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structural change and total factor productivity: evidence from germany

by Philipp Henze



Structural Change and Total Factor Productivity: Evidence from Germany*

Philipp Henze**

Abstract

This paper uses a long time series of German employment data to test the theory of Ngai & Pissarides (2007). The theory suggests that the shift of employment shares from manufacturing to services is due to divergent growth rates of total factor productivity (TFP) in the two sectors. To test the theoretical predictions, I use the "Establishment History Panel" together with sectoral data on total factor productivity. The results confirm the theoretical predictions, i.e. they show a negative relationship between employment growth and TFP growth.

Keywords: Structural Change, Economic Growth, Total Factor Productivity

JEL codes: L16, O14, O40, D24

*The calculations for this paper are based on the "Establishment History Panel" provided by the Research Data Centre of the German Federal Employment Agency at the Institute for Employment Research. For my research, I have access to the data via on-site use at the Research Data Centre in Nürnberg as well via remote data access. I thank the members of the data centre for running my Stata do-files and checking the log-files for violation of data protection. The establishment level data used are confidential but not exclusive; see <http://fdz.iab.de/> for any details regarding the access to the data.

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1 Introduction

During the last decades, most developed economies experienced a substantial structural change. Economic growth took place at very different rates across industries. Employment in manufacturing steadily declined, whereas employment in the service sector grew continuously. Several recent multi-sector growth models are able to explain the driving forces behind structural change. The models can be classified into two groups regarding their explanations: technology-driven and preference-driven structural change. The most prominent paper of the first group is the one by Ngai & Pissarides (2007), which explains structural change by divergent total factor productivity (TFP) growth rates between manufacturing and service industries. Exemplary for the second group is the paper by Kongsamut et al. (2001), who show that non-homothetic preferences can be a driving force behind structural change.¹

The current paper focuses on the first strand of literature by testing the theory of Ngai & Pissarides (2007) with German labor market data and data on German TFP from 1980 to 2009. To the best of my knowledge, this is the first analysis to test this theory. The results confirm the theoretical predictions of Ngai & Pissarides (2007) and thus identify diverging sectoral growth rates of TFP as one of the driving forces behind structural change.

In particular, this paper is the first empirical study that tests the employment effects of diverging TFP growth rates over a very long time period. This is especially important for two reasons: First, employment movements are not expected to occur immediately if TFP growth rates start to diverge. Firms observe changes in TFP ex post and therefore the reaction is, by nature, lagged. If only cross-section data are used, the effects will be underestimated, because it is not possible to account for delayed effects. Second, as the data show, there are periods where TFP growth rates between manufacturing industries and services did not diverge significantly. If only a short time period is considered that focuses on these years, the results will be misleading. Hence, it is of particular importance to analyze a long time period to identify the employment effects of diverging sectoral TFP growth rates accurately.

Ngai & Pissarides (2007) focus on total factor productivity and show that employment shares shift to industries with low TFP growth rates if the elasticity of substitution across final goods is sufficiently low, i.e. below one. The mechanism that Ngai & Pissarides (2007) describe goes back to Baumol (1967), who developed a model with two sectors that differ in their respective productivity growth: First, there is a technologically "progressive" sector in which innovations and economies of scale

¹A recent review of the literature on structural change that is dating back to the 19th century is provided by Matsuyama (2008).

are achieved and thus lead to high productivity gains.² Therefore, it is possible to decrease the overall costs of production or to offset other increasing costs of production, e.g. increasing wages. Second, there is a "stagnant" sector that, by its nature, experiences relatively smaller productivity increases because labor is the only input and "product" quality is directly related to the amount of labor that is used. The manufacturing sector represents the former, "progressive" sector, where technological progress, e.g. the increasing automatization, improves the quality of products and/or decreases the costs of production. The latter category, the "stagnant" sector, is the service sector. Hence, production costs and prices of the "stagnant" industry rise relative to those of the "progressive" sector. This phenomenon is commonly known as "Baumol's cost disease". Finally, Baumol assumed that the output shares of the two sectors are fairly constant.³ Thus, the share of production inputs, such as labor used in the "stagnant" sector has to rise continuously to compensate the relative productivity deficit. Ngai & Pissarides (2007) introduce this mechanism into a neoclassical growth model. In line with Baumol (1967), they assume a "progressive" manufacturing sector and a "stagnant" service sector in terms of total factor productivity growth. Furthermore, they assume that structural change is a process at a rather aggregated industry-level. At this level, industries and their final products differ significantly from each other such that the elasticity of substitution between final goods is sufficiently low (below one). This assumption corresponds to the constant output share assumption of the two sectors that Baumol (1967) stated. Because the elasticity of substitution between the sectors is below one, demand reacts disproportionately little to price increases in services and therefore an increasing share of workers has to work in the service sector to compensate the relative productivity losses and to satisfy the demand of consumers.

The current paper is based on a very detailed establishment-level data set, the "Establishment History Panel" (in German: Betriebs-Historik-Panel (BHP)), covering all establishments in West Germany over the time span from 1975 to 2010 and all establishments in East Germany from 1991 onwards. The data set provides a detailed insight into the German economy over a long time period and is therefore ideally suited to investigate long-term structural changes in employment shares. Among other things, it provides information on the classification of economic activities and on the employment structure of each establishment. Because the BHP

²Görg, Hanley & Strobl (2005) provide empirical evidence that international outsourcing of inputs is another source that is able to promote TFP of manufacturing firms.

³Baumol (1967) argued that the output of the "stagnant" industry tends to decline and perhaps, finally, vanishes because the demand for these products, i.e. services, is rather elastic. However, Baumol analyzed the effects if the relative output of the two sectors maintains despite changes in the relative costs and prices. Government subsidies or a sufficiently price inelastic demand for services may lead to fairly constant output shares according to Baumol.

contains no information on total factor productivity, I have to match the BHP with sectoral data on TFP from the EU KLEMS Growth and Productivity Accounts. The EU KLEMS database provides data on TFP for Germany from 1975 to 2010 at the 2-digit industry-level. Hence, I aggregate the BHP to the 2-digit level and therefore, both data sets can be matched accurately. The empirical analysis at the 2-digit level is in accordance with the theory of Ngai & Pissarides (2007), since the authors assume rather aggregated industries. As Baumol, Blackman & Wolff (1985) show, this level of aggregation ensures that industries differ sufficiently from each other such that the elasticity of substitution between final goods is below one. Hence, the 2-digit industry-level is very appropriate to test the theoretical predictions of Ngai & Pissarides (2007).

The empirical evidence on the link between TFP growth rates and employment shifts is, however, scarce. There is only a very small body of loosely related empirical literature that analyzes earlier time periods: Baumol, Blackman & Wolff (1985) use sectoral data for the U.S. between 1947 and 1976 and provide evidence consistent with the theoretical model if 2-digit industry-level data are used. They show that the output shares of the "progressive" and "stagnant" sector remained fairly constant in the postwar period. In addition, they find increasing relative prices for the "stagnant" sector. Therefore, the share of total expenditures on services and their share of the labor force rose significantly. Ngai & Pissarides (2007) conclude that this level of aggregation satisfies the key assumption of a sufficiently low elasticity of substitution. In addition, Kravis, Heston & Summers (1983) use cross-sectional UN data for 34 countries in 1975 and show that this assumption can be considered as valid. Furthermore, they show that relative price changes between services and manufacturing depict differences in TFP growth rates. Finally, the closest related study by Falvey & Gemmell (1996) also provides evidence in favor of the theory by Ngai & Pissarides (2007). Using a cross-section of 60 countries in 1980, the authors estimate a small (negative) price elasticity for services. Falvey & Gemmell (1996) also find a positive relationship between employment growth and the increase in relative prices for services if 2-digit industries are observed.⁴

The data for Germany show that total factor productivity growth rates between manufacturing and services only started to diverge in the mid-1990s. Before, TFP grew equally in both sectors. Furthermore, the data show that the employment in manufacturing steadily decreased, whereas it increased in services. All manufacturing industries at the 2-digit level lost employment shares. In contrast, almost all service sectors grew.

⁴An earlier paper by Madison (1980) also confirms this correlation by using historical data for 16 OECD countries between 1870 and 1987.

In my empirical analysis, I analyze the data set mentioned above by using a fixed-effects regression model. The dependent variable, the industry-specific employment growth, is explained by differences in lagged TFP growth rates. The results of my regression analysis support the theoretical predictions, i.e. they show that industries with increasing TFP experience decreasing employment growth, as the theory would imply. These results are confirmed by various robustness checks.

The rest of this paper is organized as follows. In the next section, I describe the data in more detail and present some stylized facts on German sectoral TFP growth as well as on sectoral employment changes. Section 3 introduces my baseline model and presents the regression results. Section 4 presents various robustness checks to confirm my findings. In section 5, I summarize the main results and conclude.

2 Data and Stylized Facts

My empirical analysis builds on two data sets: First, the "Establishment History Panel" (in German: Betriebs-Historik-Panel (BHP)) provided by the Research Data Center of the German Federal Employment Office⁵ and second, the "EU KLEMS Growth and Productivity Accounts".

The "Establishment History Panel" is a very detailed data set at the establishment-level that covers all establishments in West Germany between 1975 and 2010. Establishments from East Germany are included from 1991 onwards. It provides a detailed insight into German establishments over a long time period. For example, the BHP contains information on establishment characteristics⁶, the general employment structure⁷, the structure of employees by educational and vocational qualifications or by occupational status.⁸ Since the TFP data from the EU KLEMS database are only available at the 2-digit industry-level, I aggregate the BHP according to the industry classification of each establishment to accurately match the two data sets. Hence, I have to assume that all employees of an establishment classified as a manufacturer are engaged in manufacturing activities.⁹ The aggregated data

⁵For my research, I have access to the data via on-site use at the Research Data Center of the German Federal Employment Agency at the Institute for Employment Research (in German: Institut für Arbeitsmarkt- und Berufsforschung (IAB)) and via remote data access.

⁶Such as the industry classification of each establishment.

⁷For example the total number of full-time employees.

⁸For further information about the BHP see Eberle (2011), Gruhl et al. (2012) and Hethey-Maier & Seth (2010).

⁹All control variables are derived in the same way.

The aggregated data only allow for the analysis of inter-sectoral changes which is in line with Ngai & Pissarides (2007). Intra-sectoral movements, i.e. the increasing share of employment in service occupations within manufacturing industries, cannot be observed here. For empirical analyses concerning intra-sectoral employment changes see Henze (2014) and Boddin & Henze (2015).

are particularly favorable to test the underlying theory of Ngai & Pissarides (2007), because the authors postulate the crucial assumption of a sufficiently low (below one) elasticity of substitution across final goods. Therefore, final products have to be sufficiently different across industries. Among others, Baumol, Blackman & Wolff (1985) show that this assumption is ensured at the 2-digit level.

The EU KLEMS Growth and Productivity Accounts provide industry-level information on production, inputs, and productivity for 25 European countries, the U.S. and Japan. The measures are included in the data set from 1970 onwards.¹⁰ For the empirical analysis, I use data on total factor productivity in Germany. The EU KLEMS Accounts provide data on total factor productivity for Germany for the 1975 to 2010 period at the 2-digit industry-level.¹¹ However, I have to eliminate the 1975 to 1979 period as well as the most recent year 2010 due to missing information on total factor productivities in various industries. Finally, I am able to analyze the effects of diverging TFP growth rates on the industry-specific employment growth for the 1980 to 2009 period.

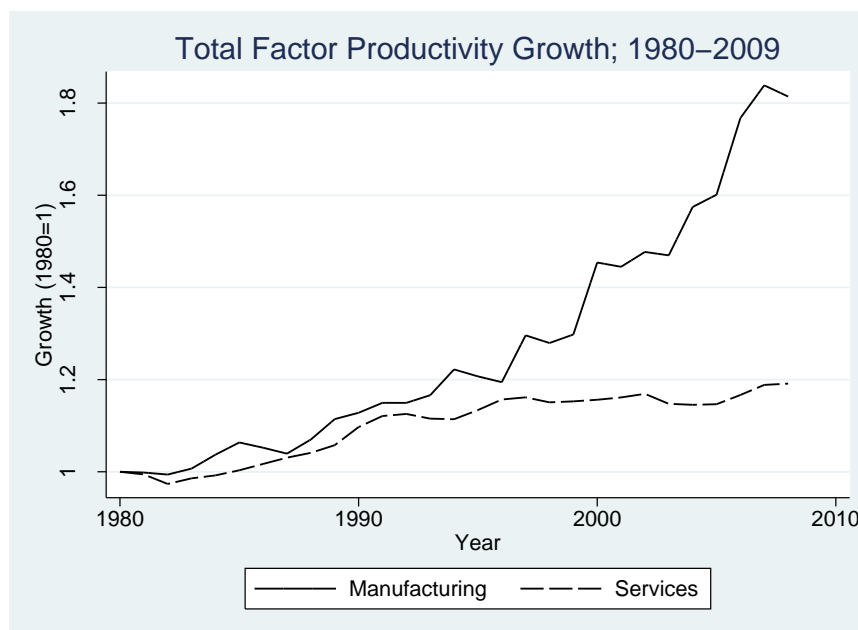


Figure 1:
Total Factor Productivity Growth in Manufacturing and Services
Source: EU KLEMS database, author's computation.

Figure 1 shows total factor productivity growth in Germany between 1980 and 2009. Here, I calculate TFP growth as the average annual TFP growth in all manu-

¹⁰The statistics are available at the website of the EU KLEMS project. For further information see <http://www.euklems.net/> and O'Mahony & Timmer (2009) as well as Gouma & Timmer (2012).

¹¹The data set covers 34 industries at the 2-digit ISIC Revision 4 classification. Since some industries of the EU KLEMS data set cover more than one of the 2-digit industries of the BHP, I have to assign the same TFP growth rates to these industries (see Tables 1 and 3).

facturing as well as in all service industries. As mentioned before, Ngai & Pissarides (2007) assume higher total factor productivity growth for the "progressive" manufacturing sector than for "stagnant" services. However, the data show that TFP grew equally in the manufacturing sector and services until the mid-1990s. Between 1980 and 1996, TFP grew approximately by 17% in both sectors. But, after 1996, TFP growth in the manufacturing sector significantly exceeded TFP growth in the service sector. Between 1996 and 2009, TFP grew by more than 50% within manufacturing industries, whereas it remained constant within the service sector. For this period, the data confirm the assumption that TFP increased faster within manufacturing industries than within the service sector. Therefore, the manufacturing sector can be defined as the "progressive" sector while the service sector is "stagnant", which is in line with the theoretical assumptions.

Table 1: Average annual Growth of Total Factor Productivity by Industry; 1980-2009

Industry Code	Industry	TFP Growth
Manufacturing		
10-14	Mining and quarrying	0.91%
15-16	Food products, beverages and tobacco	-0.56%
17-19	Textiles, wearing apparel, leather and related products	2.66%
20-22	Wood and paper products; printing and reproduction of recorded media	1.35%
23	Coke and refined petroleum products	5.51%
24	Chemicals and chemical products	3.52%
25-26	Rubber and plastics products, and other non-metallic mineral products	2.06%
27-28	Basic metals and fabricated metal products, except machinery & equipment	1.98%
29	Machinery and equipment n.e.c.	1.03%
30-33	Electrical and optical equipment	4.30%
34-35	Transport equipment	1.13%
36-37	Other manufacturing; repair and installation of machinery and equipment	1.85%
40-41	Electricity, gas and water supply	-0.10%
45	Construction	-0.09%
Services		
50	Wholesale and retail trade and repair of motor vehicles and motorcycles	2.27%
51	Wholesale trade, except of motor vehicles and motorcycles	2.44%
52	Retail trade, except of motor vehicles and motorcycles	0.49%
55	Accommodation and food service activities	-0.90%
60-63	Transport and storage	2.11%
64	Postal and courier activities	0.37%
65-67	Financial and insurance activities	0.27%
70	Real estate activities	1.33%
72	IT and other information services	-0.02%
73-74	Professional, scientific, technical, administrative and support services	-1.78%
75	Public administration and defense; compulsory social security	0.98%
80	Education	-0.66%
85	Health and social work	0.73%
92	Arts, entertainment, recreation	-1.15%
93	Other service activities	0.64%

Source: EU KLEMS database, author's computation.

Table 1 shows TFP growth within the manufacturing and the service sector in

more detail. It presents the average annual TFP growth rate of each industry at the 2-digit level between 1980 and 2009. The data show that total factor productivity within manufacturing industries grew substantially faster than within service industries. Almost all manufacturing industries experienced positive TFP growth. The highest TFP growth rates occurred in the industries "coke and refined petroleum products" and "electrical and optical equipment". Here, the average annual TFP growth rates between 1980 and 2009 were 5.51% and 4.30%, respectively. By contrast, TFP growth within service industries was substantially lower. The data reveal that one third of all service industries was characterized by negative average annual TFP growth and only four industries generated an average growth of more than one percent. Only "wholesale industries" and "transport and storage" achieved average annual growth rates above 2%.

Table 2: Average annual Growth of Total Factor Productivity within Sub-Periods

	Overall	1980-1989	1990-1999	2000-2009
	(1)	(2)	(3)	(4)
Manufacturing	1.84%	0.78%	1.41%	3.34%
Services	0.63%	0.68%	0.90%	0.41%
Source: EU KLEMS database, author's computation.				

Table 2 again presents aggregated average annual TFP growth rates in manufacturing and services but it distinguishes between different sub-periods. Column 1 shows the average annual TFP growth over the whole 1980 to 2009 period. Here, average TFP growth in manufacturing was approximately three times higher than in services. Columns 2 to 4 present the average TFP growth rates within each decade separately. Comparing the individual decades, column 2 highlights that TFP growth rates between manufacturing and services were more similar in the 1980s. Here, the average annual TFP growth rate was 0.78% in manufacturing and 0.68% in services. Afterwards, TFP grew much faster in the manufacturing sector than in services. In the 1990s, the average annual TFP growth in manufacturing was 50% higher than in services. In the last decade from 2000 to 2009, the average annual TFP growth rate in manufacturing exceeded the growth rate in services by more than a factor of eight. Hence, the findings of Table 2 confirm those of Figure 1. Especially for the last two decades the data show diverging TFP growth rates between the manufacturing sector and services.¹²

¹²In addition, Table 10 in the Appendix provides evidence that the acceleration of diverging TFP growth rates in the last two decades can also be observed if the 2-digit industries are considered separately.

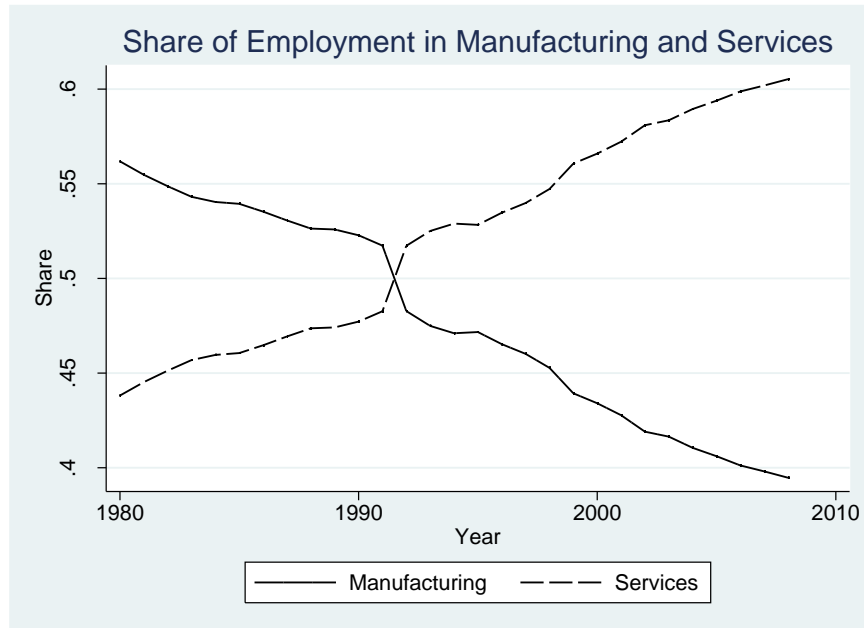


Figure 2:
Share of Employment in Manufacturing and Services; 1980-2009
Source: Establishment History Panel, author's computation.

Figure 2 shows the share of employees working either in establishments within the manufacturing sector or within services between 1980 and 2009. It supports the theoretical argument made by Ngai & Pissarides (2007) that employment shares shift to industries with a comparably low TFP growth rate, i.e. services. The share of employment in manufacturing and services is calculated on the basis of the 2-digit classification of economic activities included in the BHP. The data show that the share of employment in manufacturing declined steadily between 1980 and 2009, whereas the employment share in services increased. In 1980, 56% of all employees worked in establishments classified as manufacturers and 44% worked in the service sector. In 2009, 61% of all employees worked in the service sector and only 39% in manufacturing establishments.¹³ Thus, employment shares more than reversed. Altogether, there is an increasing share of employees working in the service sector that, in addition, experienced low TFP growth.

Table 3 shows the shift of employment in more detail. It presents the industry-specific employment shares at the 2-digit level and compares industry sizes in 1980 and 2009. The data show that the employment share declined in each industry within the manufacturing sector between 1980 and 2009. The largest drop in employment shares occurred in the industries "textiles" (-82%), and "coke and refined petroleum products" (-63%). At the same time, these industries are among the sectors with the

¹³The break in the long-run trend in 1991 is caused by German reunification. Later, in the empirical analysis, I will control for any effects that are caused by this event.

Table 3: Industry-specific Shares of Employment

Industry Code	Industry	Share of Employment		Trend
		1980	2009	
Manufacturing				
10-14	Mining and quarrying	1.55%	0.49%	↘
15-16	Food products, beverages and tobacco	3.16%	2.93%	↘
17-19	Textiles, wearing apparel, leather and related products	3.66%	0.66%	↘
20-22	Wood and paper products; printing & reproduction of rec. media	3.54%	2.65%	↘
23	Coke and refined petroleum products	0.29%	0.11%	↘
24	Chemicals and chemical products	2.94%	1.88%	↘
25-26	Rubber and plastics products, and other non-metallic products	3.71%	3.11%	↘
27-28	Basic metals and fabricated metal products	5.91%	4.26%	↘
29	Machinery and equipment n.e.c.	7.13%	5.61%	↘
30-33	Electrical and optical equipment	6.81%	5.49%	↘
34-35	Transport equipment	4.28%	3.85%	↘
36-37	Other manufacturing	1.64%	1.10%	↘
40-41	Electricity, gas and water supply	1.43%	1.28%	↘
45	Construction	9.84%	5.61%	↘
Σ		55.89%	39.03%	
Services				
50	Wholesale and retail trade of motor vehicles and motorcycles	1.79%	3.73%	↗
51	Wholesale trade, except of motor vehicles and motorcycles	5.63%	5.96%	↗
52	Retail trade, except of motor vehicles and motorcycles	5.75%	4.38%	↘
55	Accommodation and food service activities	1.19%	1.82%	↗
60-63	Transport and storage	4.55%	6.01%	↗
64	Postal and courier activities	0.69%	0.88%	↗
65-67	Financial and insurance activities	4.00%	3.75%	↘
70	Real estate activities	0.60%	0.82%	↗
72	IT and other information services	0.22%	1.81%	↗
73-74	Professional, scientific, technical & administrative services	3.93%	12.12%	↗
75	Public administration and defense; compulsory social security	7.02%	6.09%	↘
80	Education	1.43%	2.30%	↗
85	Health and social work	5.88%	8.51%	↗
92	Arts, entertainment, recreation	0.85%	1.91%	↗
93	Other service activities	0.39%	0.57%	↗
Σ		43.92%	60.66%	

Source: Establishment History Panel, author's computation.

highest TFP growth rates. In contrast, employment in almost all service industries grew, in particular in "professional, scientific, technical & administrative services", where the employment share more than tripled and "arts, entertainment, recreation", where the employment share more than doubled in the 1980-2009 period. In accordance with the theoretical examination of Ngai & Pissarides (2007), these service industries are characterized by the lowest TFP growth rates of -1.78% and -1.15%, respectively.

In summary, the stylized facts support the hypothesis of technology-driven structural change. The data on sectoral TFP growth rates show that the manufacturing sector was characterized by higher sectoral TFP growth, especially from the mid-

1990s onwards. The employment in manufacturing industries declined at the same time. In contrast, sectoral TFP growth rates were lower in services. Here, the employment shares increased.

3 Empirical Analysis

3.1 Baseline Model

3.1.1 Empirical Strategy

To check if the theoretical predictions can be confirmed by the data, I use a fixed-effects regression model to exploit the time series dimension of the panel data. To identify the employment effects of diverging TFP growth rates, I consider two important features of the transmission. First, employment movements due to diverging growth rates of total factor productivity occur with a lag because establishments observe TFP growth ex post and then adapt employment. Second, employment effects do not arise after differences in TFP growth rates in single years. Establishments do not adjust the employment if TFP growth rates deviate once, but only do so if the establishments identify a process of diverging TFP growth rates. To account for these characteristics, my baseline model estimates the employment effects of average past TFP growth rates. The estimated fixed-effects equation looks as follows:

$$\Delta E_{it} = \alpha + \beta_1 \widehat{\Delta TFP_{it-k}} + \delta' C_{it} + \lambda_i + \gamma_t + \epsilon_{it}, \quad \text{with } k = 2, 3, 4 \quad (1)$$

Equation (1) calculates the sectoral change of employment due to the average TFP growth rate in the previous two to four years. The dependent variable, ΔE_{it} , measures the annual employment growth in each industry i in year t . The first explanatory variable, $\widehat{\Delta TFP_{it-k}}$ is the average past TFP growth rate in industry i in the previous two to four years ($k=2, 3, 4$).¹⁴ C_{it} is a vector of control variables at the 2-digit industry-level accounting for further influences that may have an effect on employment growth. I include the median of wages, the average establishment size within an industry, expenditures on R&D and the initial size of each industry¹⁵ as control variables. I also add the overall workforce growth as a control variable as well as a dummy variable controlling for German reunification in 1991.¹⁶ I estimate equa-

¹⁴For example, the employment growth rate in the year 2000 is explained by the average TFP growth rate between 1998 and 1999 (for $k=2$) or between 1996 and 1999 (for $k=4$).

¹⁵The initial size of an industry is included both in terms of sectoral GDP as well as total employment.

¹⁶The dummy variable distinguishes between the period before and after German reunification, i.e. it is equal to zero before 1991 and equal to one afterwards.

tion (1) with both industry-specific effects, λ_i , to capture unobserved sector-specific variation and year-specific effects, γ_t , to control for unobserved, time varying effects as well as business cycle effects. ϵ_{it} is the error term. Furthermore, to control for time-variant heterogeneity between the industries, I estimate equation (1) with an interaction effect including industry fixed-effects and a dummy variable that divides the sample into two sub-periods. In general, interaction effects control for time-variant industry fixed-effects by combining year and industry fixed-effects ($\gamma_t \times \lambda_i$). Here, I am not able to include an interaction term with both industry and year fixed-effects, because the number of variables would exceed the number of observations. Therefore, I divide the sample into two sub-periods according to the TFP growth between manufacturing and services. Table 2 shows that TFP growth rates between manufacturing and services mainly diverged after 2000. Hence, to capture the different characteristics between these two sub-periods, I create a dummy variable that is equal to zero before 2000 and equal to one afterwards. Then I include an interaction term between the dummy variable and the industry fixed-effects into the estimations that cover the whole time period. Hence, I am able to account for time-variant industry fixed-effects between the two sub-periods.¹⁷ I estimate equation (1) over the whole time period and within sub-periods from 1980-1989, 1990-1999, and 2000-2009.

I include up to four lags in the regressions for two reasons: First, it is hardly possible to include more lags in the estimated regressions, especially when I analyze sub-periods. Each additional lag reduces the number of observations by roughly 50. Since the number of observations within sub-periods drops rapidly, no more lags can be included.¹⁸ Second and most importantly, there is an extensive literature on the employment adjustment behavior of firms. For example, Jung (2014) provides empirical evidence for Germany that establishments adjust their employment, i.e. increase or decrease the number of employees, in the median within 1.8 years.¹⁹ Because Jung (2014) uses a very similar data set (the IAB Establishment Panel)²⁰, it is appropriate to adopt his findings for my empirical analysis. Hence, it is sufficient to use up to four lags to capture the vast majority of employment adjustments due

¹⁷Robustness checks show that the results are not sensitive to changes in the chosen threshold between the two sub-periods.

¹⁸Later, in section 3.4.1, I additionally estimate another specification of the baseline model with up to five lags.

Furthermore, I include up to ten lags when the entire time period is analyzed since there is a sufficient number of observations for more lags in this case. This is done both for equation (1) and equation (2) in the following section. The results highlight that there is no long-term employment effect that was not captured before.

¹⁹The establishments adjust the employment due to cost changes, business cycles, etc.

²⁰The IAB Establishment Panel is a representative annual survey of all German establishments. Jung (2014) investigates the period 1996 to 2010.

to differences in TFP growth rates.²¹

To confirm the theoretical predictions, I expect a negative β_1 coefficient. This would imply that employment shares decrease in sectors with higher TFP growth rates.

Finally, I check both employment and TFP growth on the stationarity with Fishers unit root test for panel data by applying the Augmented-Dickey-Fuller test. The results show that the null hypothesis that the series are non-stationary is clearly rejected, i.e. the variables are stationary (I(0)).

3.1.2 Results

Table 4: Lagged Employment Effects of average TFP Growth Rates (1980-2009)

<i>Variables</i>	Fixed-Effects Regression		
	(1)	(2)	(3)
$\widehat{\Delta TFP_{t-2}}$	-0.0293* (0.0164)		
$\widehat{\Delta TFP_{t-3}}$		-0.0533 (0.0409)	
$\widehat{\Delta TFP_{t-4}}$			-0.0467 (0.0982)
Other Controls	Yes	Yes	Yes
Industry Fixed-Effects	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes
R^2	0.5132	0.5179	0.5245
Prob > F	0.0000	0.0000	0.0000
No. of Obs.	1304	1247	1190
Dep. Variable: Employment growth in year t : ΔE_{it} .			
Notes: Clustered standard errors (by industry) in parentheses, *** p<0.01, ** p<0.05, * p<0.1.			

Table 4 presents the results of the estimation. I first estimate equation (1) over the whole time period from 1980 to 2009. The first column shows the employment effect of the average TFP growth rate in the previous two years. The estimated coefficient β_1 is negative and significant, as the theory would suggest. The coefficient implies that the employment growth decreases by 0.03 percentage points if the average TFP growth rate in the two previous years increases by 1 percentage point. The result

²¹Jung (2014) additionally points out that his results are in line with results from earlier studies for Germany. The bulk of empirical studies, such as Kölling (1998) and Yaman (2011) find out that employment adjustment in Germany occurs in the median within 0.7 to 7.7 years. The wide range is caused, among others, by different data sets, empirical methods and observation periods.

shows that establishments adjust their employment within two years, which confirms Jung (2014). Columns 2 and 3 illustrate that the estimated coefficients are still negative if the employment effects of the average TFP growth rates in the previous three or four years are estimated. Now, however, they are insignificant.²²

Table 5: Lagged Employment Effects of average TFP Growth Rates (1980-1989)

<i>Variables</i>	Fixed-Effects Regression		
	(1)	(2)	(3)
$\widehat{\Delta TFP_{t-2}}$	0.0706 (0.0576)		
$\widehat{\Delta TFP_{t-3}}$		-0.0008 (0.0722)	
$\widehat{\Delta TFP_{t-4}}$			0.1271 (0.1439)
Other Controls	Yes	Yes	Yes
Industry Fixed-Effects	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes
R^2	0.4298	0.4366	0.3003
Prob > F	0.0000	0.0000	0.0000
No. of Obs.	413	364	315
Dep. Variable: Employment growth in year t : ΔE_{it} .			
Notes: Clustered standard errors (by industry) in parentheses, *** p<0.01, ** p<0.05, * p<0.1.			

Table 5 shows the findings for the first sub-period between 1980 and 1989. As Figure 1 highlights, TFP growth rates started to diverge in the mid-1990s only. Thus, no significant employment effects are expected to be induced within this decade. Consequently, the coefficient β_1 is insignificant in each column, i.e. it has no explanatory power. In addition, Table 5 shows that the number of observations decreases rapidly if only one decade is observed. Therefore, it becomes even more difficult to determine significant employment effects. Because of the low number of observations, it is not possible to check whether the calculations become significant when the number of lags is increased. Nevertheless, these findings support the theoretical predictions of Ngai & Pissarides (2007), too. The authors argue that TFP growth rates induce employment shifts if they diverge between manufacturing industries and services.

²²Since the entire time period provides sufficient observations for more lags, I also estimate equation (1) with $k= 5, \dots, 10$, i.e. the employment effects of the average TFP growth rate in the last five to ten years. The results remain all insignificant and mostly negative. Hence, there is no employment impact of TFP growth rates that is a more long-term effect. All non-reported results can be obtained upon request.

The estimations for the first sub-period show that there is no significant relationship between TFP growth and employment growth if TFP growth rates do not diverge.

Table 6: Lagged Employment Effects of average TFP Growth Rates (1990-1999)

<i>Variables</i>	Fixed-Effects Regression		
	(1)	(2)	(3)
$\widehat{\Delta TFP_{t-2}}$	-0.0469* (0.0267)		
$\widehat{\Delta TFP_{t-3}}$		-0.0795 (0.1069)	
$\widehat{\Delta TFP_{t-4}}$			0.0429 (0.2294)
Other Controls	Yes	Yes	Yes
Industry Fixed-Effects	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes
R^2	0.5258	0.1919	0.2485
Prob > F	0.0000	0.0000	0.0000
No. of Obs.	438	385	332
Dep. Variable: Employment growth in year t : ΔE_{it} .			
Notes: Clustered standard errors (by industry) in parentheses, *** p<0.01, ** p<0.05, * p<0.1.			

Table 6 displays the results for the decade from 1990 to 1999. Here, the first column provides a significant negative coefficient, which is comparable to the findings of Table 4. If the average TFP growth in the last two years increases by 1 percentage point, employment growth decreases by 0.05 percentage points. This finding indicates that employment shares shift to industries with lower TFP growth and thus supports the theoretical predictions. In contrast, columns 2 and 3 again show insignificant coefficients.

Table 7 presents the estimations for the last decade between 2000 and 2009. Since the stylized facts illustrate that sectoral TFP growth rates between manufacturing industries and services diverged especially in this period, the theoretical predictions may most appropriately be tested here. The coefficient in column 2 shows that the relationship between growth rates of TFP and employment is now negative and significant if three lags are used. In addition, the estimated effect is considerably larger than in the previous periods. Employment growth declines by 0.08 percentage points if the average TFP growth in the previous three years increases by 1 percentage point.

In summary, my findings support the theoretical predictions of Ngai & Pissarides (2007) that diverging TFP growth rates between manufacturing and services lead to

Table 7: Lagged Employment Effects of average TFP Growth Rates (2000-2009)

<i>Variables</i>	Fixed-Effects Regression		
	(1)	(2)	(3)
$\widehat{\Delta TFP}_{t-2}$	-0.0206 (0.0129)		
$\widehat{\Delta TFP}_{t-3}$		-0.0842*** (0.0259)	
$\widehat{\Delta TFP}_{t-4}$			-0.0637 (0.0473)
Other Controls	Yes	Yes	Yes
Industry Fixed-Effects	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes
R^2	0.4276	0.4704	0.4630
Prob > F	0.0000	0.0000	0.0000
No. of Obs.	357	306	255

Dep. Variable: Employment growth in year t : ΔE_{it} .

Notes: Clustered standard errors (by industry) in parentheses,
*** p<0.01, ** p<0.05, * p<0.1.

employment shifts toward services. First, if the analysis focuses on the whole 1980 to 2009 period and uses two lags, the employment effect is negative and significant. For the 1980s, there is no employment effect since TFP growth rates do not diverge until the mid-1990s. The results for the 1990s and especially for the last decade between 2000 and 2009 also provide evidence of a negative relationship between TFP growth and employment growth.

3.2 Robustness Checks

3.2.1 Employment Effects of Annual TFP Growth Rates

In equation (1), I assume that employment shifts do not occur after differences in TFP growth rates in single years. To check whether this assumption is appropriate, I estimate the employment effects of annual TFP growth rates with various lags. The estimated fixed-effects equation looks as follows:

$$\Delta E_{it} = \alpha + \beta_1 \Delta TFP_{it-k} + \delta' C_{it} + \lambda_i + \gamma_t + \epsilon_{it}, \quad \text{with } k = 0, 1, 2, \dots, 5 \quad (2)$$

Equation (2) is constructed in the same way as equation (1). It differs, however, in the measurement of total factor productivity growth. Here, I include annual TFP growth rates with various time lags to explain employment shifts. Accordingly, my first explanatory variable, ΔTFP_{it-k} is the annual growth rate of total factor productivity

in industry i in year $t - k$. ΔTFP_{it-k} is included in equation (2) without a time lag, $k=0$, as well as with lags from one to five years ($k=1, 2, \dots, 5$). The remaining variables of equation (2) equal those of equation (1).

The estimation results for equation (2) are reported in Appendix, Tables 11 to 14. Table 11 presents the estimated coefficients of equation (2) for the whole time period from 1980 to 2009 and confirms my findings from before. The first column shows the estimated employment effect of annual TFP growth if no lag is used. The coefficient is negative, but insignificant. This is to be expected since differences in TFP growth rates do not immediately lead to employment changes. Columns 2 to 6 present the results if TFP growth rates with one to five lags are included in the model, i.e. if the employment changes due to TFP growth rates one to five years ago. As before, the coefficient is negative and significant if two lags are used. Next, I estimate each decade separately. The results are reported in Tables 12 to 14. Altogether, the results vary a lot with the number of chosen lags and thus have to be interpreted with caution. In the 1980s, the estimated coefficient shows a positive relationship between TFP growth and employment growth if one lag is used. This finding contradicts the theory. However, the estimations for the last two decades from 1990 to 1999 and 2000 to 2009 again provide some evidence in line with the theoretical predictions. Table 13 presents the results for the 1990s. Now, the estimations confirm the theory by Ngai & Pissarides (2007) if two or five lags are used. In contrast, however, the coefficient is positive and significant if four lags are used. Table 14 shows the results for the latest decade between 2000 and 2009. The findings are similar to the estimation for the previous decade. The data confirm the theory if three or five lags are used.

In summary, the estimations of equation (2) show that the employment effects of annual TFP growth rates vary more than the results of equation (1). Hence, they have to be interpreted with caution. However, the results are broadly in line with the findings before. The estimations for the whole sample period, the 1990s and 2000s provide evidence of a negative relationship, which is theoretically predicted. TFP growth affects employment growth with a lag of at least two years. Thus, it seems to be more relevant to assume lagged employment shifts than to consider rather average than annual TFP past growth rates.

3.2.2 Average Employment Effects of Past TFP Growth Rates

Since establishments may not adapt the employment within a single year if TFP growth rates diverge, I additionally estimate the impact of the average TFP growth rate in past periods on the average employment growth in subsequent periods:

$$\widehat{\Delta E_{it+k}} = \alpha + \beta_1 \widehat{\Delta TFP_{it-l}} + \delta' C_{it} + \lambda_i + \gamma_t + \epsilon_{it}, \quad \text{with } k, l = 2, 3 \quad (3)$$

Equation (3) is again constructed in the same way as equation (1). The only difference is the definition of employment growth. Here, I use the average employment growth rate in subsequent years.²³

Table 8: Average Employment Effects of past TFP Growth Rates

Variables	Fixed-Effects Regression							
	Overall		1980-1989		1990-1999		2000-2009	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$k=l=2$								
$\widehat{\Delta TFP_{t-l}}$	-0.0249*		-0.1085		0.0285		-0.0037	
	(0.0137)		(0.0736)		(0.0728)		(0.0088)	
$k=l=3$								
$\widehat{\Delta TFP_{t-l}}$		-0.0217		0.0399		0.0407		-0.0278***
		(0.0349)		(0.0515)		(0.1294)		(0.0039)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.4871	0.5419	0.4836	0.4911	0.4672	0.5086	0.6613	0.7309
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
No. of Obs.	1190	1079	270	177	332	232	255	153

Dep. Variable: Average employment growth in subsequent years: $\widehat{\Delta E_{it+k}}$.

Notes: Clustered standard errors (by industry) in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 8 displays the results for equation (3). Here, I calculate the effects of average TFP growth rates in the previous two or three years on the average employment growth in the following two or three years, i.e. $k=l=2, 3$. As before, I estimate equation (3) for the whole time period from 1980 to 2009 as well as within three sub-periods. Columns 1 and 2 present the regression results for the entire time period. The coefficient is negative and significant if two lags are used, which is in line with the

²³For example, in the year 2000, I estimate the effect of the average TFP growth in the years 1998 and 1999 on the average employment growth in 2001 and 2002 (if $k=l=2$).

previous results and supports the theoretical predictions. Columns 3 to 6 show the estimated coefficients for the first two sub-periods from 1980 to 1989 as well as from 1990 to 1999. Like in previous specifications, the β_1 coefficients remain insignificant. The last two columns, 7 and 8, provide the results for the last sub-period from 2000 to 2009. The findings confirm the results from former specifications. Despite the low number of observations, the estimated coefficient is negative and significant at the 1%-level if three lags are used.

3.2.3 Dynamic Panel Models

In addition, I estimate equation (1) with the lagged dependent variable on the right-hand side of the equation. Thus, I apply a dynamic fixed-effects estimation that controls for potential serial correlation (Wooldridge (2002)). By adding the lagged dependent variable, I test if the current employment growth is unrelated to the employment growth in the previous period. If this is the case, the results for the static panel data model from before retain their validity. Still, there might be an additional bias due to the potential endogeneity of some of the independent variables used. In particular, wages, the average establishment size and the industry-specific GDP are likely to be endogenous with respect to the employment growth. To address this concern, I additionally apply the system GMM estimator.

The estimated equation for the dynamic fixed-effects model is given by:

$$\Delta E_{it} = \alpha + \rho \Delta E_{it-1} + \beta_2 \Delta \widehat{TFP}_{it-k} + \delta' C_{it} + \lambda_i + \gamma_t + \epsilon_{it}, \quad \text{with } k = 2, 3, 4. \quad (4)$$

Equation (4) is constructed in the same way as equation (1). But here, I add the lagged dependent variable of the employment growth, ΔE_{it-1} , to apply a dynamic fixed-effects regression model. Table 15 in the Appendix provides the results of the estimation.²⁴ As before, I estimate the employment effects of the average past TFP growth rate with two to four lags. Columns 1 to 3 present the regression results for the entire time period. The coefficient on TFP growth is negative and significant if two lags are used, which confirms my previous results. Moreover, the coefficient on the lagged dependent variable, ρ , is insignificant, i.e. the current employment growth is unrelated to the lagged employment growth. Hence, I can conclude that serial correlation is not a problem in my earlier regression analysis. Columns 4 to 6 of Table 15 present the results for the most recent sub-period from 2000 to 2009. The results also confirm the findings from before. The employment effect of TFP is negative and significant with three or four lags. The lagged dependent variable is insignificant if I use one or four lags. In the case of three lags, ρ becomes significant at

²⁴Table 15 shows the regression results for the entire time period as well as for the most recent sub-period from 2000 to 2009. The estimations of all other sub-periods are in line with the results from before.

the 10%-level which provides some evidence of serial correlation. Since this is the only specification where the effect of the lagged dependent variable becomes significant, I conclude that serial correlation is not a problem in my empirical analysis.

Finally, I re-estimate the dynamic panel model by applying the system GMM regression model developed by Arellano & Bover (1995) and by Blundell & Bond (1998). I use the system GMM estimator instead of the difference GMM estimator by Arellano & Bond (1991) because the latter suffers from a large finite sample bias in dynamic panel data models with rather persistent time series. The difference GMM estimator uses first differences to eliminate fixed-effects and implements lagged levels of the endogenous variables as instruments. Hence, this approach generates rather weak instruments because the correlation between time persistent endogenous variables, i.e. the growth rates, and the instruments, i.e. lagged levels (which do change), is rather weak. The system GMM estimator tries to solve this problem by considering lagged levels as well as lagged differences as instruments. It is a system of two equations: The first equation equals the differenced equation the difference GMM approach uses. The second equation uses the first differences of the variables as instruments for the levels. This reduces the weak instrument problem of the difference GMM estimator.²⁵ If the instruments are tested to be valid, they account for endogeneity caused by omitted variables as well as reverse causality.²⁶ The system GMM estimator assumes all independent variables to be endogenous if they are not explicitly defined to be exogenous. Here, I treat the past average TFP growth, the median wage, the average establishment size, the industry-specific GDP and the initial size of each industry as endogenous with respect to employment growth. In contrast, to reduce the number of endogenous variables and therefore the number of instruments, I define the overall workforce growth and the effects of German reunification as exogenous. A major concern with the system GMM estimator is the proliferation of instruments.²⁷ The number of instruments grows rapidly with T , i.e. the time period that is analyzed, and thus can outgrow the number of cross-section observations (here: the number of industries). This may overfit the variables that are treated as endogenous and therefore would weaken the Hansen J -test of the joint validity of instruments. Therefore, to further minimize instrument inflation, I use the "collapse" option in STATA in all regressions.²⁸

Table 9 presents the results of the system GMM estimation. Here, I present the estimated coefficients for the whole time period as well as for the most recent decade

²⁵For a more detailed discussion see Blundell & Bond (1998).

²⁶For a more detailed description of the system GMM estimator see Roodman (2009a).

²⁷For further information see Roodman (2009b).

²⁸The "collapse" option specifies that the system GMM estimator creates one instrument for each variable and lag rather than one for each year, variable and lag. Thus, in relatively small samples covering a long time period, the "collapse" option helps to avoid the bias that may occur if the number of instruments exceeds the number of cross-section observations.

Table 9: System GMM Estimation

<i>Variables</i>	Two-Step System GMM Regression					
	(1)	Overall (2)	(3)	(4)	2000-2009 (5)	(6)
$\Delta \widehat{\text{TFP}}_{t-2}$	-0.0953 (0.1185)			0.0096 (0.0598)		
$\Delta \widehat{\text{TFP}}_{t-3}$		-0.1969 (0.2087)			-0.1843*** (0.0740)	
$\Delta \widehat{\text{TFP}}_{t-4}$			-0.1305 (0.2163)			-0.0315 (0.0827)
No. of Obs.	1304	1247	1190	357	306	255
No. of Industries	51	51	51	51	51	51
No. of Instruments	36	35	34	20	19	18
AR(1) p-value	0.01	0.01	0.02	0.01	0.01	0.03
AR(2) p-value	0.59	0.53	0.81	0.11	0.17	0.39
Hansen <i>J</i> -test, p-value	0.49	0.32	0.62	0.39	0.41	0.21
Dep. Variable: Employment growth in year t : ΔE_{it} .						
Reported p-values for A(1) and A(2) refer to the Arellano-Bond test for first and second order autocorrelation in the first differences equations.						
<i>Notes:</i> Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.						

from 2000 to 2009.²⁹ If the whole time period is estimated, the β_1 coefficient on TFP growth is negative, but now, it is insignificant. Columns 4 to 6 present the results for the most recent period from 2000 to 2009. Here, the coefficient is negative and highly significant if the employment effect of the average TFP growth in the last three years is estimated. In addition, the effect is substantially larger than in the fixed-effects regression model. An increase in the past average TFP growth rate by 1 percentage point decreases the employment growth by 0.18 percentage points, which supports the theoretical predictions by Ngai & Pissarides (2007). Thus, accounting for endogeneity broadly confirms the results from the fixed-effects regressions. However, the size of the estimated coefficients is considerably larger, i.e. the effects from before may be underestimated due to endogeneity. The test statistics of the system GMM model (Hansen's *J*-test) show that the instruments I use are valid. Furthermore, the system GMM estimator requires high first-order but no second-order autocorrelation. The test statistics for first-order and second-order autocorrelation show that all requirements for autocorrelation of the system GMM model are fulfilled. All p-values confirm that there is high first-order autocorrelation, but the test statistics for AR (2) are insignificant, i.e. the second differences of residuals are not serially correlated.

²⁹The results for the remaining sub-periods are also in line with the fixed-effects regression model.

4 Conclusion

The purpose of the current paper is to examine theoretical models that explain structural change as a technology-driven process. A very prominent paper by Ngai & Pissarides (2007) explains the shift of employment shares from manufacturing industries to services by diverging in sectoral TFP growth rates. The authors argue that employment shares shift to industries with low TFP growth rates, i.e. services, if the elasticity of substitution across final goods is below one. Therefore, this paper analyzes the employment effects of diverging sectoral TFP growth rates to test the theoretical predictions of Ngai & Pissarides (2007). In order to calculate the employment effects, I use the "Establishment History Panel" at the 2-digit industry-level together with industry-level data on total factor productivity obtained from the EU KLEMS database. Altogether, I am able to analyze 30 years between 1980 and 2009. The data highlight that TFP growth rates between manufacturing industries and services essentially started to diverge in the mid-1990s. Furthermore, the data depict that employment in manufacturing decreased continuously, whereas employment in services grew. The results of my estimations provide evidence in favor of the theoretical predictions. The employment effects of diverging TFP growth rates are negative and significant, especially if average TFP growth rates over two or three periods are included in the calculations. Hence, the estimated coefficients indicate that industries with increasing TFP growth face a decreasing employment growth. Solely the results for the 1980s provide insignificant coefficients. However, this also confirms the theoretical predictions, because Ngai & Pissarides (2007) argue that TFP growth rates only induce employment shifts if total factor productivity diverges between sectors. Hence, it is in accordance with the theory if non-diverging TFP growth rates in the 1980s do not affect employment growth. In addition, multiple robustness checks confirm my results and show that the estimated coefficients do not suffer from serial correlation and endogeneity.

5 Appendix

Table 10: Average annual rate of total factor productivity growth by industry; sub-periods

Industry Code	Industry	TFP Growth			Trend
		1980-1989	1990-1999	2000-2009	
10-14	Mining and quarrying	-0.41%	1.64%	1.57%	↗
15-16	Food products, beverages and tobacco	-0.38%	-0.56%	-0.77%	↘
17-19	Textiles, wearing apparel, leather and related products	1.99%	2.50%	3.58%	↗
20-22	Wood and paper products; printing and reproduction of recorded media	0.01%	2.32%	1.77%	↗
23	Coke and refined petroleum products	1.33%	-7.35%	21.48%	↗
24	Chemicals and chemical products	2.16%	3.28%	5.10%	↗
25-26	Rubber and plastics products, and other non-metallic mineral products	1.20%	1.97%	3.11%	↗
27-28	Basic metals and fabricated metal products, except machinery & equipment	1.61%	2.62%	1.68%	→
29	Machinery and equipment n.e.c.	0.72%	0.89%	0.54%	→
30-33	Electrical and optical equipment	2.80%	2.71%	7.72%	↗
34-35	Transport equipment	0.18%	0.61%	2.76%	↗
36-37	Other manufacturing; repair and installation of machinery and equipment	0.71%	1.97%	3.37%	↗
40-41	Electricity, gas and water supply	-0.75%	0.22%	0.26%	↗
45	Construction	0.38%	-0.42%	-0.24%	↘
50	Wholesale and retail trade and repair of motor vehicles and motorcycles	2.93%	1.67%	2.21%	↘
51	Wholesale trade, except of motor vehicles and motorcycles	0.12%	1.02%	6.60%	↗
52	Retail trade, except of motor vehicles and motorcycles	0.91%	1.04%	-0.56%	↘
55	Accommodation and food service activities	-1.56%	-1.27%	0.25%	↗
60-63	Transport and storage	1.86%	2.96%	1.44%	↘
64	Postal and courier activities	0.46%	1.13%	-0.58%	↘
65-67	Financial and insurance activities	0.01%	1.65%	-0.86%	↘
70	Real estate activities	2.08%	1.33%	0.57%	↘
72	IT and other information services	-0.93%	-0.41%	1.28%	↗
73-74	Professional, scientific, technical, administrative and support services	-0.93%	-2.27%	-2.14%	↘
75	Public administration and defense; compulsory social security	0.59%	1.49%	0.86%	→
80	Education	1.32%	0.35%	-1.01%	↘
85	Health and social work	1.32%	1.21%	0.26%	↘
92	Arts, entertainment, recreation	-*	-1.46%	-0.83%	→
93	Other service activities	-*	0.56%	0.71%	→

Source: "EU KLEMS database", author's computation.

* TFP data for these industries are only available from 1991.

Table 11: Lagged Employment Effects of Annual TFP Growth Rates, 1980-2009

<i>Variables</i>	Fixed-Effects Regression					
	(1)	(2)	(3)	(4)	(5)	(6)
ΔTFP_t	-0.0056 (0.0118)					
ΔTFP_{t-1}		0.0005 (0.0162)				
ΔTFP_{t-2}			-0.0230** (0.0111)			
ΔTFP_{t-3}				0.0094 (0.0125)		
ΔTFP_{t-4}					0.0206 (0.0175)	
ΔTFP_{t-5}						-0.0073 (0.0077)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.5174	0.5130	0.5176	0.5224	0.5324	0.5343
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
No. of Obs.	1365	1307	1250	1198	1147	1097

Dep. Variable: Employment growth in year t : ΔE_{it}

Notes: Clustered standard errors (by industry) in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 12: Lagged Employment Effects of Annual TFP Growth Rates, 1980-1989

<i>Variables</i>	Fixed-Effects Regression					
	(1)	(2)	(3)	(4)	(5)	(6)
ΔTFP_t	-0.0077 (0.0601)					
ΔTFP_{t-1}		0.1025** (0.0437)				
ΔTFP_{t-2}			-0.0357 (0.0333)			
ΔTFP_{t-3}				-0.0450 (0.0320)		
ΔTFP_{t-4}					0.0657 (0.0508)	
ΔTFP_{t-5}						0.0304 (0.0375)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.3616	0.4357	0.4375	0.2952	0.3179	0.4077
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
No. of Obs.	463	413	364	318	272	228

Dep. Variable: Employment growth in year t : ΔE_{it}

Notes: Clustered standard errors (by industry) in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 13: Lagged Employment Effects of Annual TFP Growth Rates, 1990-1999

<i>Variables</i>	Fixed-Effects Regression					
	(1)	(2)	(3)	(4)	(5)	(6)
ΔTFP_t	-0.0007 (0.0129)					
ΔTFP_{t-1}		0.0149 (0.0124)				
ΔTFP_{t-2}			-0.0216** (0.0094)			
ΔTFP_{t-3}				0.0454 (0.0655)		
ΔTFP_{t-4}					0.0578** (0.0247)	
ΔTFP_{t-5}						-0.0600*** (0.0174)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.5341	0.5240	0.5265	0.2099	0.2617	0.2393
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
No. of Obs.	540	487	434	383	334	286
Dep. Variable: Employment growth in year t : ΔE_{it}						
<i>Notes:</i> Clustered standard errors (by industry) in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$						

Table 14: Lagged Employment Effects of Annual TFP Growth Rates, 2000-2009

<i>Variables</i>	Fixed-Effects Regression					
	(1)	(2)	(3)	(4)	(5)	(6)
ΔTFP_t	-0.0251 (0.0173)					
ΔTFP_{t-1}		-0.0302 (0.0311)				
ΔTFP_{t-2}			-0.0124 (0.0202)			
ΔTFP_{t-3}				-0.0586*** (0.0166)		
ΔTFP_{t-4}					-0.0156 (0.0269)	
ΔTFP_{t-5}						-0.0703*** (0.0268)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.2939	0.3751	0.4271	0.4959	0.4618	0.4881
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
No. of Obs.	458	407	356	305	254	203

Dep. Variable: Employment growth in year t : ΔE_{it}

Notes: Clustered standard errors (by industry) in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 15: Dynamic Panel Estimation

<i>Variables</i>	Dynamic Panel Estimation (Fixed-Effects)					
	(1)	Overall (2)	(3)	(4)	2000-2009 (5)	(6)
Two Lags						
Lagged Dep. Variable	-0.0098 (0.0536)			-0.1161 (0.0909)		
$\Delta \widehat{\text{TFP}}_{t-2}$	-0.0390* (0.0228)			-0.0124 (0.0261)		
Three Lags						
Lagged Dep. Variable		-0.0424 (0.0568)			-0.1818* (0.0999)	
$\Delta \widehat{\text{TFP}}_{t-3}$		-0.0631 (0.0567)			-0.0908*** (0.0346)	
Four Lags						
Lagged Dep. Variable			-0.0482 (0.0566)			0.0335 (0.0931)
$\Delta \widehat{\text{TFP}}_{t-4}$			-0.0484 (0.1211)			-0.1005* (0.0600)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.5136	0.5187	0.5256	0.4349	0.4878	0.5287
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
No. of Obs.	1304	1247	1190	357	306	255

Dep. Variable: Employment growth in year t : ΔE_{it}

Notes: Clustered standard errors (by industry) in parentheses, *** p<0.01, ** p<0.05, * p<0.1

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