, the coefficients of variation, the factor decomposition, the historical decomposition for the aggregates and the single sectors, the sector-specific contributions to trend GDP growth, the model-implied GDP growth, and the overall contributions.

Figures 11 and 12 present the sectoral trends for labor input and TFP growth as well as both adjustment procedures. The upper panel shows the trends for the unemployment rate-adjusted data and the lower panel the trends for the adjustment via the ifo Business Climate. All sectoral trends show similar patterns across the adjustment procedures. This similarity is also reflected in the coefficients of variation shown in Table 9. For trend labor input growth all coefficients of variation are almost identical. One difference emerges for Wholesale Trade, which is driven by a smaller sample mean. For trend TFP growth, we find one huge difference in the coefficients of variation for PBS. The major difference roots in the fact that the mean of the long-term TFP growth trend is a small negative number close to zero, which let the coefficient of variation explode. The pattern across adjustment procedures is, however, very similar.

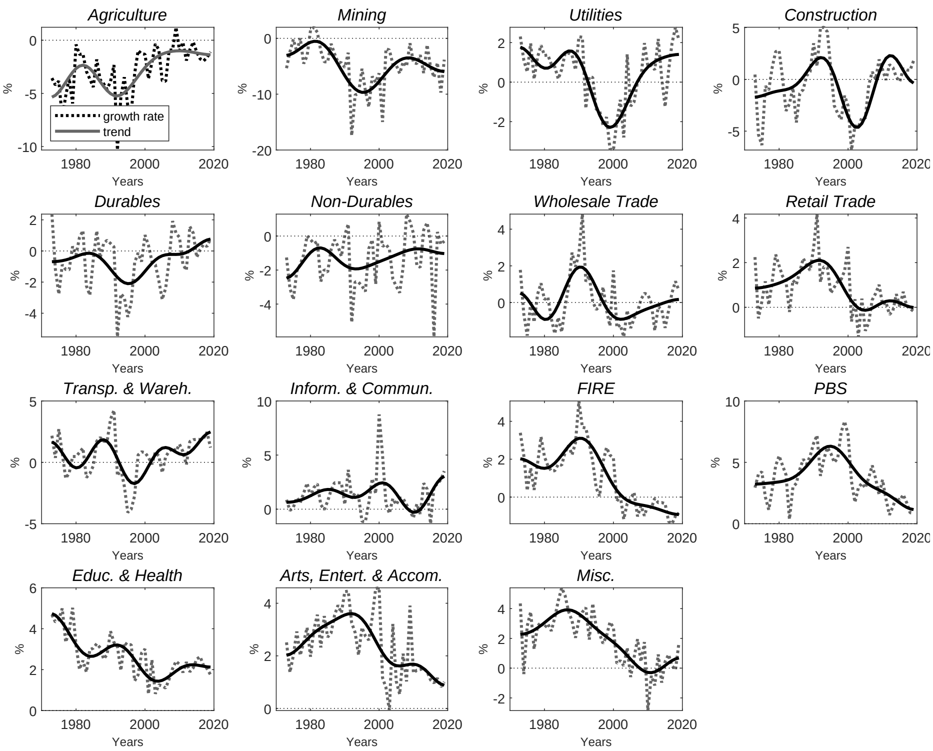
[4] The ifo Business Climate is based on approximately 9,000 monthly responses from businesses in manufacturing, the service sector, trade, and construction. Companies are asked to assess their current business situation and their business expectations for the next six months. They can describe their situation as "good", "satisfactory" or "bad" and their business expectations for the next six months as "more favorable", "unchanged" or "less favorable". The balance value of the business situation is the difference in the percentage shares of the responses "good" and "bad"; the balance value of expectations is the difference in the percentage shares of the responses "more favorable" and "less favorable". The ifo Business Climate is the geometric mean of both balance statistics.

Figure 11: Robustness of the Sectoral Trend Labor Input Growth

(a) Adjustment with the unemployment rate



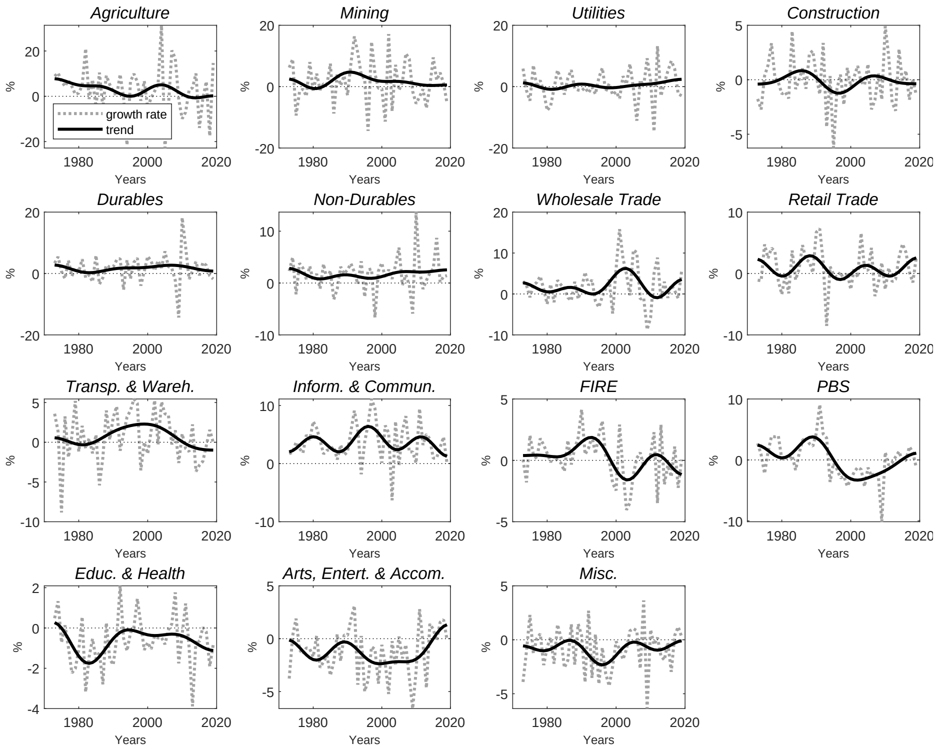
(b) Adjustment with the ifo Business Climate



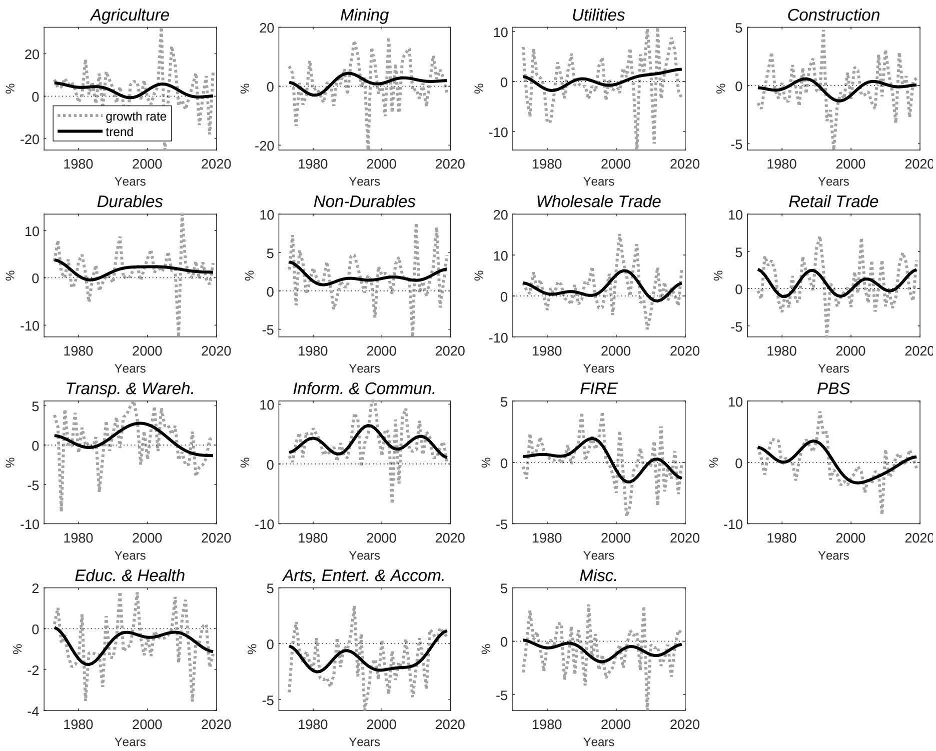
Notes: Each sectoral figure shows the cyclically adjusted growth rate of labor input (dotted line), along with its trend (solid line). The upper panel (a) shows the labor input trend growth rates from the main paper after cyclical adjustment with the unemployment rate. The lower panel (b) presents the adjustment with the ifo Business Climate. FIRE includes housing. FIRE: Financial, Insurance & Real Estate; PBS: Professional & Business Services.

Figure 12: Robustness of the Sectoral Trend TFP Growth

(a) Adjustment with the unemployment rate



(b) Adjustment with the ifo Business Climate



Notes: Each sectoral figure shows the cyclically adjusted growth rate of TFP (dotted line), along with its trend (solid line). The upper panel (a) shows the TFP trend growth rates from the main paper after cyclical adjustment with the unemployment rate. The lower panel (b) presents the adjustment with the ifo Business Climate. FIRE includes housing. FIRE: Financial, Insurance & Real Estate; PBS: Professional & Business Services.

Table 9: Robustness of the Coefficients of Variation

Sector	Labor		TFP	
	UR	IBC	UR	IBC
Agriculture	-0.5	-0.5	0.8	0.8
Mining	-0.6	-0.6	0.9	1.5
Utilities	3.2	3.7	1.8	4.1
Construction	-5.6	-3.8	-4.3	-2.8
Durable Goods	-3.4	-1.2	0.5	0.6
Non-Durable Goods	-0.6	-0.4	0.4	0.4
Wholesale Trade	4.0	14.7	1.0	1.1
Retail Trade	0.9	0.9	1.4	1.7
Transp. & Wareh.	1.3	1.9	1.6	2.0
Inform. & Commun.	0.6	0.6	0.4	0.4
FIRE†	1.3	1.3	5.3	4.8
PBS	0.4	0.4	20.7	-166.4
Educ. & Health	0.3	0.3	-0.8	-0.8
Arts, Entert. & Accom.	0.3	0.4	-0.8	-0.7
Misc.	0.6	0.8	-0.7	-0.7

Notes: The table compares the German coefficients of variation for sectoral trends in labor input and TFP growth after cyclical adjustment either by the unemployment rate (UR) or the ifo Business Climate (IBC). FIRE includes housing (†). The time period under investigation runs from 1973 to 2019. FIRE: Financial, Insurance & Real Estate; PBS: Professional & Business Services.

Comparing the shares of the sectoral trends explained by common and sector-specific factors, we note a difference in the fraction of sectoral TFP trend variation depending on the variable used for cyclical adjustment (see Table 10). For numerous sectors, common factors account for a greater proportion of the variation in TFP trends when the ifo Business Climate is employed to cyclically adjust. This is particularly evident in sectors that were identified in the baseline estimation as major investment hubs of the German economy, such as Construction and Durables. Consequently, the aggregate TFP trend is also more influenced by common factors when the ifo Business Climate is used for cyclical adjustment. A similar pattern emerges when examining labor input growth trends. On average, the share of the common factor explaining variation in the sectoral trends is higher when using the ifo Business Climate to adjust. However, when compared to TFP, the differences are relatively minor. Furthermore, the aggregate labor trend is found to be explained by more than two-thirds by common factors using both cyclical adjustment variables. With regard to the correlation between the input factors, the signs of the coefficients are found to be consistent when the ifo Business Climate is used for cyclical adjustment. However, the sizes of the coefficients differ slightly. Overall, the factor decomposition is in line with the baseline findings, with common factors being identified as an even more significant contributor to German trend growth.

Table 10: Robustness of the Factor Decomposition

Sector	UR			IBC		
	R_l^2	R_z^2	$\rho(l,z)$	R_l^2	R_z^2	$\rho(l,z)$
Agriculture	0.05	0.02	0.04	0.04	0.05	0.32
Mining	0.03	0.05	-0.65	0.01	0.14	-0.46
Utilities	0.10	0.07	0.24	0.07	0.28	0.20
Construction	0.18	0.40	0.09	0.18	0.31	0.05
Durable Goods	0.09	0.15	-0.73	0.30	0.30	-0.66
Non-Durable Goods	0.04	0.27	-0.66	0.17	0.22	-0.62
Wholesale Trade	0.88	0.02	-0.09	0.53	0.07	-0.32
Retail Trade	0.94	0.21	-0.84	0.98	0.85	-0.72
Transp. & Wareh.	0.13	0.06	-0.36	0.02	0.12	-0.46
Inform. & Commun.	0.14	0.02	-0.18	0.11	0.09	-0.33
FIRE†	0.75	0.02	0.23	0.79	0.03	0.12
PBS	0.56	0.01	-0.88	0.61	0.05	-0.79
Educ. & Health	0.25	0.04	0.31	0.37	0.07	0.14
Arts, Entert. & Accom.	0.84	0.03	-0.77	0.90	0.06	-0.81
Misc.	0.80	0.80	0.32	0.75	0.44	0.83
Aggregate	0.68	0.30	-0.08	0.68	0.48	-0.05

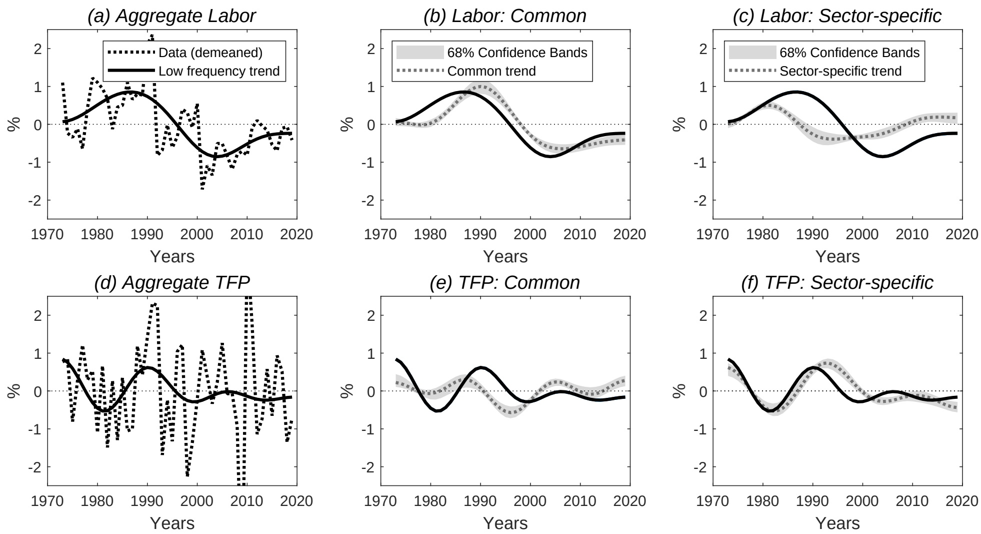
Notes: The table presents the fraction in trend variation explained by common factors for both labor input (R_l^2) and TFP (R_z^2) as well as the correlation between sector-specific trends in labor and TFP, $\rho(l,z)$. For the aggregate, $\rho(l,z)$ corresponds to the correlation between common trends. The table compares the results for the cyclical adjustment either using the unemployment rate (UR) or the ifo Business Climate (IBC). FIRE includes housing (†). FIRE: Financial, Insurance & Real Estate; PBS: Professional & Business Services.

Looking at the historical decomposition as presented in Figure 13, we again see some differences for both low-frequency aggregate labor input and TFP growth. However, they are rather small over the total sample. While variations in trend TFP growth are from the 1970s to the 1990s mostly explained by sector-specific factors when adjusting with the unemployment rate, this is found to be less pronounced when adjusting with the ifo Business Climate. The labor trends' evolution evolves more similar across the adjustment procedures. Again, the higher degree of influence of the common factors is in line with our baseline results.

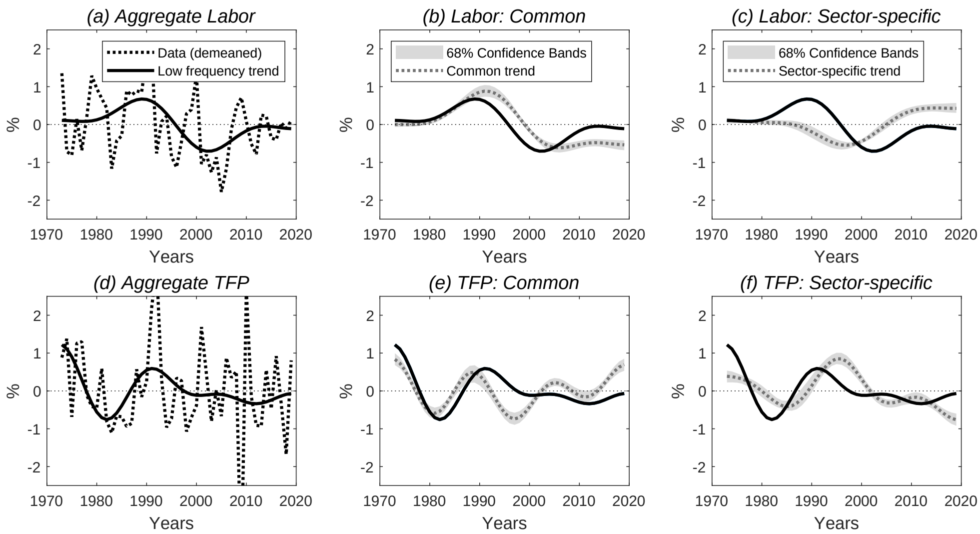
A comparison of the sector-specific trends estimated with our data, cyclically adjusted by the ifo Business Climate, with our baseline results reveals that, on average, the trend movements are similar in direction. However, the extent of those movements differs slightly for some sectors. This is visible for the Durables and Non-Durables trends in labor input growth in Figure 14. For the trends in TFP growth we can observe that adjusting with the ifo Business Climate leads to sector-specific factors having less influence on the total trend of a sector (see Figure 15).

Figure 13: Robustness of the Historical Decomposition of the Aggregates

(a) Adjustment with the unemployment rate



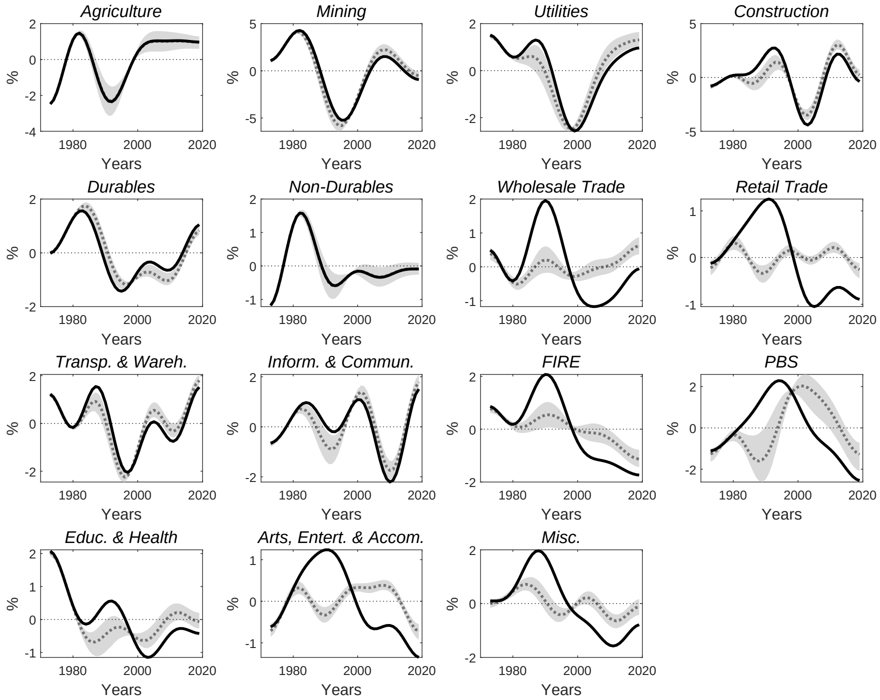
(b) Adjustment with the ifo Business Climate



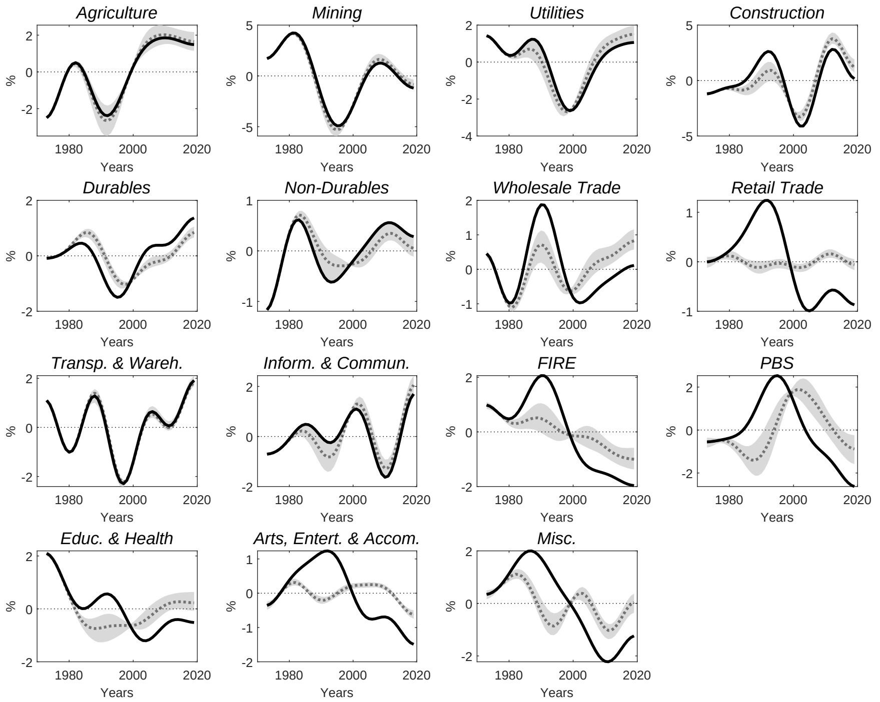
Notes: The upper panel shows the results from the main paper after cyclical adjustment with the unemployment rate. The lower panel presents the adjustment with the ifo Business Climate. The left figures show the raw labor input and TFP growth rates as deviations from their sample means (demeaned, dotted black lines), together with the estimated low-frequency trends (black lines). The figures in the middle and on the right side show the trends' decomposition into common and sector-specific components, separately shown as gray dotted lines. While the dotted lines denote the posterior median, the shaded areas are equally-tailed 68% credible intervals.

Figure 14: Robustness on the Sector-specific Components in Labor Input Trends

(a) Adjustment with the unemployment rate



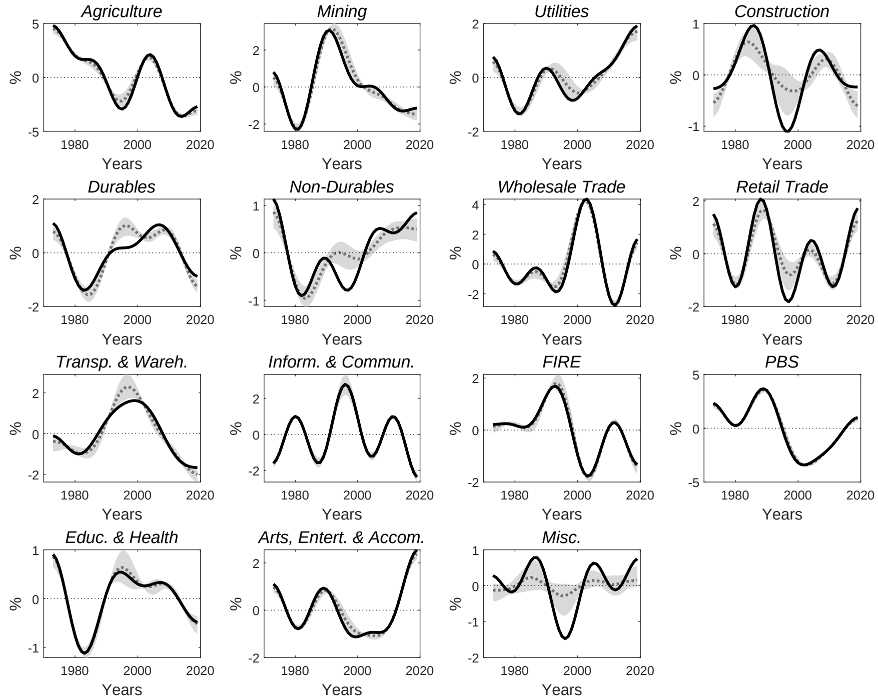
(b) Adjustment with the ifo Business Climate



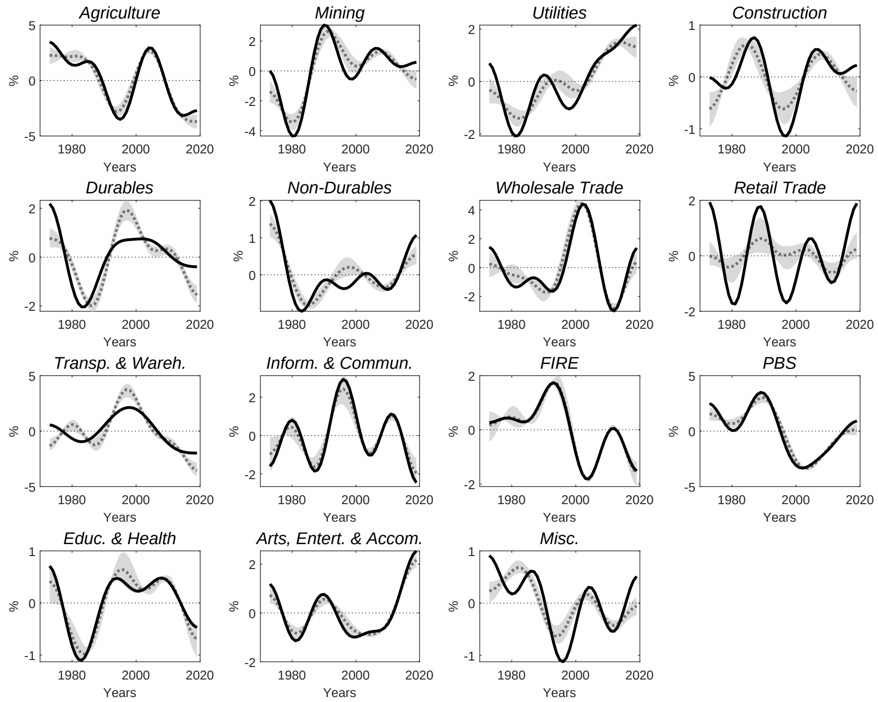
Notes: Each sectoral panel shows the low-frequency trends (solid black lines) together with its sector-specific component (dotted gray lines). The sector-specific components denote the posterior median and the shaded areas are equally-tailed 68% credible intervals. The upper panel shows the results from the main paper after cyclical adjustment with the unemployment rate. The lower panel presents the adjustment with the ifo Business Climate. FIRE includes housing. FIRE: Financial, Insurance & Real Estate; PBS: Professional & Business Services.

Figure 15: Robustness on the Sector-specific Components in TFP Trends

(a) Adjustment with the unemployment rate



(b) Adjustment with the ifo Business Climate



Notes: Each sectoral panel shows the low-frequency trends (solid black lines) together with its sector-specific component (dotted gray lines). The sector-specific components denote the posterior median and the shaded areas are equally-tailed 68% credible intervals. The upper panel shows the results from the main paper after cyclical adjustment with the unemployment rate. The lower panel presents the adjustment with the ifo Business Climate. FIRE includes housing. FIRE: Financial, Insurance & Real Estate; PBS: Professional & Business Services.

The differences between the two adjustment procedures become more pronounced when comparing the overall contributions (labor input and TFP growth) to the aggregate trend in Figure 16. Although the same patterns can be observed in the evolution of the movements, the size of the contributions differs for some sectors. In order to quantify the differences between the two adjustment procedures, we calculate the average contributions to the decline in trend GDP growth for the two periods as presented in the main paper. Table 11 shows these averages for the whole period (1973 to 2019) and for the decade following reunification (1991 to 2000). For both periods, almost all contributions show the same signs and magnitudes. For the sectors showing different signs—Wholesale Trade, Transportation & Warehouse, and Miscellaneous—the influence is very limited and the contributions take values around zero. The most pronounced differences are visible for Construction, Durables, Information & Communication, and PBS. For the whole sample, the contribution of Construction increases from 0.06 percentage points in the baseline to 0.21 percentage points by adjusting via the ifo Business Climate. The same holds true—with negative signs—for Durables (-0.47 vs. -0.61 percentage points) and PBS (-0.49 vs. -0.64 percentage points). Over the 1990s, we observe more positive contributions of Durables (0.16 vs. 0.34 percentage points) and Information & Communication (0.16 vs. 0.29 percentage points) after adjustment via the ifo Business Climate. Notwithstanding the discrepancies in the magnitudes, these findings reinforce our principal findings and even underline them, as the influences of the most significant sectors are enhanced and do not disappear after the adjustment with another cyclical indicator.

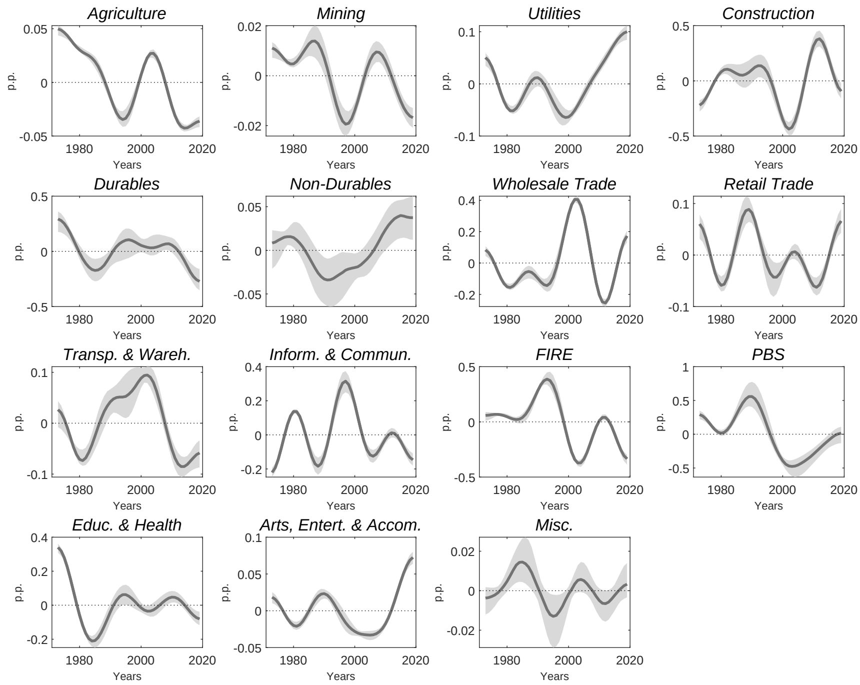
Table 11: Robustness of the Sectoral Contributions to the Decline in Trend GDP Growth

Sector	**1973–2019**		**1991–2000**	
	UR	IBC	UR	IBC
Agriculture	-0.09	-0.07	0.03	0.02
Mining	-0.03	-0.01	-0.03	-0.04
Utilities	0.04	0.06	-0.10	-0.11
Construction	0.06	0.21	-0.77	-0.80
Durable Goods	-0.47	-0.61	0.16	0.34
Non-Durable Goods	0.04	0.00	0.00	0.01
Wholesale Trade	0.05	-0.03	0.28	0.29
Retail Trade	-0.03	-0.04	-0.21	-0.22
Transp. & Wareh.	-0.10	-0.14	-0.02	0.00
Inform. & Commun.	0.05	0.06	0.16	0.29
FIRE†	-0.41	-0.48	-0.61	-0.54
PBS	-0.49	-0.64	-1.51	-1.47
Educ. & Health	-0.46	-0.46	-0.15	-0.14
Arts, Entert. & Accom.	0.04	0.02	-0.11	-0.10
Misc.	0.00	-0.03	-0.03	-0.03

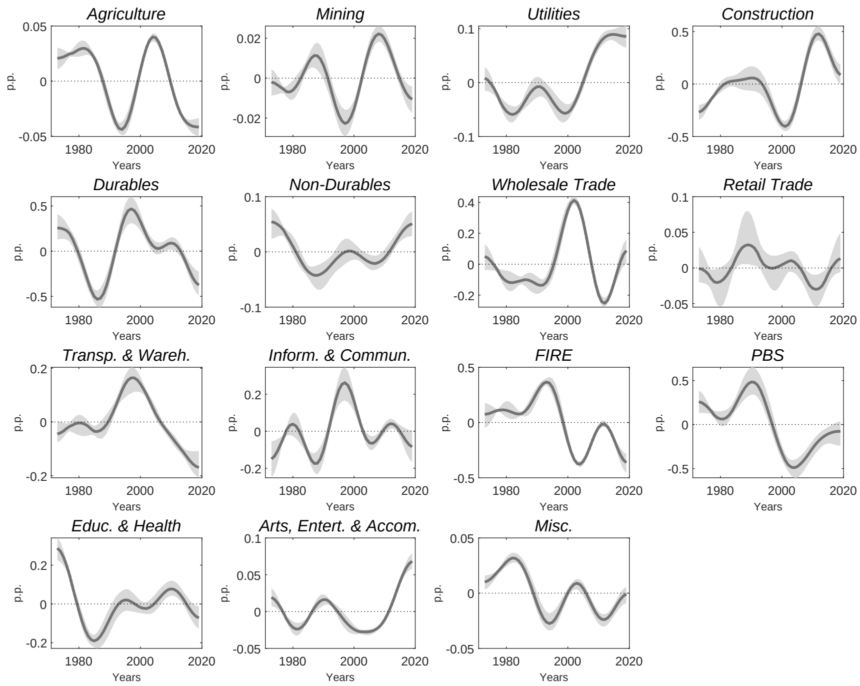
Notes: The table shows the sector-specific contributions (in percentage points) of trend labor input and TFP growth to the decline of trend GDP growth for two separate time periods. The calculation of contributions are based on constant sectoral multipliers for the year 2018. FIRE: Financial, Insurance & Real Estate; PBS: Professional & Business Services.

Figure 16: Robustness of the Sector-specific Contributions to the Overall Trend

(a) Adjustment with the unemployment rate



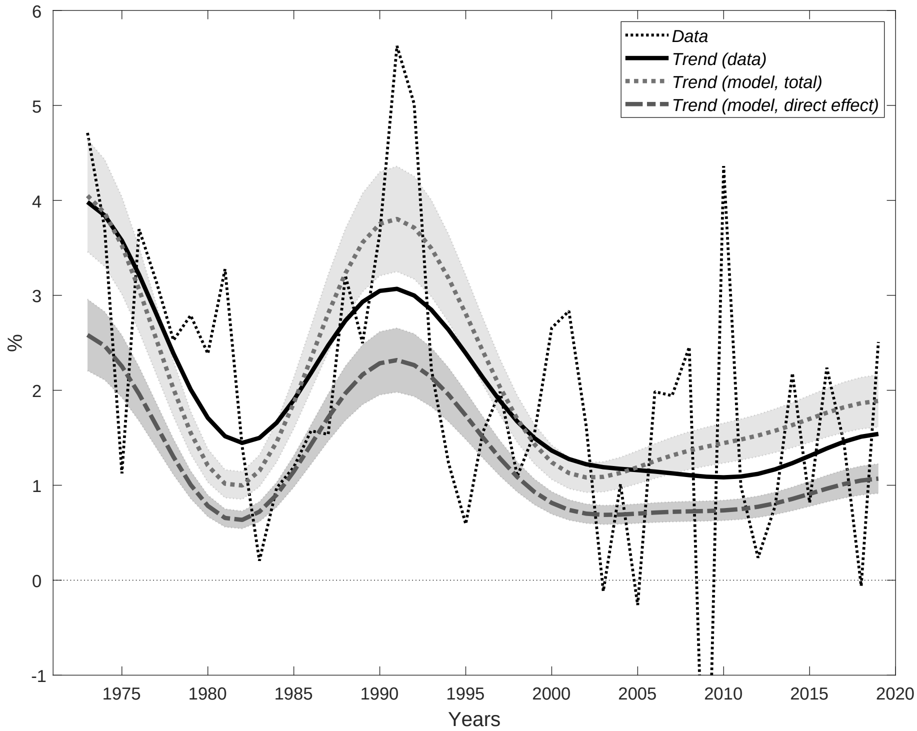
(b) Adjustment with the ifo Business Climate



Notes: Each sectoral panel shows the contributions (in percentage points) of sector-specific trends for trend GDP growth using the model-implied multipliers along the balanced growth path. The solid lines denote the posterior median and the shaded areas are equally-tailed 68% credible intervals. The upper panel shows the results from the main paper with the adjustment by the unemployment rate. The lower panel presents the result from adjustment with the ifo Business Climate. FIRE includes housing. FIRE: Financial, Insurance & Real Estate; PBS: Professional & Business Services.

The picture for model-implied GDP growth based on the adjustment by the ifo Business Climate looks similar to the baseline result (see Figure 17). The direction of movements and the magnitude of the trend in GDP growth decline are almost identical. When the unemployment rate is used for adjustment, aggregate trend GDP growth declines by 2.1 percentage points over the entire period. However, when the data is cyclically adjusted with the ifo Business Climate, the decline in total GDP growth is 2.4 percentage points.

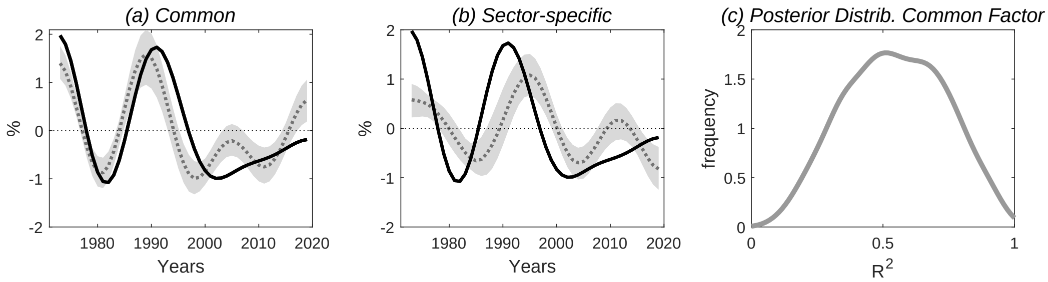
Figure 17: Robustness of the Model-Implied Trend GDP Growth



Notes: The figure shows the cyclically adjusted GDP growth rate (thin dotted black line) and its estimated low-frequency trend (thick black line). The raw data were cyclically adjusted with the ifo Business Climate. The dotted gray line marks the model-implied trend growth rate along the balanced growth path. The dashed gray line, instead, presents the trend growth rate based on the value added shares, or direct effects, only. These lines represent the baseline case and are calculated from the 2018 IO as well as capital-flow matrices and constant value added shares, respectively. The shaded areas mark the one standard deviation bands from estimates based on either time-varying IO and capital-flow matrices or non-constant value added shares.

Finally, we discuss the influence of the cyclical adjustment procedure on the overall contributions of common and sector-specific factors to model-implied trend GDP growth. Figure 18 shows the robustness of this decomposition. In summary, the overall picture is similar to that of our baseline results. However, the fraction explained by common factors is slightly larger in magnitude. This finding is consistent with our baseline results, which indicate that common forces play a larger role in German trend GDP growth compared to the US, where sector-specific forces explain a larger fraction in low-frequency movements.

Figure 18: Robustness of the Decomposition of Trend Growth in GDP



Notes: Panels (a) and (b) show the demeaned model-implied trend GDP growth (black line) together with the changes stemming from common factors and sector-specific developments (gray lines), respectively. The cyclical adjustment is based on the ifo Business Climate. Panel (c) shows the posterior distribution for the fraction of the total variance explained by common factors.

As previously stated, the unemployment rate may not fully capture all fluctuations in the German business cycle. Using the ifo Business Climate Index, however, may result in an overestimation of the degree of variation, as business cycle dynamics vary across sectors. Therefore, we have chosen to present the unemployment rate results as our baseline. We suggest that these baseline results represent the upper bound, while the results obtained from the ifo Business Climate-adjusted data represent the lower bound for low-frequency trends and thus the contributions to trend GDP growth. The true values may most likely lie somewhere between these bounds, but both procedures yield qualitatively similar results.

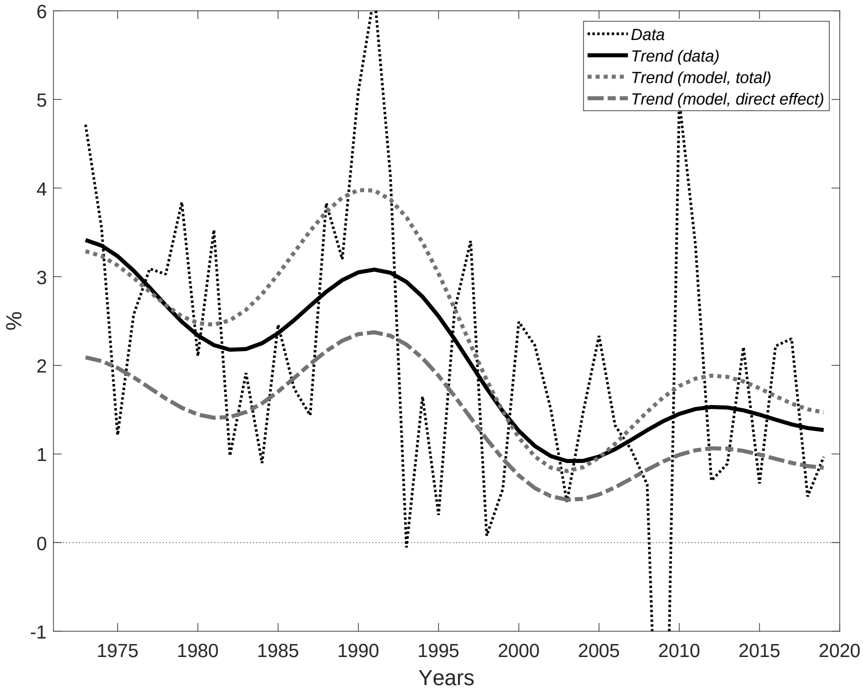
4.2 Parameter and Prior

The estimations might heavily depend on the parameters and priors chosen. We therefore discuss the robustness of our baseline results to changes in both the length of the low-frequency movements (q) and the degree of aggressiveness to shrink the factor loadings against unity (η). In the baseline we set $q = 6$ and $\eta = 1$. In the following, we either set $q = 5$ and $q = 7$ or $\eta = 0.5$ and $\eta = 2$, keeping the other parameters as in the baseline.

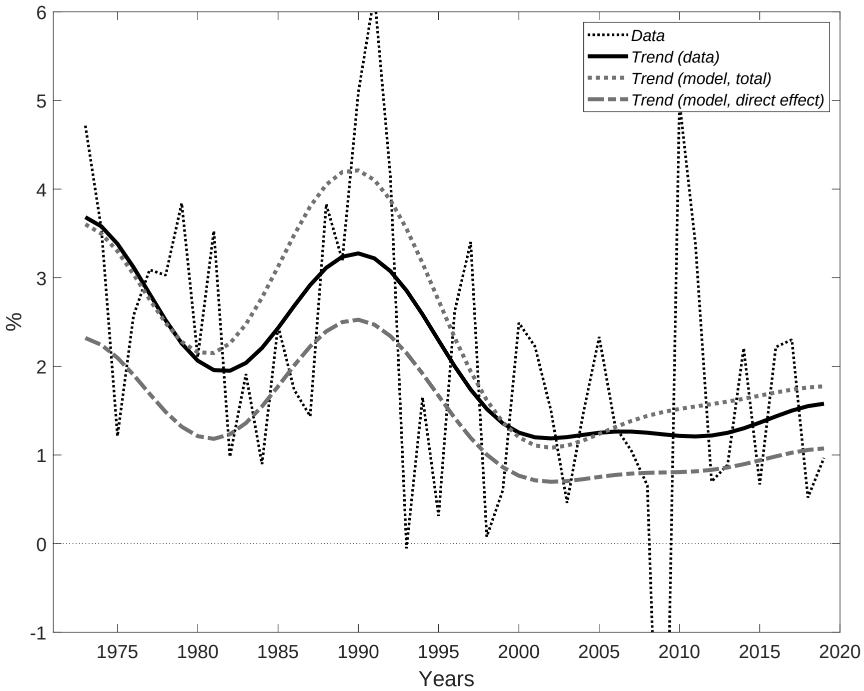
Length of the low-frequency movements. In the following we vary the definition of the low-frequency length by holding the prior for the loadings' variance constant. Instead of setting $q = 6$, we apply $q = 5$ (periodicities longer than 18.8 years) and $q = 7$ (periodicities longer than 13.4 years). Figure 19 shows the model-implied trend GDP growth for both parameter values. Overall, the variation in the periodicity length does not change our baseline results. Furthermore, we carry out a robustness check on the decomposition of trend GDP growth (see Figure 20). For $q = 5$, the results are almost identical to the baseline, with half of the variation explained by common factors. We observe some small changes at the end of the sample by applying $q = 7$ and thus a slightly shorter periodicity. Here, the influence of sector-specific factors gets a bit more pronounced. Nevertheless, the median of the posterior distribution is approximately 0.5, indicating that the qualitative results of our baseline analysis remain consistent also in this case.

Figure 19: Robustness of the Model-Implied Trend GDP Growth, Varying q

(a) $q = 5$



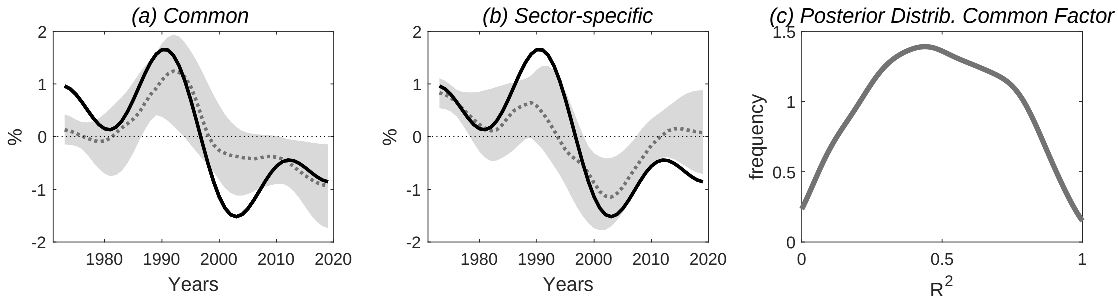
(b) $q = 7$



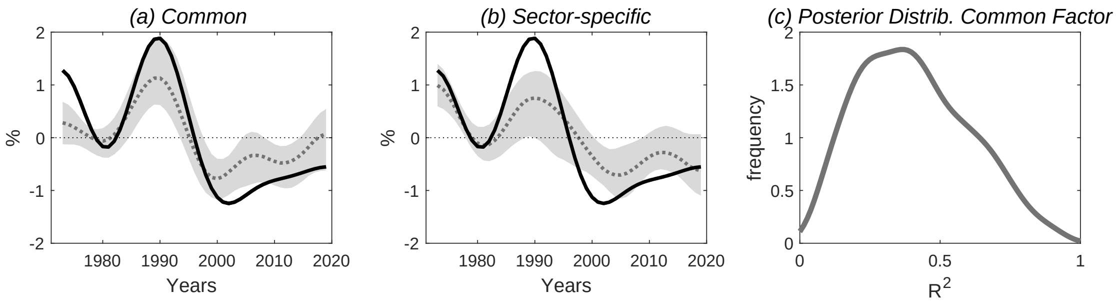
Notes: The figure shows the cyclically adjusted GDP growth rate (thin dotted black line) and its estimated low-frequency trend (thick black line). The dotted gray line marks the model-implied trend growth rate along the balanced growth path. The dashed gray line, instead, presents the trend growth rate based on the value added shares, or direct effects, only. These lines represent the baseline case and are calculated from the 2018 IO as well as capital-flow matrices and constant value added shares, respectively. The upper panel shows the estimates for $q = 5$, implying low-frequency movements larger than 18.8 years. The lower panel presents the results for $q = 7$, implying periodicities longer than 13.4 years. In the baseline case, we apply $q = 6$ with low-frequency movements larger than 15.5 years.

Figure 20: Robustness of the Decomposition of Trend Growth in GDP, Varying q

(a) $q = 5$



(b) $q = 7$

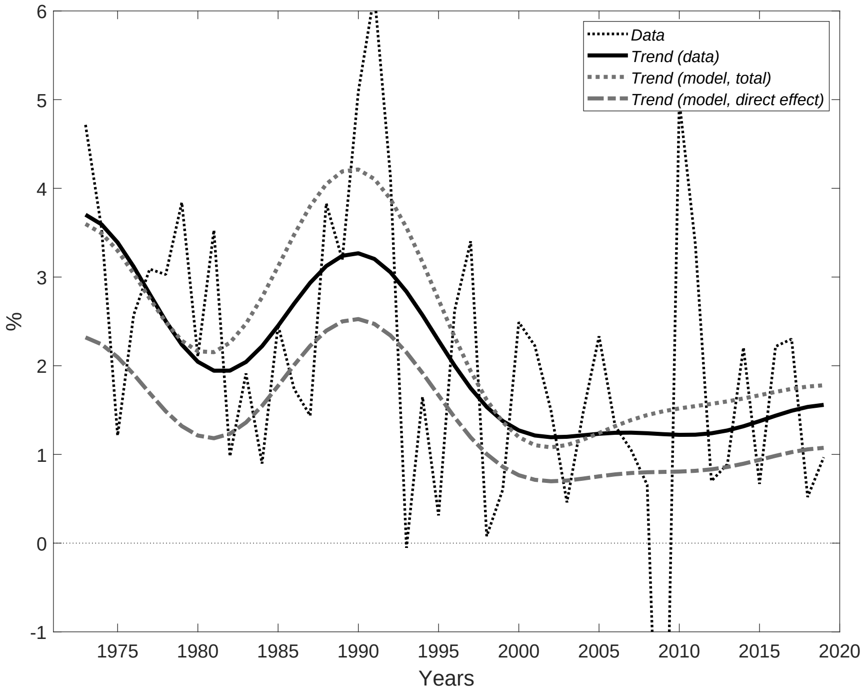


Notes: Notes: Panels (a) and (b) show the demeaned model-implied trend GDP growth (black line) together with the changes stemming from common factors and sector-specific developments (gray lines), respectively. Panel (c) shows the posterior distribution for the fraction of the total variance explained by common factors. The upper panel shows the estimates for $q = 5$, implying low-frequency movements larger than 18.8 years. The lower panel presents the results for $q = 7$, implying periodicities longer than 13.4 years. In the baseline case, we apply $q = 6$ with low-frequency movements larger than 15.5 years.

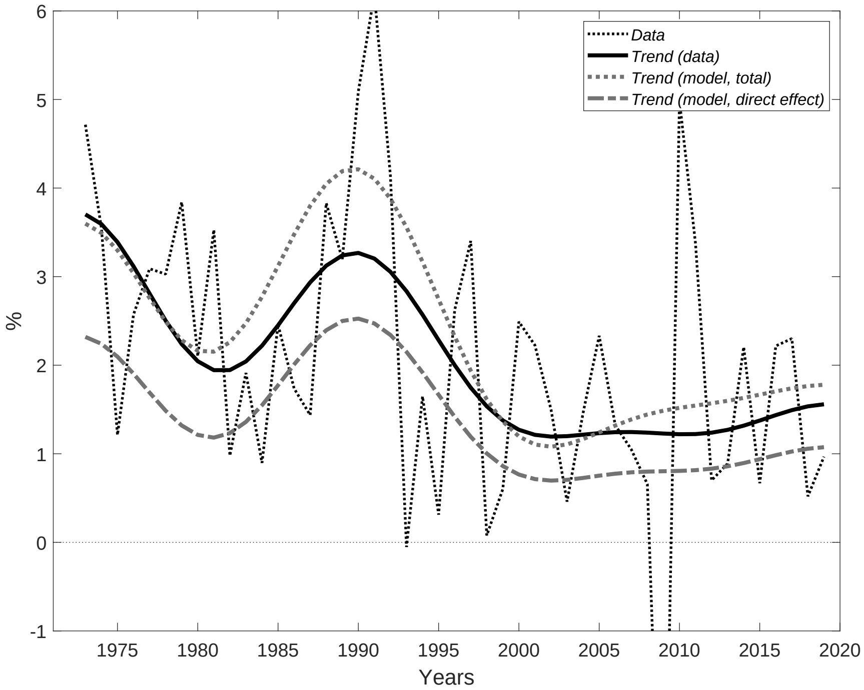
Degree of shrinkage. We below demonstrate that the choice of η, the prior parameter governing the aggressiveness of shrinking the estimates of the factor loading's towards their mean, has only negligible influence on the decomposition of trend GDP growth. We observe that both a tighter constraint, with $\eta = 0.5$ as well as a wider constraint of $\eta = 2$, which allows for more negative factor loadings, do not result in completely different shares of the trend explained by common and sector-specific components. The model-implied trend GDP growth rates are identical per construction (see Figure 21). The median fraction explained by common factors is 50% in the case of $\eta = 0.5$ and close to a half by applying $\eta = 2$ (see Figure 22). Hence, all our baseline results also hold by varying this prior.

Figure 21: Robustness of the Model-Implied Trend GDP Growth, Varying η

(a) $\eta = 0.5$



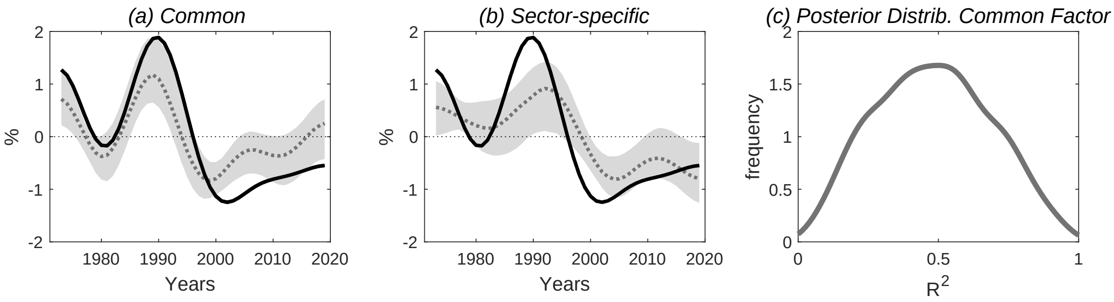
(b) $\eta = 2$



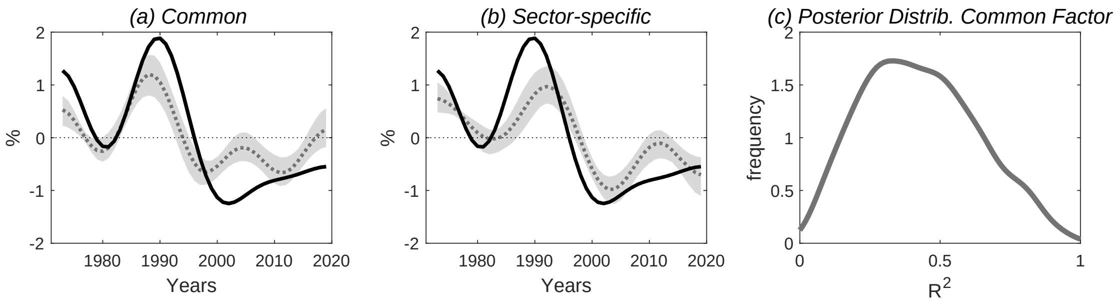
Notes: The figure shows the cyclically adjusted GDP growth rate (thin dotted black line) and its estimated low-frequency trend (thick black line). The dotted gray line marks the model-implied trend growth rate along the balanced growth path. The dashed gray line, instead, presents the trend growth rate based on the value added shares, or direct effects, only. These lines represent the baseline case and are calculated from the 2018 IO as well as capital-flow matrices and constant value added shares, respectively. The upper panel shows the estimates for $\eta = 0.5$ and the lower panel the results for $\eta = 2$. In the baseline case, we apply $\eta = 1$. Per construction, the figures have to be identical.

Figure 22: Robustness of the Decomposition of Trend Growth in GDP, Varying η

(a) $\eta = 0.5$



(b) $\eta = 2$

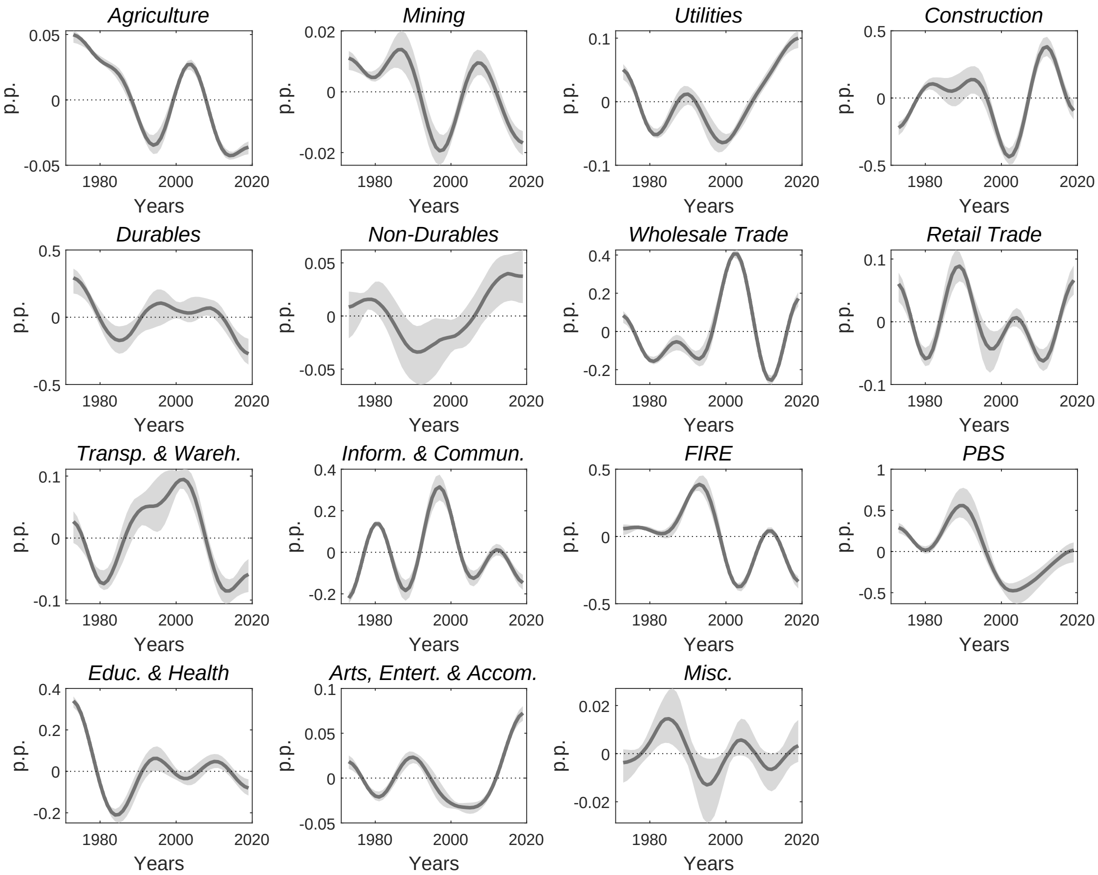


Notes: Notes: Panels (a) and (b) show the demeaned model-implied trend GDP growth (black line) together with the changes stemming from common factors and sector-specific developments (gray lines), respectively. Panel (c) shows the posterior distribution for the fraction of the total variance explained by common factors. The upper panel shows the estimates for $\eta = 0.5$ and the lower panel the results for $\eta = 2$. In the baseline case, we apply $\eta = 1$.

4.3 Sectoral Shares

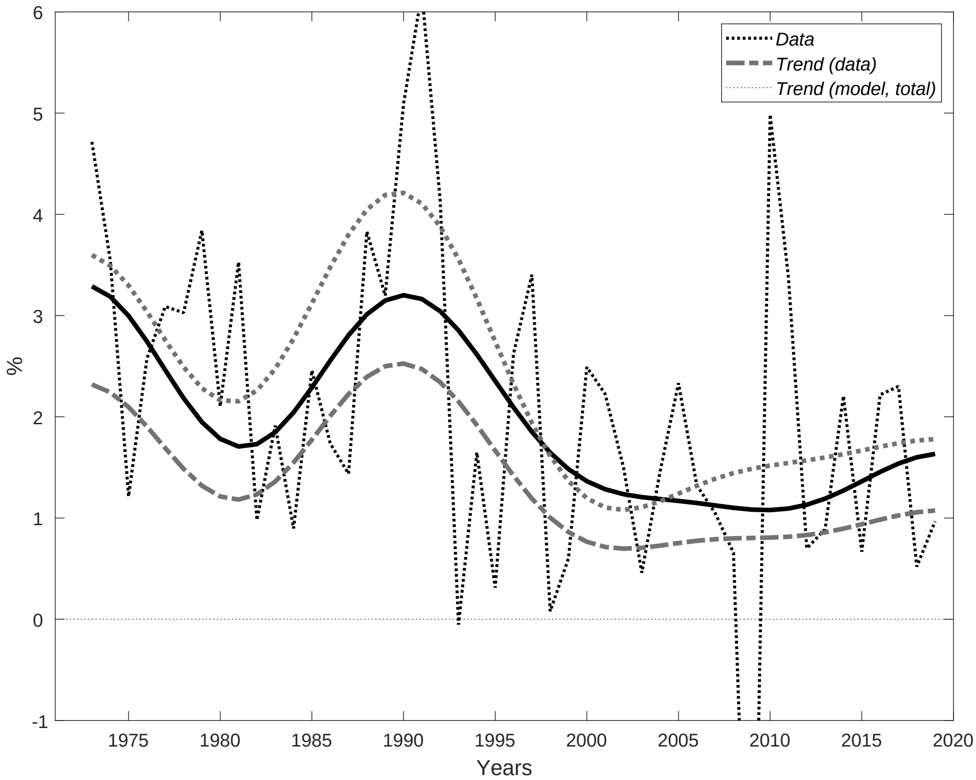
In the following, we examine the impact of the sectoral aggregation scheme on our estimates. As a baseline case, we apply mean sectoral gross value added shares for the full sample. In national accounting, chain-weighting is applied instead, and we re-estimate the models based on aggregated data by this weighting scheme. All other parameters are left unchanged (cyclical adjustment by the unemployment rate, $q = 6$, and $\eta = 1$). Figures 23, 24 and 25 present the sectoral contributions, the model-implied GDP growth, and the overall decomposition of German trend GDP growth, respectively. The weighting scheme does not change our baseline picture, leaving the evolution of long-term trends almost untouched.

Figure 23: Robustness of the Sectoral Contributions, Chain-weights



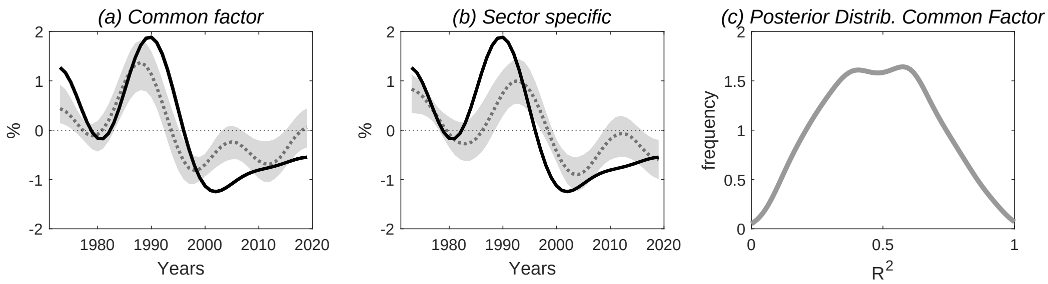
Notes: Each sectoral panel shows the contributions (in percentage points) of sector-specific trends for trend GDP growth using the model-implied multipliers along the balanced growth path. The solid lines denote the posterior median and the shaded areas are equally-tailed 68% credible intervals. Aggregates are calculated by chain-weighting sectoral figures. FIRE includes housing. FIRE: Financial, Insurance & Real Estate; PBS: Professional & Business Services.

Figure 24: Robustness of the Model-Implied Trend GDP Growth, Chain-weights



Notes: The figure shows the cyclically adjusted GDP growth rate (thin dotted black line) and its estimated low-frequency trend (thick black line). The raw data were cyclically adjusted with the unemployment rate. The dotted gray line marks the model-implied trend growth rate along the balanced growth path. The dashed gray line, instead, presents the trend growth rate based on the value added shares, or direct effects, only. These lines are calculated from the 2018 IO as well as capital-flow matrices. The aggregate values are achieved by chain-weighting the sectoral values.

Figure 25: Robustness of the Decomposition of Trend Growth in GDP, Chain-weights



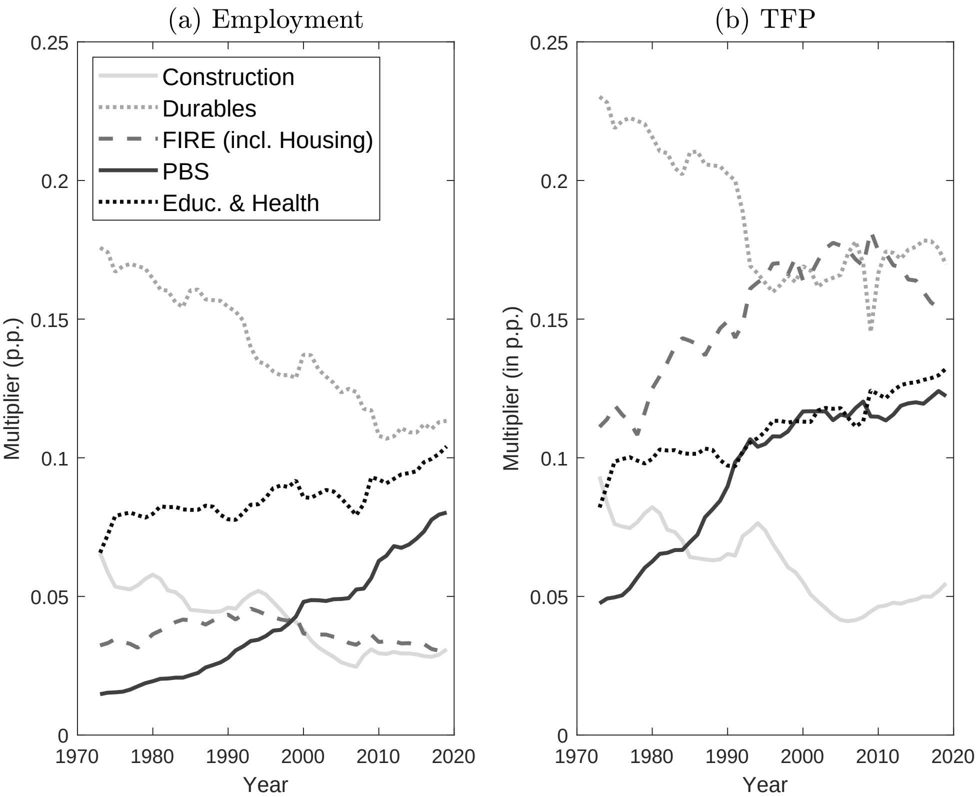
Notes: Panels (a) and (b) show the demeaned model-implied trend GDP growth (black line) together with the changes stemming from common factors and sector-specific developments (gray lines), respectively. Aggregates are achieved by chain-weighting the sectoral figures. Panel (c) shows the posterior distribution for the fraction of the total variance explained by common factors.

5 Structural Change in the German Economy

5.1 Multiplier Composition and Evolution

A major advantage of our data set is the availability of time-varying sectoral multipliers. For the five sectors with the overall largest sectoral multipliers, Figures 26 and 27 present the evolution of the sectoral multipliers' direct and indirect effects for both labor input and TFP. We observe steady declines in the direct effects in labor input for Construction and Durables, while the share of PBS and Education & Health increases. The direct effect of FIRE in labor input remains relatively constant over time. In contrast, for TFP, the direct effect of Durables declines until the 1990s and then stabilizes around 0.18. Similarly, the direct effect for Construction steadily declines until the mid-2000s and slightly increases afterwards. At the end of the sample it amounts to 0.05. The sectors PBS, Education & Health and FIRE show steady increases of their direct effects, with the latter decreasing in the 2010s.

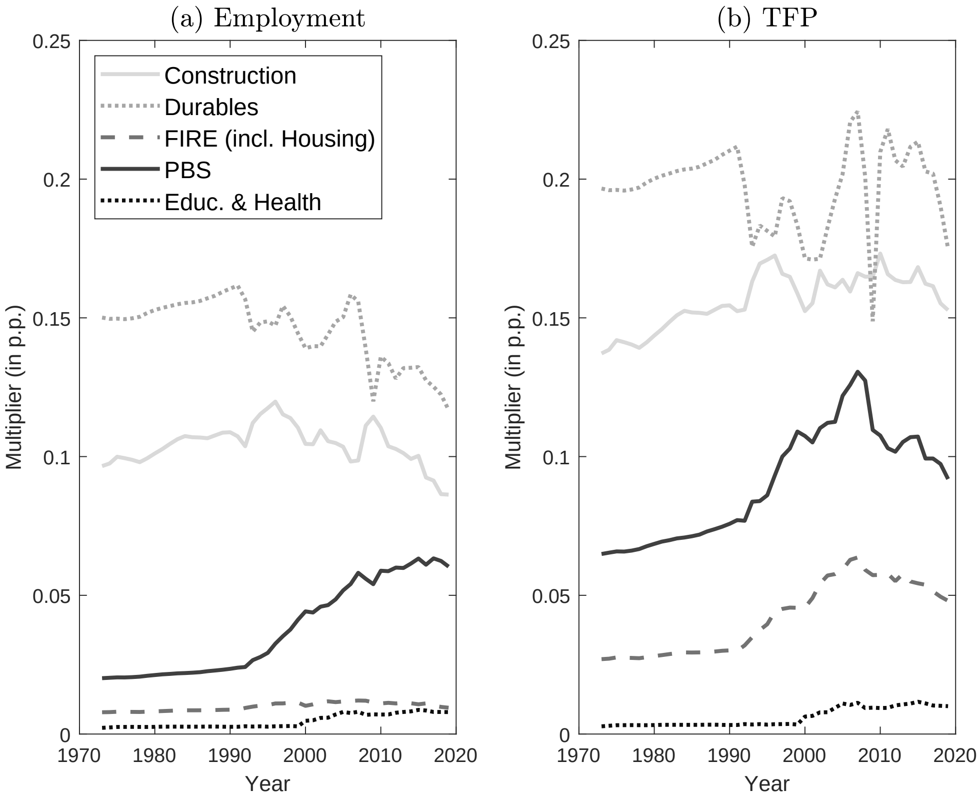
Figure 26: Evolution of Sectoral Multipliers, Direct Effects



Notes: The figure shows the timely evolution of the sectoral multipliers' direct effects, constructed from the overall sectoral multiplier of the composite variable g^a: $s^v + \Xi\Omega\alpha_d s^v$. FIRE: Financial, Insurance & Real Estate; PBS: Professional & Business Services.

The indirect effects of the labor input multiplier in the Construction and Durable Goods sectors have exhibited a downward trend since the 1990s. In contrast, the indirect multiplier effect of PBS has demonstrated an upward-sloping trend. For FIRE and Education & Health, the indirect effects move rather sideways. The indirect effects for TFP of Construction and Durables vary over time but remain at a rather average level. For PBS we observe a strong increase until the mid-2000s, followed by a decrease until the end of the sample. The same holds true for FIRE. For Education & Health, the indirect effect increases in the first decade of the 2000s and moves sideways afterwards.

Figure 27: Evolution of Sectoral Multipliers, Indirect Effects



Notes: The figure shows the timely evolution of the sectoral multipliers' indirect effects, constructed from the overall sectoral multiplier of the composite variable g^a: $s^v + \Xi\Omega\alpha_d s^v$. FIRE: Financial, Insurance & Real Estate; PBS: Professional & Business Services.

5.2 Results with Average Sectoral Multipliers

In the following we re-estimate all our results by applying sectoral multipliers averaged over the entire sample period in stead of using the 2018 values. Table 12 presents the average sectoral multipliers. We again discuss the influence of these multipliers for the sectoral contributions, the model-implied GDP growth, and its overall decomposition.

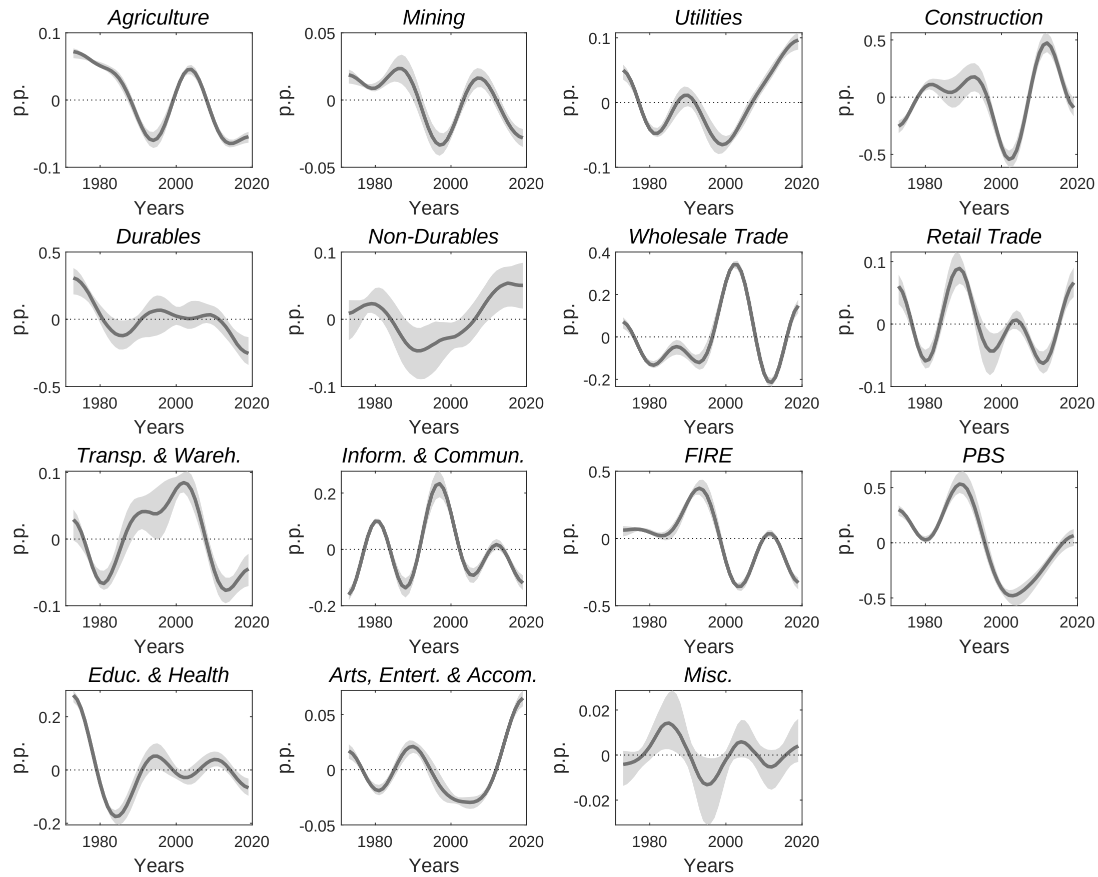
Table 12: Average Sectoral Multipliers

Sector	**Labor Input**			**TFP**		
	direct	indirect	total	direct	indirect	total
Agriculture	0.00	0.00	0.01	0.01	0.01	0.02
Mining	0.00	0.01	0.01	0.00	0.01	0.01
Utilities	0.01	0.00	0.02	0.03	0.01	0.04
Construction	0.03	0.10	0.14	0.05	0.16	0.22
Durable Goods	0.12	0.14	0.26	0.17	0.19	0.36
Non-Durable Goods	0.05	0.02	0.07	0.07	0.03	0.10
Wholesale Trade	0.03	0.02	0.06	0.05	0.04	0.09
Retail Trade	0.05	0.00	0.05	0.06	0.01	0.07
Transp. & Wareh.	0.03	0.01	0.04	0.05	0.02	0.06
Inform. & Commun.	0.02	0.02	0.05	0.05	0.05	0.09
FIRE†	0.04	0.01	0.05	0.17	0.05	0.22
PBS	0.05	0.05	0.10	0.11	0.10	0.22
Educ. & Health	0.09	0.01	0.10	0.12	0.01	0.13
Arts, Entert. & Accom.	0.02	0.00	0.02	0.03	0.01	0.04
Misc.	0.01	0.00	0.01	0.03	0.00	0.03

Notes: The table shows the average sectoral multipliers over the entire sample period. FIRE includes housing (†). FIRE: Financial, Insurance & Real Estate; PBS: Professional & Business Services.

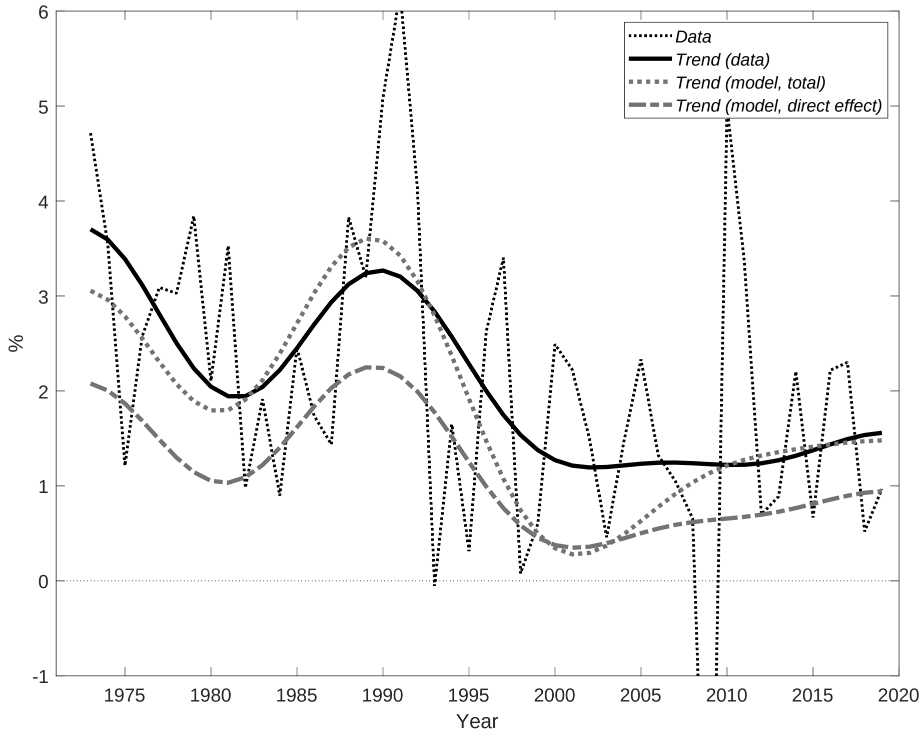
The Figures 28, 29, and 30 show the corresponding results based on average sectoral multipliers. All baseline results hold, but we can achieve an even better fit of the model-implied trend GDP growth rate along the balanced growth path for the low-frequency trend. Consequently, the average sectoral multiplier appears to be a more accurate approximation than the 2018 values when attempting to approximate low-frequency movements through the multi-sector growth model. In the following section, we will discuss the application of annual-specific multipliers.

Figure 28: Discussion of the Sectoral Contributions, Average Multipliers



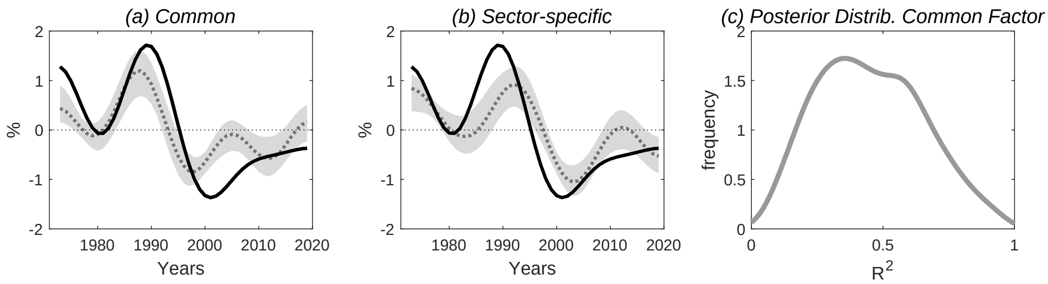
Notes: Each sectoral panel shows the contributions (in percentage points) of sector-specific trends for trend GDP growth using the model-implied multipliers along the balanced growth path. The solid lines denote the posterior median and the shaded areas are equally-tailed 68% credible intervals. Average sectoral multipliers are applied instead of the 2018 values. FIRE includes housing. FIRE: Financial, Insurance & Real Estate; PBS: Professional & Business Services.

Figure 29: Discussion of the Model-Implied Trend GDP Growth, Average Multipliers



Notes: The figure shows the cyclically adjusted GDP growth rate (thin dotted black line) and its estimated low-frequency trend (thick black line). The raw data were cyclically adjusted with the unemployment rate. The dotted gray line marks the model-implied trend growth rate along the balanced growth path. The dashed gray line, instead, presents the trend growth rate based on the value added shares, or direct effects, only. These model-implied trends are calculated from average sectoral multipliers.

Figure 30: Discussion of the Decomposition of Trend Growth in GDP, Average Multipliers

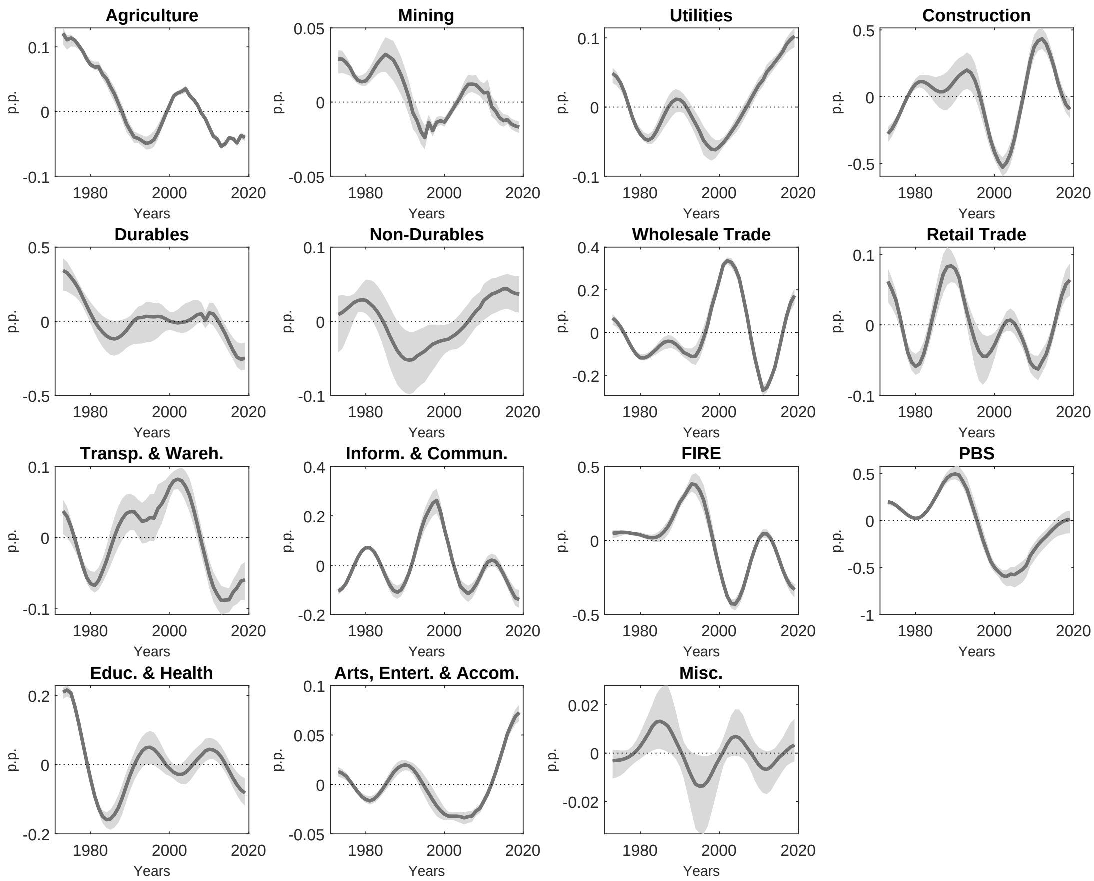


Notes: Panels (a) and (b) show the demeaned model-implied trend GDP growth (black line) together with the changes stemming from common factors and sector-specific developments (gray lines), respectively. Panel (c) shows the posterior distribution for the fraction of the total variance explained by common factors. Average sectoral multipliers are used instead of 2018 values.

5.3 Results with Annual-specific Sectoral Multipliers

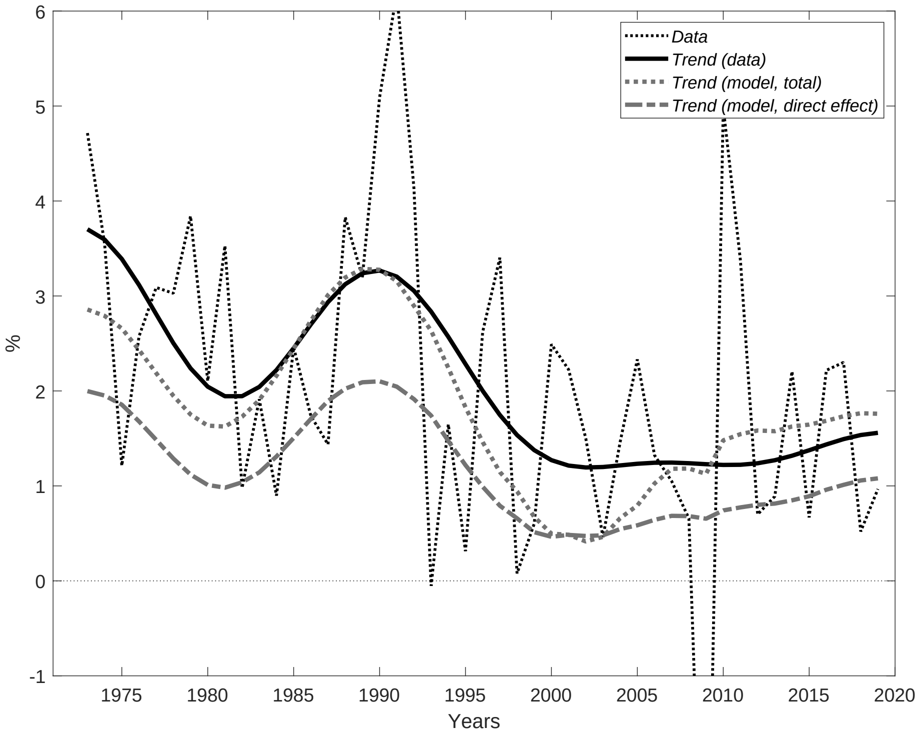
As we can access sectoral multipliers for each year between 1991 and 2018, we apply these annual-specific multipliers in the following (fixing the preceding / following multipliers for the years before and after). Again Figures 31, 32, and 33 show the outcomes for the sectoral contributions, the model-implied GDP growth, and its overall decomposition, respectively. All qualitative statements from the main paper remain. And as we have seen in the previous section, the variation in sectoral multipliers increases the fit of the model-implied trend GDP growth along the balanced growth path for the low-frequency movements.

Figure 31: Discussion of the Sectoral Contributions, Annual-specific Multipliers



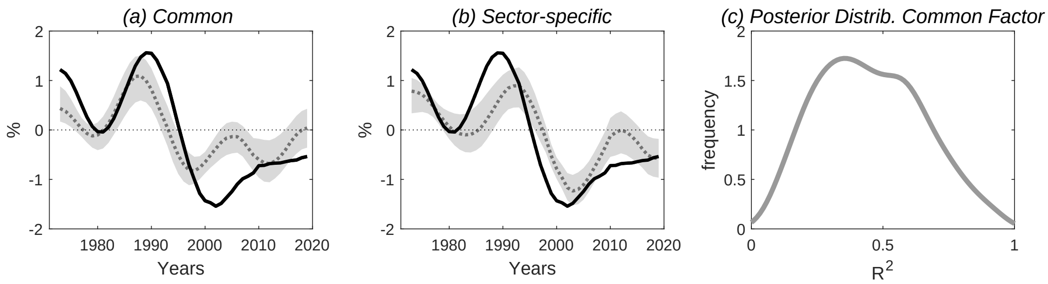
Notes: Each sectoral panel shows the contributions (in percentage points) of sector-specific trends for trend GDP growth using the model-implied multipliers along the balanced growth path. The solid lines denote the posterior median and the shaded areas are equally-tailed 68% credible intervals. Annual-specific sectoral multipliers are applied instead of the 2018 values. FIRE includes housing. FIRE: Financial, Insurance & Real Estate; PBS: Professional & Business Services.

Figure 32: Discussion of the Model-Implied Trend GDP Growth, Annual-specific Multipliers



Notes: The figure shows the cyclically adjusted GDP growth rate (thin dotted black line) and its estimated low-frequency trend (thick black line). The raw data were cyclically adjusted with the unemployment rate. The dotted gray line marks the model-implied trend growth rate along the balanced growth path. The dashed gray line, instead, presents the trend growth rate based on the value added shares, or direct effects, only. These model-implied trends are calculated from annual-specific sectoral multipliers.

Figure 33: Discussion of the Decomposition of Trend Growth in GDP, Annual-specific Multipliers



Notes: Panels (a) and (b) show the demeaned model-implied trend GDP growth (black line) together with the changes stemming from common factors and sector-specific developments (gray lines), respectively. Panel (c) shows the posterior distribution for the fraction of the total variance explained by common factors. Annual-specific sectoral multipliers are used instead of 2018 values.

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