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Contradictory effects of technological change across developed countries

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Abstract

Will productivity gains lead to technological unemployment in a region or to new prosperity? In our article, we formally show that under general assumptions the price elasticity of demand on product markets is decisive: technological change leads to employment growth if product demand is elastic and it leads to employment decline if product demand is inelastic. In our empirical analysis, we use industry-level time series data on output, prices, employment, wages, and national income for nine countries (including Germany, UK, USA) to estimate aggregate Marshallian product demand functions based on IV regressions and state space models with time-varying coefficients. The resulting income and price elasticities are used as inputs in a second step in which we estimate the employment effects of productivity changes as interactions with the elasticities. The results correspond to theoretical expectations: demand is generally inelastic and the employment effect of technological progress is therefore moderately negative.

KEYWORDS

labor market dynamics, productivity growth, technological change

JEL CLASSIFICATION

O33, J21, R11

1 | INTRODUCTION

Differences in employment rates are huge across countries. These differences are routinely explained by macroeconomic and institutional differences (e.g. Carlin & Soskice, 2014; Layard et al., 2005). However, even in the European Union with a harmonized regulatory setting and a coordinated macroeconomic regime there are still substantial differences in labor market performance. For example, in 2019, before the Covid pandemic, the employment rate was 63.5% in Italy and 81.0% in the Netherlands (Eurostat, 2022). We propose that a substantial part of these labor market differences across countries can be explained by the interplay of technical progress, price elasticities on product markets and the different industry composition of countries.

The employment effects of technological change have been the focus of considerable attention in recent years after Brynjolfsson and McAfee (2011, 2014) and especially Frey and Osborne (2017); Frey & Osborne (2017) raised fears about massive job losses as a consequence of "computerization." They estimate that 47% of jobs in the US are at high risk of being substituted by computer technology in the next two decades. For other developed countries, Autor and Salomons (2018) also find positive effects of technological change during the past four and a half decades. However, in a recent meta-study, Terzidis et al. (2019) find almost as many studies with positive employment effects as studies with negative ones.

Furthermore, recent empirical studies[1] examining the effects of technological progress on labor markets do not explicitly discuss the role of price elasticities in this context. At least to our knowledge, Bessen (2019) is one rare exception. He uses a theoretical model, which forms the basis of an empirical analysis for three US markets (cotton, steel and cars). He tracks the development of production and employment over the last 100–200 years and finds that though there have always been strong productivity gains in these markets, the development of employment exhibits an inverted U-shaped pattern. Bessen relates this shape to shifts in price elasticities.

Overall, we see great variety across countries in the empirical results on the relationship between technological progress and employment effects. The factor that we argue explains these differences, namely, the price elasticities on product markets, has so far only been rarely considered and only for single countries and industries. Thus, a comparative analysis of these effects not only helps to understand the drivers of differences in labor market outcomes but also the drivers of the differences in the results of previous studies on this issue.

In this article, we demonstrate that technological change itself has contradictory labor market effects: on the one hand, profit-oriented firms use new technologies to save labor, thereby generating a *substitution effect*. On the other hand, due to higher productivity, firms sell products at lower prices in order to increase their market shares. Lower prices usually result in higher product demand, which in turn leads to increased production and thus higher demand for labor, giving rise to a *compensating effect*.

We develop a theoretical model that uses standard economic elements and show that the relative strength of the substitution and the compensation effect depends on the demand conditions on product markets. More precisely, we demonstrate that the price elasticity of demand determines the direction of the effect of technological change on overall employment development. Thus, country differences in the industry composition, price elasticity of demand, or technological progress lead to differences in labor market outcomes.

Furthermore, we conduct an empirical test on the interplay between country- and industry-specific price elasticities and the employment effects of technological change based on data for nine developed countries. We apply state space models in order to estimate time-varying, industry- and country-specific elasticities. These elasticities are used as inputs in a second step in which we estimate the employment effects of technological change by means of IV regressions. The results correspond to our theoretical expectations. Overall demand is inelastic in the industries and countries considered and the employment effect of technological progress is therefore moderately negative.

This article is organized as follows: Section 2 presents a very brief survey of the current discussions concerning the effects of technological change. In Section 3 we develop our micro-founded theoretical model. Sections 4 and 5 describe the empirical approach and the data used. Results are presented in Section 6, and Section 7 concludes.

2 | THEORETICAL AND EMPIRICAL BACKGROUND

Research on the effects of technological change on employment has boomed enormously in recent years. The first wave of publications concentrated on the distribution of effects across different groups of workers. For example, in their seminal paper on the US, Autor et al. (2003) focus on shifts in the skill and task composition of labor and treat total employment as given. Goos et al. (2014) analyze the same aspects for 16 Western European countries and Autor and Dorn (2013) provide a regional application for the US. All these studies use microdata in order to show that technological change leads to changes in the workforce composition. The analyzes often conclude that a polarization process is taking place. For example, Autor and Dorn (2013) show that occupations in the middle of the wage distribution are losing, whereas high- and low-income occupations are gaining importance.[2]

Papers in the second wave of publications take a closer look at total employment. Some of these analyzes examine job descriptions to ascertain whether jobs with specific tasks can be substituted by computer technology (i.e. Frey & Osborne, 2017 and Arntz et al., 2017 for the US, and Dengler & Matthes, 2018 for Germany). Furthermore, Brynjolfsson and McAfee (2011, 2014) observe an acceleration of the innovation process and an increasing probability that computers will win the "race" against workers. Frey and Osborne (2017) focus only on the expected substitution of specific categories of workers by (computer) technology and discuss no compensating effects for the US. Autor and Salomons (2018) for 19 developed countries, Partridge et al. (2021) for the US, Acemoglu and Restrepo (2020) also for the US and Dauth et al. (2017) for Germany analyze the net effects either of productivity changes or of special technologies, such as industrial robots. All these studies do not compare the employment effects for different countries.

Some of these studies acknowledge that the labor market effects of technological change cannot be explained entirely by the substitution effect. Acemoglu and Restrepo (2020) theoretically derive two employment-boosting effects of technological change in the US. One is called the "price-productivity effect" of technological progress, which increases demand for the final product and consequently also demand for labor. The "scale-productivity effect" is due to the expansion of all industries and thus also the growth of the social product. Autor and Salomons (2018, see also the previous version of 2017) emphasize for 19 developed countries the indirect effects on employment (whereas Hornbeck and Moretti (2018) analyze direct and indirect effects on wages and rents) and the challenges involved in identifying them empirically. The empirical studies require a rather intricate design in order to identify these effects. However, they find that the indirect positive effects on employment are stronger than the direct negative effect.

In fact, the counteracting, compensating effect is due to price decreases that exploit higher productivity. Lower prices usually boost demand for a product, which in turn results in increased production, and hence in higher demand for labor. The price elasticity of demand on product markets therefore plays a crucial role for the overall effect of technological change on employment. As a consequence, differences in product market conditions and industry composition across countries can explain differences in labor market performance of these countries. To illustrate this, we introduce a simple macro model following Appelbaum and Schettkat (2001) (see also Möller, 2001; Partridge et al., 2021), which is similar to Bessen's (2019) and is based on three equations:

$$\pi_j = \frac{Q_j}{L_j}, \tag{1}$$

$$P_j = \frac{z_j W_j}{\pi_j}, \tag{2}$$

$$Q_j = f\left(P_j, y\right), \text{with } \partial Q_j/\partial P_j < 0, \ \ \partial Q_j/\partial y > 0, \tag{3}$$

where π_j is labor productivity (in industry j) given by production quantity Q_j divided by the level of employment L_j. Equation (2) is a price-setting function based on a mark-up calculation. Price P_j is the result of productivity, the wage (W_j) and a mark-up factor (z_j) which includes capital expenditures. Product demand is given by Equation (3), which is a function of prices and national income y. We assume that all products and firms within an industry are identical and that the growth rate of the mark-up factor $\hat{z}_j$ is equal to zero. Calculating growth rates and rearranging the equations lead to expressions using elasticities (the price elasticity $\varepsilon_j = \frac{P_j}{Q_j}\frac{\partial Q_j}{\partial P_j}$ and $= \frac{y}{Q}\frac{\partial Q_j}{\partial y}$, the income elasticity). Inserting dynamic versions of Equations (2) and (3) into Equation (1) leads to (see especially Partridge et al., 2021):

$$\widehat{L}_j = \eta_j \cdot \hat{y} - \left(\varepsilon_j + 1\right) \cdot \hat{\pi}_j + \varepsilon_j \cdot \widehat{W}_j. \tag{4}$$

Equation (4) shows that as a consequence of technological change ($\hat{\pi}_j > 0$), employment decreases if product demand is inelastic ($\varepsilon_j > -1$) and increases if demand is elastic ($\varepsilon_j < -1$). Although the model structure is rather simple, it clearly shows that the effects of productivity increases (or of technological change) on employment depend on genuine economic conditions. Furthermore, technological change can lead to very different outcomes: shrinkage, growth, or stagnation of employment. In the next section we show that the results of our micro-founded model closely correspond to this rather simple macro model.

Overall, there is a wealth of literature on the impact of technological change on employment. However, most of these studies only deal with one country, predominantly the US. A few studies use data from different countries but do not perform a comparative analysis, but rather use the variation in the data to estimate the effects. In addition, there are hardly any studies that look at the role of price elasticities for a large set of countries and industries.

3 | THEORETICAL FRAMEWORK

In order to draw conclusions about the effects of technological change on employment in different countries we develop a micro-model containing product and the labor markets. In this model, the change in employment is modeled as the development of labor demand in individual firms. The decisive factor influencing employment development is technological change or productivity growth.

3.1 | Cobb–Douglas production function and fixed wages

Following Combes et al. (2004), we first describe our micro-model based on a Cobb–Douglas production function (L: labor, K: capital, A: technology factor) and with fixed wages given by:

$$Q = AL^{1-\beta}K^{\beta\psi}\text{with } 0 < \beta \psi< 1 \text{ and } K \text{ fixed.}\psi \tag{5}$$

Although the equations in this section are formulated for individual firms, we drop the subscript for the sake of simplicity. We assume that technological and demand conditions are homogeneous within an industry.[3] We assume that the general level of productivity is reflected by a "technology" parameter A. This assumption of "Hicks-neutral" technological change is not restrictive, because with a Cobb–Douglas production this neutral form is basically the same as labor-saving and capital-saving technological change. If technological change is labor-saving $Q = (AL)^{1-\beta}K^{\beta}$, parameter A could be redefined as $A' = A^{1-\beta}$, which results in $Q = A'\left(L^{1-\beta}K^{\beta\psi}\right).\psi$ Product demand increases with income (y) and decreases with the product price (P) as given in the following equation:

$$Q = Q(P, y).\psi \tag{6}$$

The global income y results from a weighted aggregation of all products. The growth of y corresponds directly to the weighted growth of the technology factors A. We assume perfect competition on product markets and that the contribution of each industry j to y is so small that the effect is negligible. The cost function $c(r, w, Q)$ shows the minimal-cost combinations of factors for a given set of factor prices. This makes it necessary to determine the quantity of each production factor that is required for a certain production level (W: wage, r: interest).

$$c(r, W, Q) = \min(rK + WL) \text{ s.t. } : Q = AK^{\beta}L^{1-\beta\psi}.\psi \tag{7}$$

This cost minimization problem leads to the following conditional factor demand function for a given production quantity for L:

$$L(r, W, Q) = \left[\frac{(1-\beta)r}{\beta W}\right]^{\beta\psi} A^{-1}Q \tag{8}$$

and the conditional factor demand function for K is:

$$K(r, W, Q) = \left[\frac{\beta W}{r(1-\beta)\psi}\right]^{1-\beta\psi} A^{-1}Q.\psi \tag{9}$$

Inserting Equations (11) and (12) into the cost function gives:

$$c(r, W, Q) = r \cdot K(r, W, Q) + W \cdot L(r, W, Q) = \beta\bar{\psi}^{\beta}(1-\beta)^{\beta-1}W^{1-\beta}r^{\beta}A^{-1}Q. \tag{10}$$

Let $\mu\psi = \beta\bar{\psi}^{\beta}(1-\beta)^{\beta-1}$ then the price P, which is equal to the marginal costs, is given by:

$$\frac{\partial c(r, W, Q)\psi}{\partial Q} = \psi\frac{\mu W^{1-\beta}r^{\beta}A^{-1}Q}{\partial Q} = r^{\beta}W^{1-\beta\psi}\mu A^{-1} = P.\psi \tag{11}$$

To show that labor demand depends on product demand, which in turn depends on the technology parameter A, we take Equations (5), (6), (8), and (11) to derive the change in labor demand resulting from technological change:

$$\frac{\partial L}{\partial A} = -\left(\frac{K^{\beta} L^{1-\beta}}{A}\left(\frac{\beta W}{(1-\beta) r}\right)^{-\beta}\right) \cdot \left(1 + \frac{P}{Q}\frac{\partial Q}{\partial P}\right) = -\phi(1+\varepsilon). \tag{12}$$

Equation (12) directly yields the fundamental theorem of the employment effects of technological change. The employment response to increases in productivity is positive if the elasticity of demand ε is smaller than -1. This condition is always fulfilled for individual firms under perfect competition. However, if we aggregate all firms at industry level, the total employment in that industry can be related to the total demand for that aggregate. Then, Equation (12) applies to the entire industry. The aggregation is possible because the production function shows constant economies of scale.

To obtain an equation that can be estimated, we use total differentiation of the aggregated L (from Equation (8)):

$$dL = \frac{\partial L}{\partial A} dA + \frac{\partial L}{\partial W} dW + \frac{\partial L}{\partial y} dy. \tag{13}$$

Calculating partial derivatives and dividing by the level of L results in:

$$\frac{dL}{L} = -\left(1 + \frac{P}{Q}\frac{dQ}{dP}\right)\frac{dA}{A} - \left(\beta + (\beta - 1)\frac{P}{Q}\frac{dQ}{dP}\right)\frac{dW}{W} + \frac{y}{Q}\frac{dQ}{dy}\frac{dy}{y} \tag{14}$$

or

$$\hat{L} = -(\varepsilon + 1)\hat{A} - (\beta + (\beta - 1)\varepsilon)\widehat{W} + \eta\hat{y}. \tag{15}$$

This result is striking: although (4) was obtained in a simple macro-model and (15) is based on a standard micro-model, the results are almost identical. With respect to the crucial demand and income elasticities, they are the same. With regard to the controlling variable W our micro-founded model yields a different result since the partial production elasticities from the production function appear as weights. The growth of the social product has the effect of an additional shift parameter in the equation because it influences product demand and thereby labor demand.

3.2 | CES production function

We can also show that the underlying assumption of a Cobb–Douglas production function is not essential. If we assume the more general CES function

$$\left(Q = A\left[K^{\rho} + L^{\rho}\right]^{1/\rho}\right)$$

instead, conditional labor demand is given by:

$$L = W^{\frac{1}{\rho-1}}\left[W^{\frac{\rho}{\rho-1}} + r^{\frac{\rho}{\rho-1}}\right]^{-\frac{1}{\rho}} A^{-1} Q(P, y). \tag{16}$$

A slightly more complicated calculation, as with the Cobb–Douglas case, leads to:

$$\frac{d\mathrm{L}}{\mathrm{L}} = -\left(1 + \frac{\mathrm{P}}{\mathrm{Q}}\frac{\partial Q}{\partial P}\right)\frac{d\mathrm{A}}{\mathrm{A}} + \left(\frac{1}{\rho - 1} + \left[\mathrm{W}^{\frac{\rho}{\rho-1}} + \mathrm{r}^{\frac{\rho}{\rho-1}}\right]^{-1}\mathrm{W}^{\frac{\rho}{\rho-1}}\left[\frac{\partial Q}{\partial P}\frac{\mathrm{P}}{\mathrm{Q}} - \frac{1}{\rho - 1}\right]\right)\frac{\mathrm{dW}}{\mathrm{W}}$$

$+\frac{y}{Q}\frac{\partial Q}{\partial y}\frac{dy}{y}$ or with a function of wages ($F(W)$):

$$\hat{L} = -(\varepsilon + 1)\hat{A} - F(W)\varepsilon\widehat{W} + \eta\hat{y}. \tag{17}$$

This result is sufficiently similar to (15).

3.3 | The case of endogenous wages

The previous section assumes that wages are fixed. Since this assumption is restrictive, in this section we describe the effect of technological change on employment if wages are endogenous. To do this, we assume that wages respond inversely to unemployment. This is called the wage-setting curve in the macro-models of Layard et al. (2005) and Carlin and Soskice (2014) or the wage curve in the regional models of Blanchflower and Oswald (1994, 2005). This relationship has been tested empirically for many countries (see the publications by Blanchflower & Oswald and others, e.g. for Germany Baltagi et al., 2012) and can be derived on the basis of efficiency wage and wage negotiation approaches. Brücker et al. (2014) estimated a wage setting curve at the national level for three countries (Denmark, Germany, and the UK).

We measure employment L as a share of the active population N, which is in turn standardized to $N = 1$. Accordingly, unemployment is $U = 1{-}L$. To facilitate calculations, we assume that the wage (setting) curve is linear:

$$W = \gamma - \tau U = \gamma - \tau\frac{1 - L}{1} = \gamma + \tau L. \tag{18}$$

If we use a Cobb–Douglas production function, we can substitute (18) in the labor demand Equation (8):

$$L = A^{-1}\left(\frac{\beta(\gamma + \tau L)}{(1 - \beta)r}\right)^{-\beta} Q,$$

$$L = A^{-1}\beta^{-\beta}(\gamma + \tau L)^{-\beta}(1 - \beta)^{\beta} r^{\beta} Q. \tag{19}$$

The implicit function is given by:

$$G = L(\gamma + \tau L)^{\beta} - A^{-1}\beta^{-\beta}(1 - \beta)^{\beta} r^{\beta} Q = 0. \tag{20}$$

The change in labor demand resulting from technological change is then given by:

$$\frac{dL}{dA} = -\frac{\partial G/\partial A}{\partial G/\partial L} = -\frac{\left(\frac{K^{\beta}L^{1-\beta}}{A}\right)\left(\frac{\beta}{(1-\beta)r}\right)^{-\beta}\left(1 + \frac{PdQ}{QdP}\right)}{(\gamma + \tau L)^{\beta} + \beta L(\gamma + \tau L)^{\beta-1}\tau - \frac{\partial Q}{\partial P}A^{-2}\left(\frac{(1-\beta)r}{\beta}\right)^{\beta}\left[r^{\beta}(1 - \beta)(\gamma + \tau L)^{-\beta}\tau\mu\right]}. \tag{21}$$

Compared with labor demand under exogenous wages (12), the version with endogenous wages (21) contains an additional factor S with $0 < S < 1$, if $\frac{\partial Q}{\partial P} < 0$.

Because S is between zero and one, the effect of an increase in productivity is weaker in the case of endogenous wages. However, the turning point of the development, that is the price elasticity of minus one, remains the same as can be seen from (21). Thus, the previous finding, that employment at industry level depends on the price elasticity of demand and that consequently the development of employment in a country is dependent on the industry composition, still holds.

4 | DESIGN OF EMPIRICAL ANALYZES: THE TWO-STEP APPROACH

This section describes the empirical application of our micro-model. Since technological change is included in an interaction with price elasticity in our model, we need to estimate them. We therefore carry out the empirical analyzes in two steps. First, we estimate the country- and industry-specific price and income elasticities. Second, we estimate employment in relation to the interaction between productivity changes and these country-specific elasticities and several other control variables.

Our data relate to the industries that make up manufacturing (see the following section). We regard each industry in each country as a market of its own. The advantage of this data base is that it covers the "core" of each economy. However, the drawback is that each industry is rather large because it is an aggregation of markets. Estimated elasticities are then averages of smaller markets.

4.1 | Step 1: Identifying elasticities

Despite the theoretical simplicity of the price elasticities of demand, there are some challenges involved in identifying these empirically. For example, to estimate a classical Marshallian demand function for a specific good it would be necessary to include a vector of the prices of all other goods or at least of all other industries. This is hardly feasible, however, due to the associated loss of degrees of freedom and missing data.

Therefore, we follow Möller (2001) and assume that the products of each industry are substitutes for a composite good, which represents the product mix of all other goods. Additionally, we assume that the respective industries are small compared to the total economy, yielding the following Marshallian demand function for industry j in country k:

$$q_{kjt} = \beta_{0kj} + \beta_{1kj}\left(p_{kjt} - p_{kt}\right) + \beta_{2k} \cdot y_{kt} + u_{kjt}.\psi \tag{22}$$

Equation (22) specifies a simple linear model with time constant parameters, where q_{kjt} is the industry real output, p_{kjt} is the industry price level, y_{kt} is the national disposable income, and u_{kjt} is the usual error term. All variables are in logarithmic form, so estimates for β_{1kj} provide the price elasticities ε at industry-country level and those for β_{2k} the income elasticities η. This specification also implies that domestic and foreign consumers are identical and that the concept of income elasticities applies to intermediate goods. The variable $-p_{kt}$ indicates that all prices are normalized by the price level (the index uses 2010 as its basis). All prices are set relative to the global level.

For the price elasticities ε, we expect negative values. Demand is inelastic if the estimated value lies between 0 and -1 and it is price-elastic if $\varepsilon < -1$ holds. Industries with $\eta > \psi 1$ face income-elastic demand. They produce superior goods. Those with $0 \leq \eta \leq 1$ sell relatively inferior products and those with $\eta < 0$ provide absolutely inferior ones.

This simple linear model is useful to estimate time invariant parameters/elasticities. However, given our long observation period, the elasticities cannot be expected to be constant. We therefore estimate time-varying elasticities for each industry and each country by means of the Kalman filter. But, we use the results of the simple linear model with constant parameters as a reference in the empirical applications and also as starting values for the Kalman filter.

The Kalman filter was originally designed to solve practical engineering problems, for example to estimate the flight path of the US Apollo spacecraft during the moon landing (Tabor, 2019). Since then, however, it has also been used increasingly in other disciplines, especially in economics and finance, for time series analysis (see e.g. Clark, 1987; Koopman et al., 2009; Morley et al., 2003). In order to be able to estimate the time-varying coefficients in this way, we first have to convert Equation (22) into a state space form. In our case, the general linear Gaussian state space model with time-varying parameters is given by:

$$q_{kjt} = \beta_{0kjt} + \beta_{1kjt}\left(p_{kjt} - p_{kt}\right) + \beta_{2kt} \cdot y_{kt} + u_{kjt}, \psi \tag{23}$$

$$\beta_{0kjt} = \delta_{ki} \cdot \beta_{0jkt-1} + \omega_{kjt}, \psi \tag{24}$$

$$\beta_{1kjt} = \phi_{ki} \cdot \beta_{1jkt-1} + e_{jkt}, \psi \tag{25}$$

$$\beta_{2kt} = \theta_k \cdot \beta_{2kt-1} + \tau_{kt}, \psi \tag{26}$$

where $\omega_{kjt} \sim N(0, H_t)$, $e_{jkt} \sim N\left(0, Q_{t_r}\right)$, and $\tau_{kt} \sim N(0, R_t)$.ψThe error terms are assumed to be serially independent and independent of each other at all points in time. Hence, $H_t, Q_t, \psi$and R_t are diagonal matrices. Equation (23) is the observation equation that links the observation vector q_{kjt} to the unobservable state vector $\alpha_t = \psi\left(\beta_{0jkt}, \beta_{1jkt}, \beta_{2kt}\right)$. Equations (24)–(26) are the state equations. Each state (time-varying coefficient) is assumed to vary according to a random walk. We estimate this model with quasi-ML methodology via the Kalman filter approach with standard errors robust to heteroskedasticity (cf. Hamilton, 1994, see also Durbin & Koopman, 2012) using the *dlm* R-package (Giovanni Petris, 2010). Prices and wages are likely to suffer from endogeneity. To take this problem into account, we instrument them with their lagged values.

4.2 | Step 2: Employment response to productivity increases

Our theoretical model states that the employment response to productivity increases is positive (negative) if demand is price elastic (inelastic). Therefore, we expect countries with industries with smaller price elasticities to exhibit better labor market outcomes than those with larger ones. Furthermore, the larger the share of industries with elastic demand in each country the better the overall labor market outcome. We define labor market performance as the change in employment in the respective year.

Our main analysis is a regression of the development of employment on interactions with the two elasticities that were derived in the first step:

$$\Delta L_{kjt} = \alpha_0 + \alpha_1 \left(\varepsilon_{kjt} + 1\right) \Delta A_{kjt} + \alpha_2 \eta_{kt} \Delta Y + \alpha_3 X_{kjt} + \nu_{kjt}.\psi \tag{27}$$

ΔL is the empirical employment growth rate, included as a difference between logs. X is a set of control variables that includes ΔW, wage growth, a set of year dummies to take care of business cycle effects, and a set of country dummies to control for country-specific fixed effects. Since wages are also likely to suffer from endogeneity, we instrument them by means of their lagged values.

Equation (27) is a generalized version of the theoretically derived Equations (15) and (17). The signs of the coefficients are important. Because we expect countries with industries with more price-elastic demand to exhibit a better labor market outcome, we expect a negative sign for α_1 (the coefficient of the interaction between price elasticity and productivity growth). For α_2 we expect a positive coefficient.

In order to test the robustness of our results, we estimate two further models, which include interactions between world gross income and cross-price elasticities as further explanatory variables. The interaction between world gross income and income elasticity represents additional demand effects originating in foreign countries/international trade, while the interaction between cross-price elasticities and price elasticity represents spillover effects from other markets (see Blien & Sanner, 2014).

5 | DATA

Most of the data we use are from the EU KLEMS project, which collected data on productivity and growth accounts based on the NACE 2 industry classification for the member states of the European Union, as well as several EU aggregates and the United States. The EU KLEMS project ran from 2003 until 2008 and was funded by the European Commission's Directorate-General for Research and Innovation. An updated and revised EU KLEMS dataset was released in July 2018 and can be downloaded here: http://www.euklems.net/.

Due to data restrictions for specific industries and years, we cannot use all the countries and industries available in the EU KLEMS data. We utilize the data from nine countries to obtain the longest possible time series for the variables of interest (for a complete list of countries, time periods, and variables, see Tables 1 and A1 in the Appendix). Further, we include US data to cover the largest economy and the country that has been analyzed by many other studies on this topic although the time span available for the second step is relatively short.

Table 2 contains a list of the industries included in the analyzes. We concentrate on manufacturing, construction, and mining and quarrying. The selection of industries is based on the reliability of long time series. Tests have also shown that data on service industries are not reliable enough, because the units exchanged via markets are not defined precisely enough. Therefore, we exclude this sector from the analysis.

The variable of interest in the first step of our analysis (estimation of elasticities) is the gross value added at current prices. National incomes and consumer prices are taken from the World Bank (World Development Indicators: GNI and consumer price index). 2010 is the base year for all the variables.

The second step of our analysis is also based on data from the EU KLEMS database. It provides different options with regard to our productivity measure since it contains information on

TABLE 1 Countries and periods included in the analysis

Country	Time period
Austria	1970–2015
Belgium	1995–2015
Germany	1970–2015
Finland	1980–2015
France	1975–2015
Italy	1970–2015
Netherlands	1970–2015
United Kingdom	1970–2015
United States	1972*/1998–2015

Note: *first step only.
Source: EU KLEMS.

TABLE 2 List of industries

#	WZ 2008	Sector
1	13–15	Textiles, wearing apparel, leather and related products
2	16–18	Wood and paper products; printing and reproduction of recorded media
3	20–21	Chemicals and chemical products
4	22–23	Rubber and plastic products, and other nonmetallic mineral products
5	24–25	Basic metals and fabricated metal products, except machinery, and equipment
6	28	Machinery and equipment n.e.c.
7	29–30	Transport equipment
8	31–33	Other manufacturing; repair and installation of machinery and equipment
9	B	Mining and quarrying
10	F	Construction

Source: EU KLEMS.

both the number of people employed and the total hours worked by them. For our main analysis, we calculate the gross value added divided by total hours worked. However, in order to test the robustness of our results, we also use another productivity measure, the gross value added divided by the number of people employed (see Table A2 in the Appendix).[4]

6 EMPIRICAL RESULTS

6.1 First step: Estimated elasticities

As outlined in Section 5, we first use a standard regression model to estimate time-constant elasticities. These constant elasticities are used as a comparison for our main results and as starting

TABLE 3 Time-constant elasticities from a regression model without time-varying parameters—prices are instrumented

	Price elasticity	*t*-values	Income elasticity	*t*-values
Textiles	.18***	4.50	−0.80***	−13.40
Wood and paper products	.01	.11	.45***	6.43
Chemicals	−0.27***	−4.08	1.51***	31.50
Rubber and plastic products	−0.04	−0.76	.66***	13.04
Metals	.00	.05	.36***	3.83
Machinery and equipment	−0.25***	−2.84	.96***	7.38
Transport equipment	−0.21***	−6.74	1.10***	16.87
Other manufacturing	−0.44***	−10.34	1.24***	22.86
Mining and quarrying	−0.11*	−1.67	.11	.77
Construction	−0.06**	−2.30	.33***	5.92
Total	−0.19	−1.52	.67**	2.27

Note: ***, **, and * denote significance at the .01, .05, and .1 levels, respectively.
Source: EU KLEMS, own calculations.

values for the Kalman filter. The results are shown in Table 3. The variables we use are shown in Table A1 in the Appendix.

However, as we assume that elasticities are not constant over our long observation period, we estimate time-varying elasticities by means of the Kalman filter. The results are shown in Figure 1, which depicts the mean price and income elasticities across all industries and countries between 1972 and 2015. As can be seen, both elasticities vary over time. The mean income elasticity varies between 1.0 and 1.3. The mean price elasticity varies between −0.2 and − 0.1. Although these are only mean elasticities across industries and countries and do not reflect the full variation, this finding clearly underscores the necessity to estimate time-varying elasticities instead of constant ones.

There are also noteworthy differences between countries, as can be seen from Figure 2, which shows a comparison of Germany and the Unites States. However, in both countries demand is getting more inelastic during the first half of the observation period which is according to our model an indicator of deteriorating conditions for the labor market.

Figure 3 displays the industry variation of the mean price and income elasticities across time and countries. The numbers on the x-axis represent the industries listed in Table 2. The results are in line with our expectations formulated on the basis of the theoretical model: the values of the coefficients for the income and the price elasticity of demand have the "right" signs and are in a "reasonable" range. What is slightly surprising is that the demand corresponding to the various industries is uniformly estimated as being in the inelastic range. Therefore, we can generally expect technological change to have negative effects on employment in the industries considered. Of course, this might partly be an aggregation effect. Smaller subindustries exhibiting elastic demand are grouped together with the majority of industries that are characterized by inelastic demand.

Figure 4 displays the country variation of the mean price and income elasticities across time and industries. Both, price elasticity and income elasticity, again show the expected signs. In

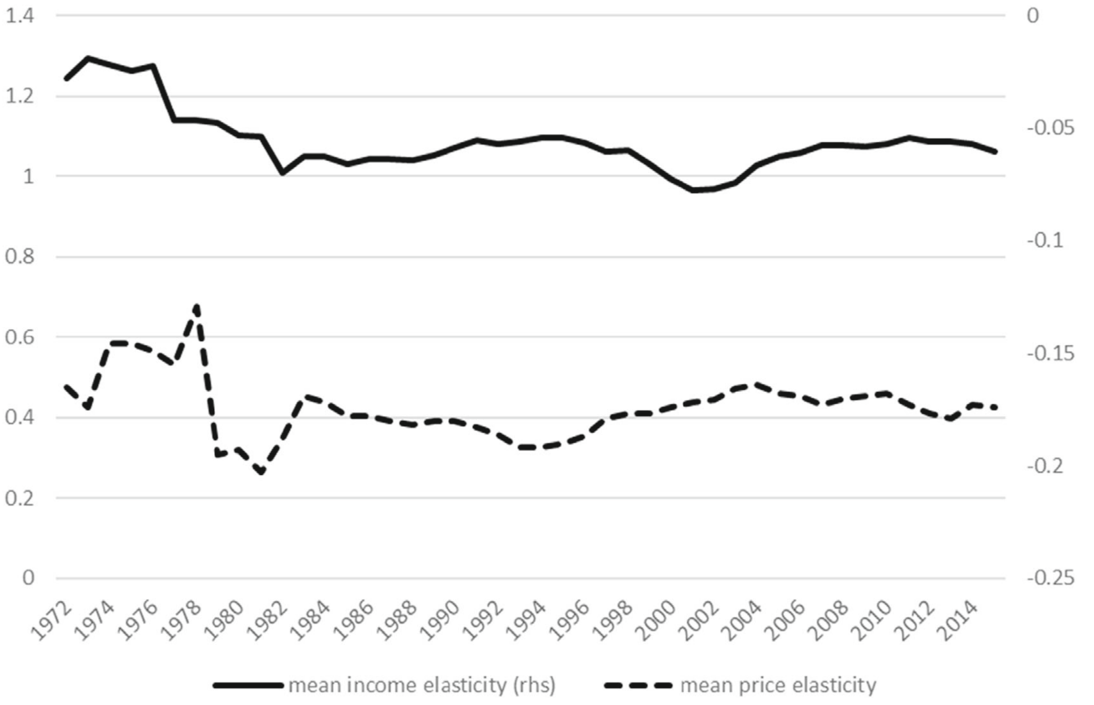

FIGURE 1 Mean elasticities across all industries and countries between 1972 and 2015—prices are instrumented, estimates based on state space models. Source: EU KLEMS (2017), own calculations

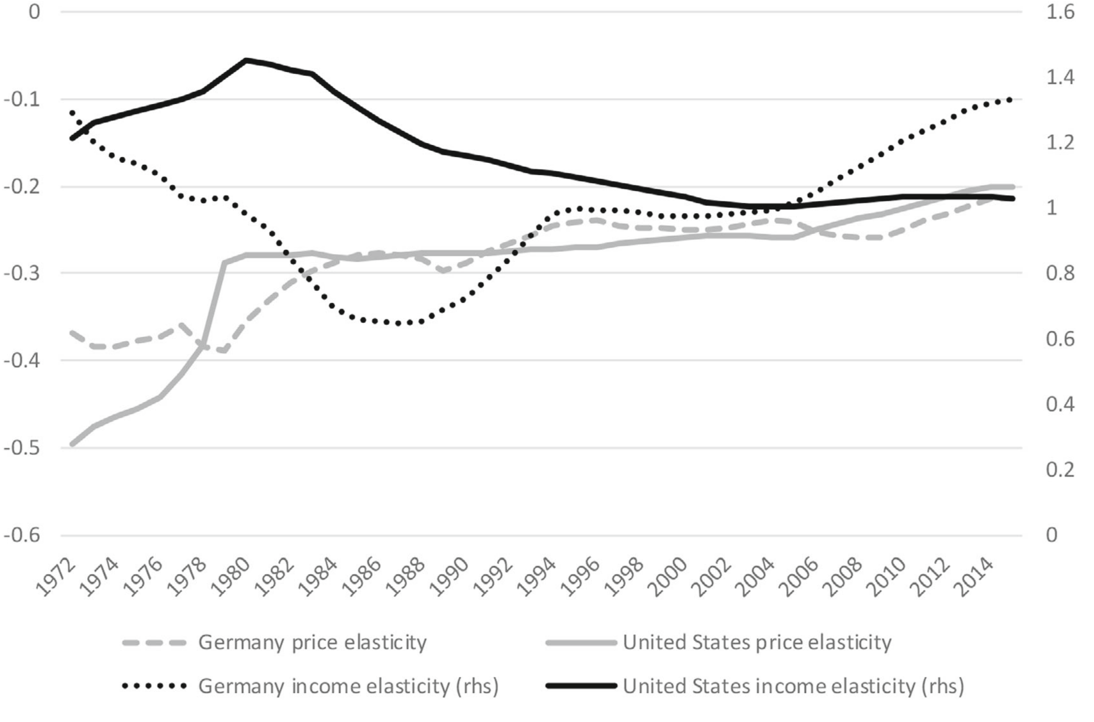

FIGURE 2 Mean elasticities across all industries between 1972 and 2015 for US and Germany—prices are instrumented, estimates based on state space models. Source: EU KLEMS (2017), own calculations

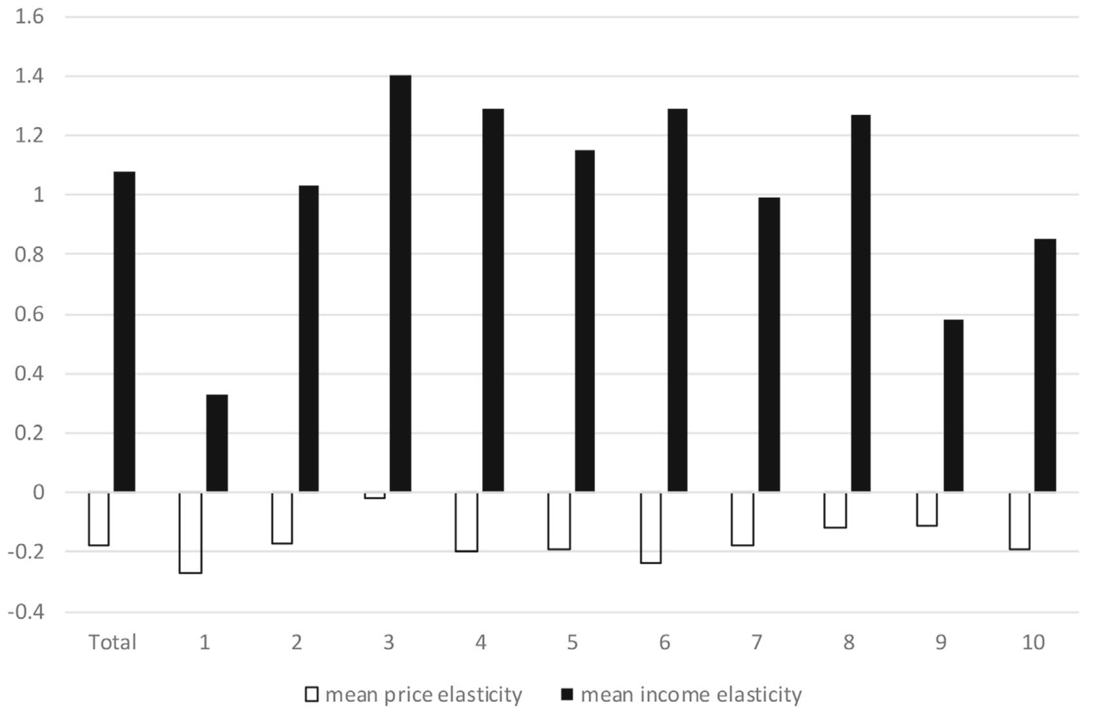

FIGURE 3 Mean elasticities for single industries. Source: EU KLEMS (2017), own calculations

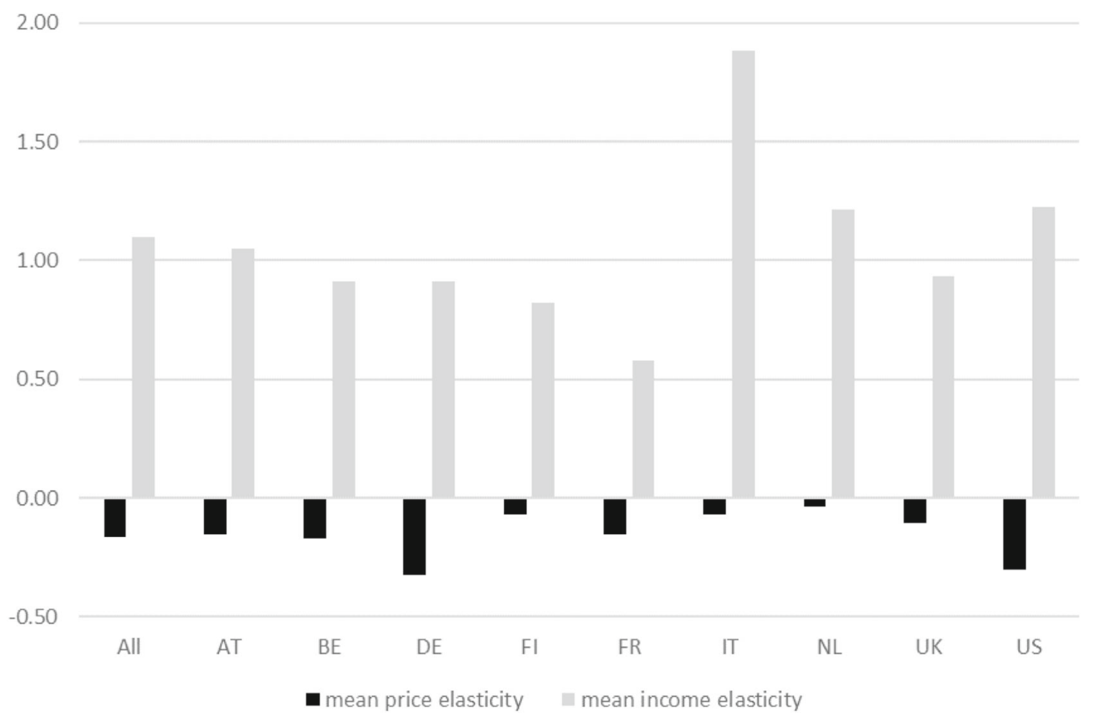

FIGURE 4 Mean elasticities for single countries. Source: EU KLEMS (2017), own calculations

addition, however, it can also be seen that the magnitude of the elasticities varies across countries. The income elasticity varies from 0.58 in France to 1.88 in Italy. The mean price elasticity over all industries and years varies from −0.04 in the Netherlands to −0.32 in Germany.

6.2 | Second step: Employment response to technological change

In the second step of the analyzes, the estimated elasticities are used as inputs in the employment regressions. The results of the six basic model specifications can be seen in Table 4. The test results of the instrumentation of prices (first step) and wages (second step) are listed in Table 5.

All the models use instrumental variables. These are lagged values for prices (first step) and wages (second step). The only exception is model three, where only prices are instrumented. Model (1) serves as a benchmark for the comparison with the more refined versions. It is a regression model without elasticities, as is used by other authors. In this case, the crucial variables are productivity growth and national income growth. The first variable is weakly significant, the second one highly significant. For this and the other models, national income is assumed to be large enough not to be influenced by the individual industries chosen for the analyzes. The negative sign of the coefficient for productivity growth indicates that a 1% increase in productivity leads to a 0.18% fall in employment.

According to our theoretical model, however, this is not our preferred specification. Model (2), which includes interactions with the respective elasticities is a step in the right direction. In this model, the elasticities are assumed to be constant and are estimated via OLS. Both coefficients of interest have the expected signs. The coefficient of the interaction between productivity change and price elasticity is negative and that of the interaction between the change in the national income and income elasticity is positive. However, the latter coefficient is not significant.

The remaining models (3)–(6) include time-varying elasticities that have been estimated by means of the Kalman filter. While only prices (first step) are instrumented in model (3), prices and wages (second step) are instrumented in models (4)–(6). The corresponding tests of our instruments do not reject our assumption that the instruments are not weak and that they are exogenous (Table 5).

The coefficient of the interaction between productivity change and price elasticity is negative and highly significant in all three models, as expected from our theoretical model. It is necessary to remember that although there is always a compensation effect due to increasing product demand, the tipping point for the net employment effect in our model is a price elasticity of −1. In the empirical reality, however, product demand is inelastic (elasticity around −0.2), so the net employment effect of technological change is negative. However, the quantitative size of the negative effect differs with respect to countries, industries and time. Overall the composite term for the effects of technological change on employment in Equation (27) is: $\alpha_1 \left(\varepsilon_{kjt} + 1\right) \Delta A_{kjt}$. α_1 is estimated in Model (4) as −0.18 and the elasticity ε_{kjt} is about −0.2. Hence, a hypothetical 1% increase in productivity A_{kjt} will result in a change in employment L_{kjt} of −0.144%. A price elasticity of −0.5, as we found for the US during the 1970's, reduces the employment loss to −0.09.

However, real productivity increases are substantially higher. The average annual increase in labor productivity for all countries with data for the whole observation period (1973–2015) amounts to 3%. For the period 2000 to 2015 and all nine countries of our data set it amounts to 2%, reflecting the productivity slowdown. Using these productivity values, the coefficient of the composite term (−0.18) and the year- and country-specific price elasticities from our first step, we calculate the hypothetical aggregated employment effects by assuming a starting level of 100

TABLE 4 Regression results—dependent variable: employment growth

	(1) without elasticities	(2) constant elasticities	(3) IV (only prices)	(4) IV (prices and wages)	(5) with world income growth	(6) with cross-price elasticities
Interaction price elasticity & productivity change		−0.13	−0.18***	−0.18***	−0.20***	−0.14***
		(−1.50)	(−23.85)	(−13.40)	(−15.34)	(−9.01)
Interaction cross-price elasticity & productivity growth						−0.04***
						(−3.57)
Productivity growth	−0.18*					
	(−2.91)					
Interaction income elasticity & national income growth		.37***	.43***	.49***	.58***	.51***
		(6.39)	(20.32)	(19.39)	(21.63)	(17.97)
Interaction income elasticity & world income growth					.52***	
					(16.06)	
National income growth	.61***					
	(6.56)					
Wage growth	−0.21	−0.35	−0.17***	−0.09*	−0.07	−0.07
	(−1.68)	(−2.05)	(−15.62)	(−1.98)	(−1.67)	(−1.42)
Constant	−0.01	.00	.02***	−0.03***	−0.03	−0.03***
	(−0.91)	(0.11)	(4.38)	(−4.56)	(−5.15)	(−4.68)
Observations	2640	2640	3179	2640	2640	2580
R^2	.357	.350	.452	.398	.437	.389
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: ***, **, and * denote statistical significance at the .01, .05, and .1 levels, respectively, *t*-values in parentheses.
Source: EU KLEMS, own calculations.

TABLE 5 Test results of IV regressions

		(1) without elasticities	(2) constant elasticities	(3) IV (prices)	(4) IV (prices and wages)	(5) with world income growth	(6) with cross-price elasticities
Prices (first step)	Hansen J statistic (p-value)	.21	.21	.21	.21	.29	.52
	Kleibergen-Paap LM test (p-value)	.04	.04	.04	.04	.04	.03
	Anderson- Rubin test (p-value)	.02	.02	.02	.02	.02	.00
Wages (second step)	Hansen J statistic (p-value)	.08	.08		.08	.09	.09
	Kleibergen- Paap LM test (p-value)	.03	.03		.03	.03	.03
	Anderson- Rubin test (p-value)	.04	.04		.04	.04	.08

Source: EU KLEMS, own calculations.

for each country and then adding the yearly employment effects of productivity change. These yearly employment effects are mostly negative, thus the hypothetical employment levels in 2015 are below 100. Table 6 presents the results for both time periods and each country. We also added the difference of the employment effect of each country and the highest employment level of all countries in the sample.

The country with the highest employment level, Germany, and the one with the lowest, the Netherlands, have a difference in employment levels of 4.66 percentage points due to the difference in average price elasticities of 0.24. Taking another EU-major economy, Italy, there is a difference in the hypothetically employment level with Germany of almost four percentage points. This is caused by a difference of 0.2 in the price elasticities. Thus, rather small differences between countries in the price elasticities lead in the long run to a considerable difference in employment effects for the same level of productivity changes.

However, a shorter time period yields a smaller employment effect. The difference between Germany and Finland of almost one percentage point in employment is caused by a difference of 0.17 in the price elasticity. As we assume that the productivity increase is the same in all countries, similar elasticises like between the US and Germany, both around −0.24, yield of course similar labor market outcomes. Summing up, for a given productivity change, difference in the price elasticity of product demand across countries, result in substantially different labor market outcomes in these countries. Since productivity changes are not the same across countries, we elaborate these issues in more detail in chapter 6.3.

The other composite term, the interaction between income elasticity and national income growth, acts in the opposite direction. The associated coefficient α_2 is positive and significant in all models. The control variables also yield a consistent picture: the wage-growth variable has a uniformly negative coefficient. It is often not significant or only slightly significant, especially

TABLE 6 Hypothetical employment levels for the periods 1973–2015 and 2000–2015

	Productivity change of 3% each year 1973–2015		Productivity change of 2% each year 2000–2015	
	Hypothetical employment level 2015	Highest employment level minus country level	Hypothetical employment level 2015	Highest employment level minus country level
Austria	82.89	−1.41	95.30	−0.42
Belgium			94.98	−0.74
Germany	84.30	.00	95.72	.00
Finland			94.76	−0.96
France			95.38	−0.34
Italy	80.32	−3.98	94.89	−0.83
Netherlands	79.65	−4.66	95.04	−0.68
UK	81.66	−2.64	95.38	−0.34
US			95.69	−0.04

if wages are instrumented. The country and time fixed effects are important in order to control for country-specific developments and business-cycle effects. Interestingly, the regression constant is very small in all models and slightly significant in only one case. This corresponds to expectations as the theoretical model does not include a constant term. Estimates in models without a regression constant differ only slightly from those we present and are available upon request from the authors. At this point, we can derive two main results from the empirical analysis: first, estimates with real world data fit very well with our theoretical model. Second, we show for 9 developed countries that in manufacturing the net employment effect of technological change is negative because of inelastic product demand in all countries. However, the negative effects differ with respect to countries due to the different level of elasticities depending on the country.

The remaining two models (4) and (5) take account of the effects of world income growth (as an interaction with income elasticity) and of cross-price elasticity (as an interaction with productivity growth). The interaction between world gross income and income elasticity represents additional demand effects originating in foreign countries/international trade, while the interaction between cross-price elasticities and price elasticity represents spillover effects from other markets (see Blien & Sanner, 2014). These robustness checks are also in line with the results of the basic model (4). International trade amplifies income effects and boosts employment. Cross-price elasticities can have the same effects as own-price elasticities. As the latter can be positive or negative, the same happens with cross-price elasticities. In the case of model (5), the direct effects are reinforced by cross-price effects.

6.3 | Global and country results

After deriving the results from the model on employment development, it is possible to assess the global and country-specific effects of technological change. In the following, we always use

TABLE 7 Average values of two terms: (1) the interaction of price elasticity with productivity and (2) the interaction of income elasticity with income growth

	(1) **T_1: Int. of price elast. and productivity growth**	**(2)** **T_2: Int. of income elast. and income growth**
Textiles	−0.38	.33
Wood and paper products	−0.47	1.06
Chemicals	−0.87	1.20
Rubber and plastic products	−0.34	1.18
Metals	−0.40	.88
Machinery and equipment	−0.44	1.11
Transport equipment	−0.55	.92
Other manufacturing	−0.32	1.06
Mining and quarrying	−0.39	.41
Construction	−0.05	.67
Total	**−0.42**	**.88**

Abbreviations: elast., elasticity; Int., interaction.
Source: EU KLEMS, own calculations.

the results from model (4) and look at the two important terms that contribute to employment growth:

$$T_1 = \alpha_1 \left(\varepsilon_j + 1\right) \Delta A_j,\psi \tag{28}$$

$$T_2 = \alpha_2 \eta_j \Delta Y.\psi \tag{29}$$

For each year, we use the actual values of variables and the coefficients of the interaction effects. The expressions (28) and (29) for T_1 and T_2 are averages across points in time and across countries: T_1 could be interpreted as the average net effect of technological progress, T_2 as the average net effect of income growth.

Table 7 shows the results for T_1 and T_2. The first column (for T_1) summarizes the effects of technological progress for single industries. It indicates that the global effect of increases in productivity—that is the substitution and compensating effects taken together—is uniformly negative. This mirrors the finding that demand for single industries is always in the inelastic range.

The net effect of technological progress varies in size between industries. It is largest for the chemical industry and smallest for construction. However, there is always a further counteracting effect, given by T_2, which is larger than the net effect of technical progress. This explains why the repercussions of technological progress on employment are barely visible, they are "masked" by the positive stimuli of income growth on employment. The total effects of all industries are summarized in the last row of Table 7. They can be broken down in time, which is shown in Figure 5. The effects of time dummies and wages are added and also included. Now, we need

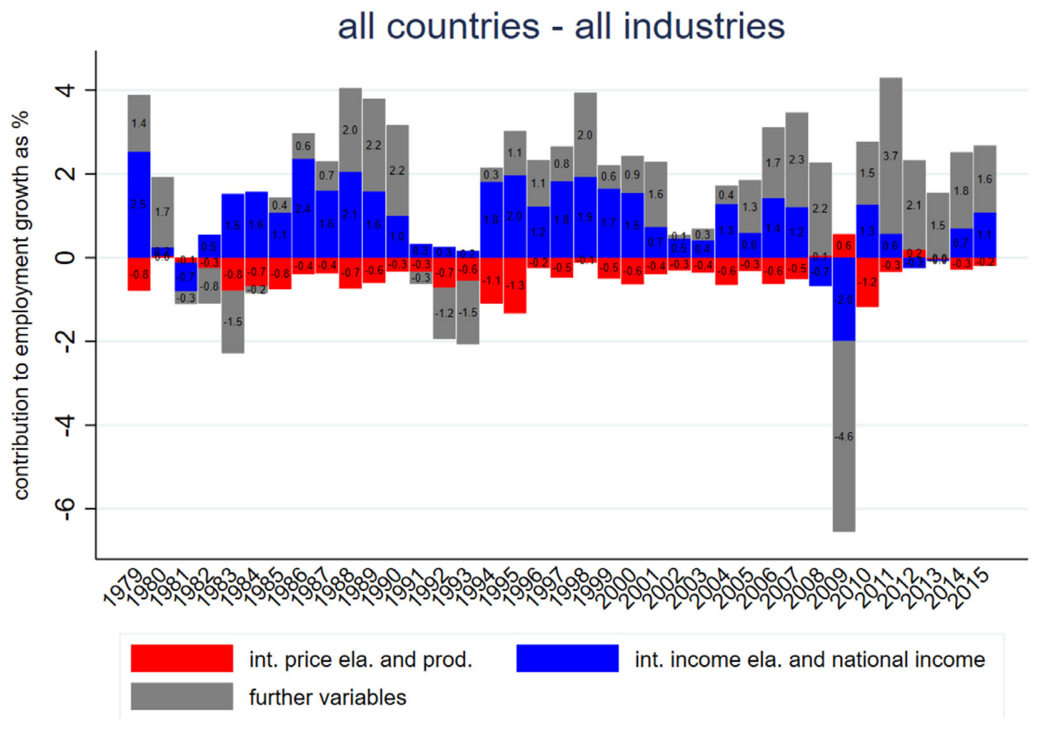

FIGURE 5 Contributions to employment growth across all countries and industries. Source: EU KLEMS, own calculations [Colour figure can be viewed at wileyonlinelibrary.com]

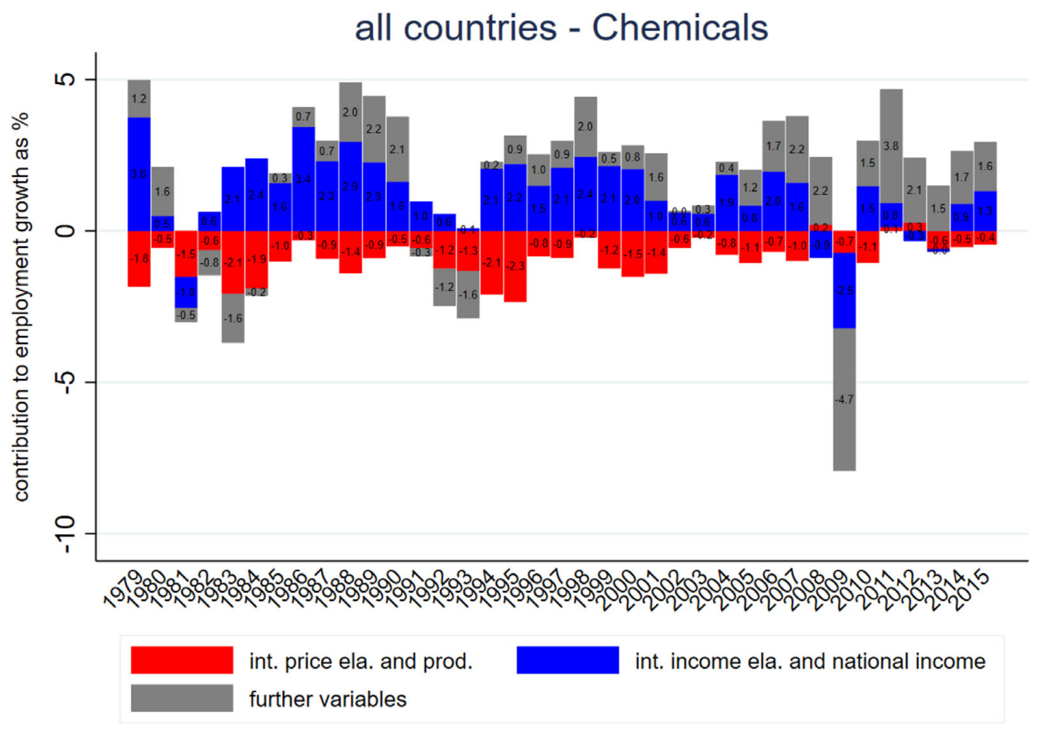

FIGURE 6 Contributions to employment growth in chemicals and chemical products across all countries. Source: EU KLEMS, own calculations [Colour figure can be viewed at wileyonlinelibrary.com]

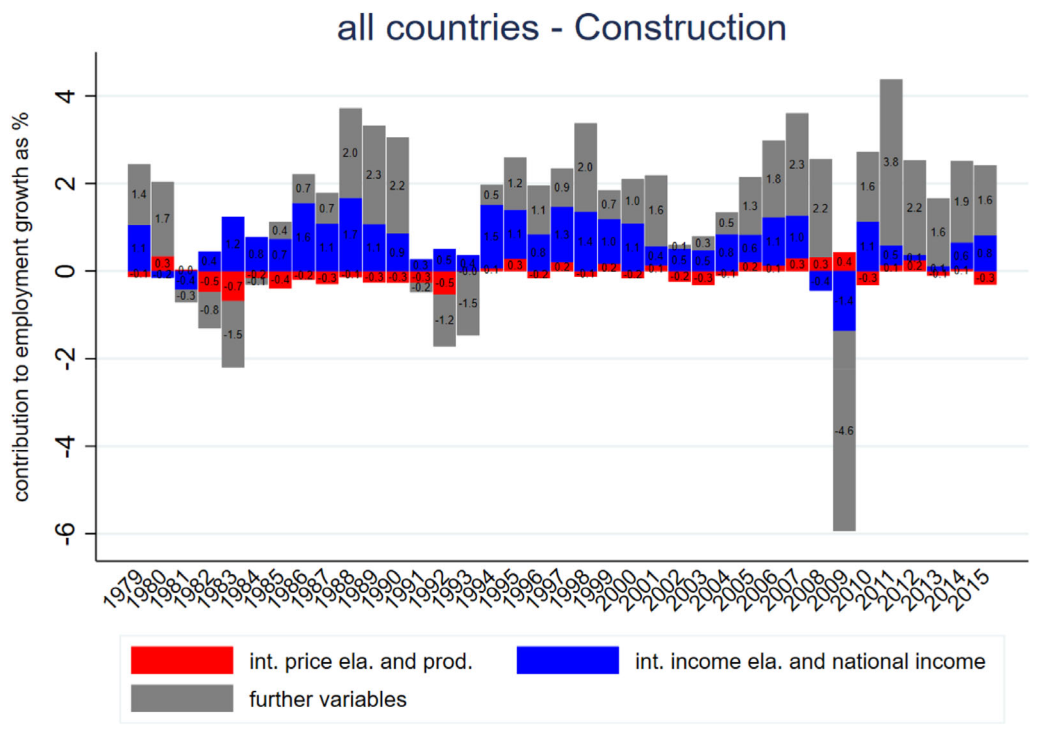

FIGURE 7 Contributions to employment growth in construction across all countries. Source: EU KLEMS, own calculations [Colour figure can be viewed at wileyonlinelibrary.com]

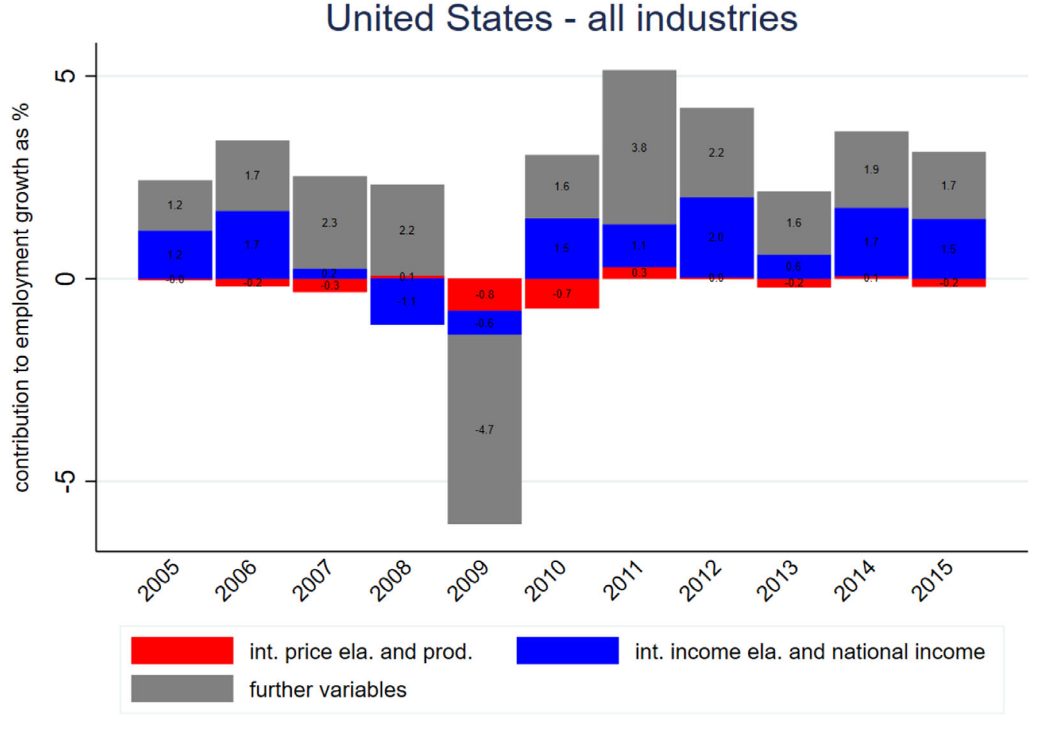

FIGURE 8 Contributions to employment growth in the USA across all industries. Source: EU KLEMS, own calculations [Colour figure can be viewed at wileyonlinelibrary.com]

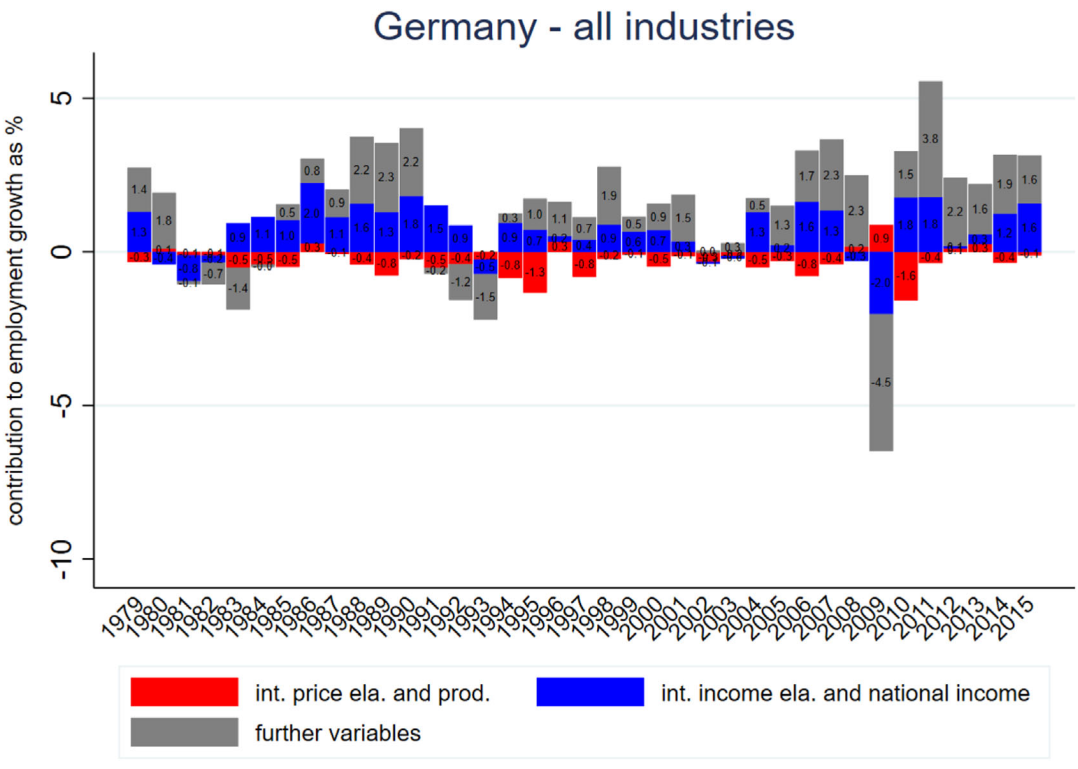

FIGURE 9 Contributions to employment growth in Germany across all industries. Source: EU KLEMS, own calculations [Colour figure can be viewed at wileyonlinelibrary.com]

modified versions of Equations (28) and (29) to represent single years' values for T_{1t} and T_{2t}:

$$T_{1t} = \alpha_1 \left(\varepsilon_{jt} + 1\right) \Delta A_{jt}, \psi \tag{30}$$

$$T_{2t} = \alpha_2 \eta_{jt} \Delta Yt.\psi \tag{31}$$

Figure 5 shows the contribution of our model variables to total employment growth across all countries and all industries. It is obvious that the term T_{1t}, the interaction between productivity growth and price elasticity, is generally negative, whereas the interaction between income elasticity and the growth of national income is generally positive. The sum of the other variables included reflects the development of the business cycle and of structural changes not mapped by our variables. The fluctuations of the business cycle are clearly recognizable. The financial crisis of 2009 stands out clearly. Employment fell sharply in that year, though both businesses and employment recovered later. The productivity and income effects are also affected by the crisis: In 2009 there is a reversal in the roles of the two interaction effects. This is simply due to the change in the signs of productivity and national income. In that year, productivity growth (due to labor hoarding etc.) and the development of national income are negative, which explains their reversed effects.

Figure 5 also shows that technological change has negative direct effects on employment. This is due to the fact that for all the industries we regard demand as globally inelastic. Under

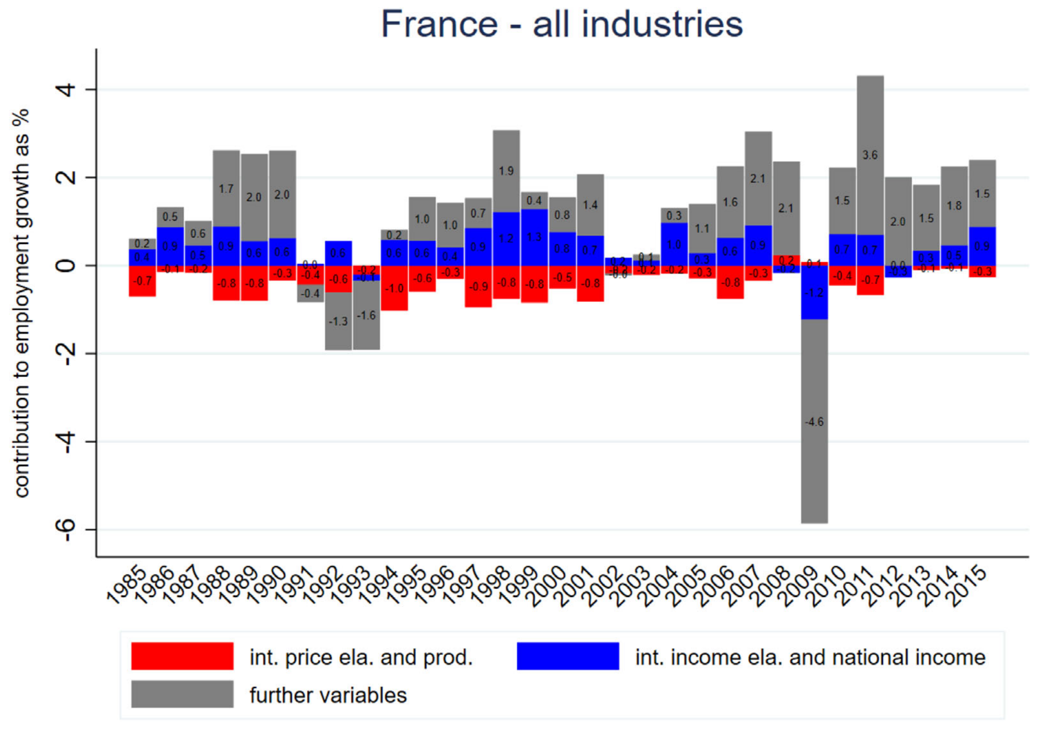

FIGURE 10 Contributions to employment growth in France across all industries. Source: EU KLEMS, own calculations [Colour figure can be viewed at wileyonlinelibrary.com]

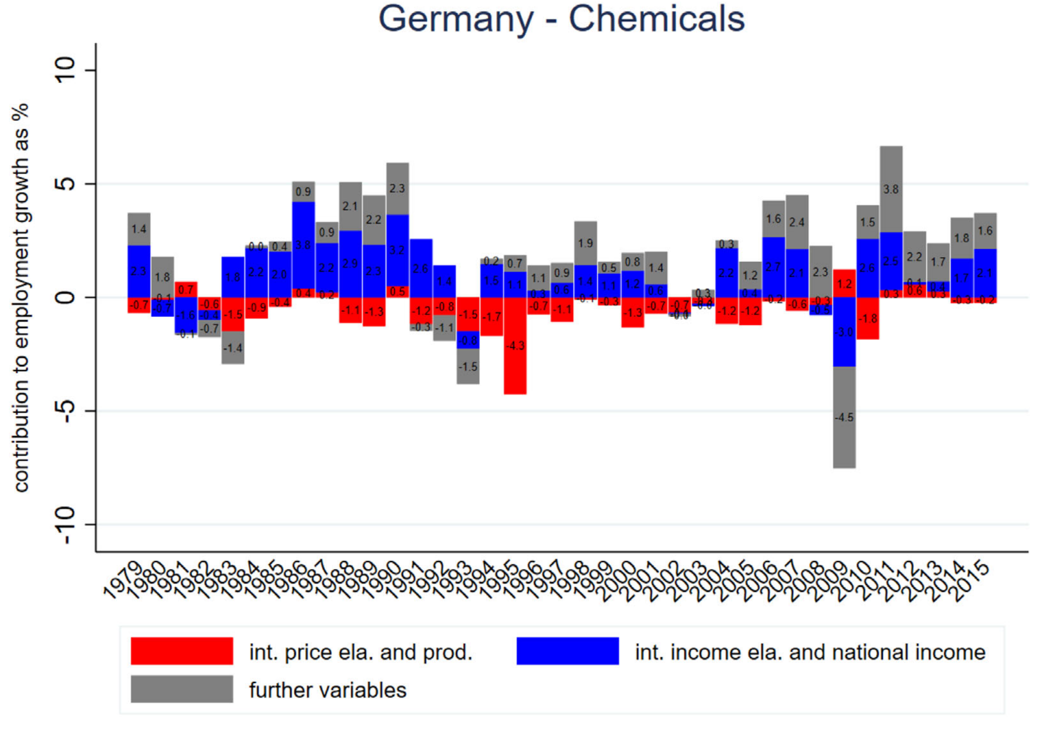

FIGURE 11 Contributions to employment growth in the chemical industry in Germany. Source: EU KLEMS, own calculations [Colour figure can be viewed at wileyonlinelibrary.com]

these circumstances, the substitution effect outweighs the compensating effect. Firms use technological change to save labor. For a subset of markets smaller than entire industries they can be expected to be characterized by elastic demand. There, we expect technological change to be accompanied by gains in employment. These smaller units are aggregated to larger ones characterized by inelastic demand. This is why the positive side of technological progress is not visible in the results. Markets with inelastic demand dominate, while smaller units with elastic demand are not visible.

However, there is considerable variation in the size of the effect and in the patterns it forms across industries and countries. The effects of technological change can be compared in the following graphs. Figures 6 and 7 document the development for two industries, which show marked differences. The negative effect of the interaction between productivity growth and price elasticity T_1 is largest for chemicals, whereas it is smaller for construction. The development patterns of the two industries show some small similarities but are mainly distinct from each other.

Figure 8 documents the global results for the US industries. In this case the time span, which can be used in the second step, is shorter. It is clear, however, that during this period the negative employment effect is much smaller than it is for other countries. The only exception are the years of the financial crisis, 2009/2010.

Figures 9 and 10 show the development of employment for Germany and France. It is more volatile in the first case than in the second case. Finally, in Figure 11 we show an example of one industry within a country. There the fluctuation is greater as is usually the case with aggregated observations. We therefore abstain from presenting more of these disaggregated results.

7 | CONCLUSIONS

This article presents research on the theorem regarding the employment effects of productivity growth under different conditions of product demand and its power to explain international differences in labor market outcomes. Although, there is a wealth of literature on the impact of technological change on employment, most studies only deal with single countries. Furthermore, there are hardly any studies that asses the role of price elasticities for a large set of countries and industries.

We therefore first develop a simple theoretical model establishing the relationship between technological change and employment. The main result is that profit-oriented firms use technological improvements to substitute labor by technological means. However, there is a counteracting effect, as the same firms lower their prices in order to increase the demand for their products. If this demand is elastic, they sell disproportionately more products and subsequently expand their workforce. In this case of elastic demand, the counteracting effect is stronger than the substitution effect. Hence, technological progress in markets with elastic demand has favorable consequences for employment, whereas it has detrimental effects in markets with inelastic demand. In this way, productivity changes also can lead to different labor market effects depending on the product market condition and the industry composition of different countries.

We then generalize this model by taking the wage effect into account. Lower labor demand leads to decreasing wages, which dampens the employment effect of technological change. However, under general conditions, the turning point of the balance between the substitution and the compensating effect is preserved: it is the price elasticity of product demand of −1.

The second major contribution of this article is an empirical application of the theoretical model. To this end, we apply a two-step approach in which we first estimate country- and industry-specific, time-varying price and income elasticities in state space models via the Kalman filter. We use these elasticities in the second step and assess the impact of country- and industry-specific product demand conditions on labor market performance. Our empirical application is based on data for 10 industries, mainly from manufacturing, in nine countries (including the US, UK, Germany and others) supplied by the EU KLEMS database.

Our findings indicate that technological change is associated with direct employment losses in the industries and countries covered by our study, because markets with inelastic demand dominate there. Further, our results, especially the analyzes of the interplay between technical progress and the price elasticity of demand, extends the results of previous studies (e.g. Bessen, 2019). We show that technological progress is not a self-sufficient force of its own as is often presented in the popular media. Rather, it is implemented according to the interests of economic agents, in this case of the owners of firms. The consequences for the employment level depend on economic processes based on market constellations which differ across countries. The economy is not a purely technical system in which the replacement of one unit (say labor) by technical equipment leads to a decrease in labor demand. The opposite might be the case due to counteracting economic effects. "Rapid" technological progress can be a threat to the labor market, but it might also be an advantage as in general it can lead to especially high employment. However, our empirical findings show that, in the recent past, technological change has resulted in moderate employment losses in a number of countries due to inelastic product demand.

This has some interesting implications for policy-making. Promoting technological progress can have undesirable consequences due to a decline in employment. However, if the promotion is aimed at markets with a large share of innovative products that can be expected to exhibit elastic demand, this may even lead to employment gains. However, our analysis also shows how difficult it is to assess the employment effects of a specific industry in a specific phase of development. In most cases, the respective agents have no information regarding the size of the elasticities. Furthermore, price elasticity is not constant and differs across countries.

The results of this article leave space for further research. Foremost, with our theoretical model we are not able to study the inter-county links that affect labor market outcome in detail. Channels through which such inter-country links affect labor market outcomes could be (1) the fact that technology itself is not random, but there are spillovers that may "travel" by the same means as economic-outcome interdependence (i.e. through trade, capital flows, and migration) and (2) economic outcome (including wages and employment) are determined (to some extent) jointly internationally due to trade, capital flows, and migration.

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DATA AVAILABILITY STATEMENT

The main data that support the findings of this study are available in the EU KLEMS data set at http://www.euklems.net/. Further data are openly available at the World Bank at https://databank.worldbank.org/source/world-development-indicators.

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ENDNOTES

[1] Neisser (1942) already argued that the elasticity of aggregate demand plays a crucial role. If price elasticity on product markets is less than minus one, the product sales increase and thus more work is required. However, he did not provide a formal model for his argument and his idea was scarcely noticed by economics experts.

[2] See also Feng & Graetz, 2020 and Lafortune et al., 2019, both also using US data.

[3] We do not follow the example of other recent papers on technological growth which discriminate between different jobs or tasks (see e.g. Ray, Mookherjee 2021).

[4] Data on productivity might be affected by problems of adequate measurement (Brynjolfsson et al. 2021). However, we use the best data available.

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APPENDIX A

TABLE A1 Detailed information on data and sources

Variable		Source
VA_QI	Gross value added, volume (2010 = 100)	EU-KLEMS
VA_P	Gross value added, price indices, 2010 = 100	EU-KLEMS
H_EMP	Total hours worked by persons engaged (thousands)	EU-KLEMS
LAB	Labor compensation (in millions of national currency)	EU-KLEMS
GNI, World	Gross national income (World)	World Bank
CPI	National consumer price index	World Bank
National GNI	Gross national income	World Bank

TABLE A2 Regression results with productivity growth based on people engaged—dependent variable: employment growth

	(1) without elasticities	(2) constant elasticities	(3) IV (only prices)	(4) IV (prices and wages)	(5) with world income growth	(6) with cross-price elasticities
Interaction price elasticity & productivity change		−0.13 (−2.25)	−0.15*** (−34.06)	−0.13*** (−10.93)	−0.15*** (−13.54)	−0.12*** (−7.59)
Interaction cross-price elasticity & productivity growth						−0.02 (−1.85)
Productivity growth	−0.20** (−4.66)					

(Continues)

TABLE A2 Continued

	(1) without elasticities	(2) constant elasticities	(3) IV (only prices)	(4) IV (prices and wages)	(5) with world income growth	(6) with cross-price elasticities
Interaction income elasticity & national income growth		.34** (6.31)	.32*** (16.46)	.40*** (17.96)	.46*** (19.04)	.35*** (15.35)
Interaction income elasticity & world income growth					.49*** (17.15)	
National income growth	.47** (4.68)					
Wage growth	−0.03 (−0.36)	−0.18 (−2.25)	−0.07*** (−7.01)	−0.24*** (−6.10)	−0.23*** (−5.81)	−0.18*** (−4.28)
Constant	−0.01 (−1.58)	.01* (3.21)	.01** (2.70)	.00 (0.10)	−0.01 (−0.97)	−0.02*** (−3.39)
Observations	2910	2910	3180	2910	2910	2840
R^2	.301	.304	.425	.340	.382	.326
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: ***, **, and * denote statistical significance at the .01, .05, and .1 levels, respectively, *t*-values in parenthesis.