The Bias of Technological Change in Europe

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Socio-economic Sciences and Humanities Europe moving towards a new path of economic growth and social development - Collaborative project

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Contribution to the Project

This paper provides empirical evidence in favour of a policy strategy that can make economic growth both more socially inclusive and ecologically sustainable. Thus it contributes significantly to the WWWforEurope project, which aims to achieve a more dynamic growth path for Europe that also involves greater social inclusion and ecological sustainability. In modern growth theories, the speed of economic growth is determined by the rate of technological change, and the intensity of use of various factor inputs in production is influenced by the factor bias or direction of technological change. Our research addresses the question how to shift the bias of technological change towards using more labour and less energy. To this end, we first measure the bias for European countries, and upon finding that it has been labour-saving and energy-using, we identify policy variables that can stimulate labour-using and energy-saving technological change. The results indicate that to make economic growth both more socially inclusive and ecologically sustainable, one strategy would be to reduce energy use by increasing energy taxes and to raise employment of low-skilled workers, who have seen demand for their labour decline the most according to our estimates, by making employers pay less social security for them. Governments could accomplish this shift in the bias of technological change away from saving labour towards saving energy in a budget-neutral fashion by using the revenue generated through higher energy taxes to make up for the shortfall in social security payments. A follow-up study, currently in progress, will simulate the overall economic impact of changes in the policy instruments on labour and energy demand, taking into account feedback effects throughout the economy. This allow for an evalution whether overall, the strategy proposed in this paper entails a trade-off between raising employment and reducing energy use. In general however, the changes in energy taxes and social security contributions can be adjusted in a way that maximises the desired positive employment and negative energy demand effects.

The Bias of Technological Change in Europe

Johanna Vogel*, Kurt Kratena‡, Kathrin Hranyai§

Abstract

This paper is concerned with measuring and influencing the direction of technological change. First, it provides a comprehensive assessment of the factor bias of technological change using panel data from the World Input-Output Database (WIOD) for 25 EU countries from 1995 to 2009. We measure the bias with respect to the inputs capital, energy, non-energy materials and three types of labour (low-, medium- and high-skilled). For this purpose, the factor cost share approach based on the duality of production theory is applied. Estimating the system of cost share equations derived from a translog cost function, we find that technological change was low- and medium-skilled labour-saving, high-skilled labour-using, and energy- and materials-using. Second, the paper addresses the question how technological change could be redirected towards saving more energy and less labour. Patent applications in energy- and labour-saving technology fields are used to model the direction of technological change. We construct stocks of patents in these fields and integrate them into the system of cost share equations as proxies for the level of technology. Upon finding that they were indeed energy and labour saving over our sample period, we regress them on policy variables to identify instruments for shifting the bias away from saving labour towards saving energy. We conclude that one way to achieve this, at least partly, would be an increase in the energy tax rate coupled with a matching reduction in the social security contributions paid by employers for low-skilled workers.

Keywords: Factor bias of technological change, translog cost function, induced innovation, environmental innovation, ICT, robotics, count data models for panel data, Europe, WIOD.

JEL Codes: O33, O31, D24, Q55, Q58, C33, C35.

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1. Introduction

Technological change and its direction are among the most discussed issues of our time in economic circles and among the interested public. In modern theories of economic growth (Romer, 1990; Aghion and Howitt, 1992; Acemoglu, 2002), the rate of technological change determines the speed of growth, while its direction or factor bias indicates which factor inputs are used more intensively in production: labour, capital, energy or other intermediate inputs.

Evidence from research on skill-biased technological change and labour market polarisation suggests that technological change has tended to be labour saving in industrialised countries since the mid-20th century. In particular, advances in computing and other information and communications technologies (ICT) have been complementary to highly skilled labour performing non-routine cognitive tasks, while substituting for routine tasks performed by medium-skilled workers. As a result, some of the latter have shifted into low-skilled service occupations, where non-routine manual tasks have so far not been easily automatable. The consequence has been a "hollowing-out" of the employment distribution across skill levels, with medium-skill employment levels declining the most (Acemoglu and Autor, 2011; Autor and Dorn, 2013; Goos, Manning and Salomons, 2009). For the future, Frey and Osborne (2013) and Brynjolfsson and McAfee (2014) predict that technological change may be even more strongly biased against labour, as advances in machine learning and robotics coupled with big data will enable machines to replace workers even in non-routine tasks, both manual and cognitive. According to Frey and Osborne (2013), although occupations at all skill levels will be affected, the most dramatic impact will be on low-skilled jobs - with almost every other American job under threat over the next decades - while high-skilled occupations requiring tasks like perception, manipulation and social or creative intelligence are less susceptible to automation.

For policy-makers in Europe, where unemployment levels are high following the financial and economic crisis of the late 2000s, the prospect of further technological unemployment poses considerable challenges. The prediction that most of the gains from technological progress will accrue only to the most talented and creative individuals, if fulfilled, has major implications for economic inequality, a problem that has gained renewed attention since the crisis.[1] Although the previous major waves of technological change, the first and second industrial revolutions, have over the long term led to the emergence of new industries with new opportunities for employment, in the short term it may be difficult to avoid big disruptions. Hence the question arises whether government policy can influence the direction of technological change to steer it away from saving labour. The state has already played an important role in supporting the emergence of major new technologies in the last decades, among others in energy-related fields (Mazzucato, 2013). While arguments of economic efficiency can be made in favour of the latter - reducing the negative environmental externalities associated with current technologies - equity considerations would support stimulating labour-friendly technological change. To date however, little research is concerned with how this could be achieved.

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[1] The remarkable success of Thomas Piketty's "Capital in Twenty-First Century" is a good indication. In a dedicated recent special report, The Economist (2014) forecasts "the global eclipse of labour", as "the digital revolution opens up a great divide between a skilled and wealthy few and the rest of society".

Regarding energy, the long-standing problems of climate change and finite fossil energy resources have given rise to a substantial literature evaluating the effectiveness of government climate policy instruments like taxes and subsidies in terms of reducing energy use and emissions in computational models of the economy (e.g. CGE models). Within these, the representation of technology plays a major role. Early models often used a simple time trend, implying that technology changes at a constant exogenous rate. The recent literature incorporates insights from endogenous growth theory and represents technology as a stock of knowledge which accumulates as a result of firm R&D investments and is sometimes measured using patent data (Sue Wing, 2006; Gillingham, Newell and Pizer, 2008). Technological change is then the outcome of innovative activity within the model and therefore endogenous.[2] Moreover, when environmentally-friendly innovations respond to policy instruments, the direction or bias of technological change itself becomes endogenous. How to redirect technological change away from fossil fuels by inducing energy-saving innovation has been an active area of research for almost two decades. Among the policy instruments considered are taxes on carbon emissions and (fossil) energy consumption, government expenditures on R&D in environment- and energy-related fields or subsidies for private R&D, and regulations like environmental performance or technology standards (Popp, Newell, and Jaffe, 2010).

This paper sets out to address two issues. First, it aims to measure the factor bias of technological change in Europe from 1995 to 2009 using panel data at the country and sector level from the socio-economic and environmental accounts of the World Input-Output Database (WIOD). The results indicate that over the period under investigation, technological change had a small energy-using bias and a substantial labour-saving bias, especially regarding low- and medium-skilled workers; for high-skilled labour, our evidence is consistent with skill-biased technological change. Second, based on these results, the paper aims to identify policy variables that could shift the bias towards being more labour using and energy saving.[3] To do so, we endogenise the direction of technological change regarding energy and labour in the first part by modelling the level of technology in energy- and labour-saving fields as stocks of knowledge based on cumulated patent applications. Measuring the bias of technological change in these fields confirms its energy- and labour-saving nature. This sets the stage for part two of the empirical analysis, where we econometrically relate technological change in energy- and labour-saving fields, proxied with the flow of patent applications, to policy variables that could induce more of the former and less of the latter. In a follow-up study, we will bring the two parts of the analysis together to simulate the overall economic impact of changes in the policy instruments on labour and energy demand. This will be done within the dynamic New Keynesian (DYNK) model developed in Kratena and Sommer (2014a), which is a complete model of the economy and thus allows us to take into account feedback effects of policy changes.

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2 Sue Wing (2006) emphasizes the difference between short-run substitution effects and long-run impacts of endogenous technological change. Hence policy instruments like taxes influence the input of production factors not only in the short run but, in the case of endogenous technological change, also in the long run. This additional impact can reinforce the desired outcome and significantly reduce the costs of adjustment of environmental policy.

3 The idea behind this shift is to alter the direction of technological change while leaving its rate unchanged. However, if a given unit change in the policy variables affects the biases to different orders of magnitude, the overall impact on the rate of technological change may not be neutral.

To date, little empirical evidence exists on the factor bias of technological change, particularly across the EU countries. Following Hicks' original conceptual discussion in *The Theory of Wages* (1932), an early literature analyses it using data for the United States (Sato, 1970; Binswanger, 1974a; Kalt, 1978; Stevenson, 1980). More recently, empirical research on the skill bias of technological change and labour market polarisation investigates the bias for a subset of production factors, namely labour of different skill levels. Starting with Berman, Bound, and Griliches (1994), this literature has documented a positive empirical association between ICT investment, R&D or computer use and the increasing share of highly educated workers performing nonroutine cognitive tasks observed across industrialised countries (Autor, Levy, and Murnane, 2003; Michaels, Natraj and Van Reenen, 2014).[4]

A related empirical literature assesses the relationship between innovation and total employment using firm- or sector-level data, mostly from innovation surveys, for the European countries. At this level of disaggregation, it is possible to investigate the different channels through which innovations affect employment - both negatively (displacement effects) and positively (compensation effects) - and to distinguish between product and process innovations, which can have countervailing effects via the demand and productivity increases they generate. At the firm level, studies in this tradition tend to find a positive overall effect of innovation (e.g. Van Reenen, 1997), while at the sector level, negative impacts also emerge (Antonucci and Pianta, 2002).[5] For product innovations and high-tech industries, a positive association with employment has been established (Bogliacino and Pianta, 2010; Bogliacino, Piva, and Vivarelli 2012). For process innovations, empirical results are more ambiguous, although Harrison et al. (2014) show that accounting for positive compensation mechanisms turns a negative effect at the firm level into a positive one. More closely related to our research, which focuses on the country level and uses patent data to measure innovation, Feldmann (2013) finds a positive relationship between patenting and unemployment for a panel of 21 countries over 24 years.

In general however, the literature on productivity and growth assumes a certain direction of technological change without exploring it further. For example, growth accounting studies following Solow (1957) assume Hicks-neutral technological change, while labour-augmenting technological change underlies many models of economic growth. Two recent studies, Doraszelski and Jaumandreu (2014) and Verschelde et al. (2014), use firm-level data from Spain and Belgium to measure the bias. However, they focus on a single country and do not analyse energy as a separate input. They also remain silent on the second research question of this paper, how to shift the bias between two inputs, labour and energy in our case.

Hence the first contribution this paper makes to the literature is to comprehensively measure the bias of technological change across 25 EU countries with respect to the factor inputs capital, energy, non-energy intermediates and three types of labour (low-, medium- and high-skilled). The WIOD provides a suitable dataset on these inputs as well as on output and respective prices at the sectoral level. To measure the bias of technological change, we apply

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4 See also Autor, Katz, and Krueger (1998) for the USA, Machin and Van Reenen (1998) for OECD countries and Piva, Santarelli, and Vivarelli (2005) for Italy, who highlight the role of skill-biased organisational change.

5 The sectoral level of analysis allows evaluating the overall outcome of the firm-level mechanisms, including the indirect effect of innovations introduced at the firm level on demand for the output of competing firms (Pianta, 2005).

the standard empirical approach of estimating the system of factor cost share equations derived from a minimised cost function of the flexible translog form (Binswanger 1974a; Jorgenson, 2000; Jin and Jorgenson, 2010). This approach is dual to estimating the factor demand equations derived from a production function and recovering factor-augmenting rates of technological progress from the estimates, as for instance Kalt (1978) and Doraszelski and Jaumandreu (2014) do. The main advantage of the cost share approach is that it avoids assuming a production function and hence imposing restrictions on technology parameters. For example, the frequently employed constant elasticity of substitution (CES) functional form essentially requires the elasticity of substitution to be identical for all input pairs, a restriction that is unlikely to hold in practice. By contrast, the translog functional form that is often assumed in the cost share approach is very general, as it approximates any twice-differentiable function to the second order. It imposes no a priori restrictions on substitution parameters and yields very simple expressions for the bias of technological change with respect to each factor input.

Related to the second question addressed in this paper - how to shift the bias of technological change - there is an older theoretical literature on so-called induced innovation (e.g. Ahmad, 1966; Binswanger, 1974c) which is concerned with the effect of relative factor prices on the factor bias. This concept also originates in Hicks (1932), who noted that a change in factor prices should encourage inventions directed at saving the factor that had become relatively more expensive. In his models of directed technological change, Acemoglu (2002, 2007) extends this earlier work by considering not only a price effect, but also an effect of relative factor supplies ("market size") on the bias of technological change. The concepts of induced innovation and directed technological change have been applied most widely in environmental economics, where mechanisms for directing technological change away from energy-using "dirty" technology towards energy-saving or otherwise environmentally-friendly "clean" alternatives have been investigated (Acemoglu et al, 2012).

Most closely related to the second part of our empirical analysis is Popp (2002), who estimates the effect of energy prices and energy R&D expenditures by the U.S. government on energy-saving innovation, measured by successful patent applications in energy-saving technology fields, for the United States from 1970 to 1994. Recently, Kruse and Wetzel (2014) have carried out a similar analysis for OECD countries. Both papers include as a third factor that can induce innovation in a certain direction a measure of the existing stock of knowledge available for inventors to build on at the time they carry out their research. This allows for path dependence in technological change and a "standing on the shoulders of giants" externality in knowledge production as in Romer (1990) and other models of endogenous growth. We implement this approach in the second part of our analysis, where we regress patent applications in energy- and labour-saving technology fields on factor prices, which can be raised and lowered through taxation, government R&D in energy- and labour-saving technologies and stocks of cumulated past patents. Thus we aim to identify policy levers that can stimulate energy-saving and attenuate labour-saving innovation.

Overall, endogenously modelling technological change in energy- and labour-saving fields allows us to recommend a strategy that governments could follow to redirect (some part of) technological change away from saving labour towards saving energy. In addition, in doing so we add to the existing empirical literature that measures the factor bias of technological change based on the same empirical approach as this paper - deriving factor biases from estimated parameters of a system of factor cost share equations - where technology is still often proxied with an exogenous time trend. The two-step approach we employ is very similar to Popp (2001, 2002), who combines estimates from a model of induced energy-saving technological change with those from a system of factor share equations where the stock of energy-saving patents represents the level of technology. He estimates the overall impact of an energy tax, via its effect on energy-saving innovation, on energy demand and finds a substantial long-run negative impact. We are not aware of empirical research using this framework to investigate induced labour-using technological change and shifting the factor bias from energy to labour.

Therefore, our second contribution to the literature is endogenously modelling labour-saving technological change in this setup by constructing a stock of patents in relevant fields and identifying policy instruments to induce less of it. Based on existing empirical evidence and the current policy debate, we use patent applications in ICT and advanced manufacturing technology fields to capture the potentially labour-saving nature of computers and robots. We take this route because classifications of labour-saving or -using technologies do not exist, while for energy-saving fields, we can rely on classifications of environment-related technologies developed at the OECD and the World Intellectual Property Office (WIPO) based on the International Patent Classification. The WIOD data also allow us to distinguish factor biases of technological progress in ICT and advanced manufacturing with respect to low-, medium- and high-skilled labour. Hence, to the extent that workers with different education levels sort into occupations requiring capabilities in different tasks, we are able to test the hypothesis that these technologies vary in their effects on labour demand across skill categories.

In part two of the analysis, we find that a higher energy tax rate is associated with more energy-saving patents, while lower compensation of low-skilled labour is associated with less patenting in our measure of labour-saving fields. In particular, a ten percent increase in the energy tax rate would induce 2.1% more energy-saving patenting, and a ten percent decrease in low-skilled labour compensation would induce 5.1% fewer patent applications in ICT and advanced manufacturing. Hence the rate of energy-saving technological change could be stimulated by raising energy taxes, while the rate of technological change in labour-saving fields could be attenuated by reducing the compensation of low-skilled workers from the employer's point of view, thus making them more attractive to hire. This can be achieved in a way that maintains their wage income by subsidising the social security contributions paid for them by employers, which together with wages and salaries constitute total labour compensation. By using the revenue generated through higher energy taxes to make up for the shortfall in social security receipts, governments could accomplish the shift in the bias of technological change away from saving labour towards saving energy in a budget-neutral fashion.[6]

The aim of this strategy is to affect the direction of technological change while leaving its overall rate unchanged. The required changes in the policy instruments can be calibrated accordingly based on our estimates. The caveat applies, however, that our modelling strategy

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6 In terms of the measures taken, this strategy resembles a classical green tax reform, which uses taxes raised on environmentally harmful activities to lower the tax burden on labour. Based on our model however, they can have stronger effects on employment and energy use via their additional impact on the bias of technological change.

leaves part of technological change unexplained or exogenous, so only the component that is captured by our patent measures and amenable to policy influence can be redirected. The overall economic impact of changes in the policy instruments on the demand for labour and energy is the subject of ongoing research.

The remainder of the paper is organised as follows. The next section introduces our approach to measuring the bias of technological change and compares it with related literature. Section 3 sets out the empirical framework, presenting the models we estimate to measure the bias and to investigate induced innovation in labour- and energy-saving fields. In section 4, the data are described, while in section 5 we present and discuss our estimation results. Section 6 concludes and indicates directions for future research.

2. Theoretical background and related literature

2.1 Measuring the bias of technological change

Conceptually, the factor bias of technological change was first described by Hicks (1932, p.121-2): *"[Concentrating] on labour and capital, ... we can classify inventions according as their initial effects are to increase, leave unchanged or diminish the ratio of the marginal product of capital to that of labour. We may call these inventions 'labour-saving', 'neutral' and 'capital-saving' respectively. 'Labour-saving' inventions increase the marginal product of capital more than they increase the marginal product of labour; 'capital-saving' inventions increase the marginal product of labour more than that of capital; 'neutral' inventions increase both in the same proportion."* Hence following Hicks, the bias can be defined in terms of changes in the relative marginal products of two inputs, at given factor proportions, due to technological change. In the two-input case, technological change is biased towards capital or capital-using if:[7]

$$B = \left.\frac{\partial \ln \frac{MP_K}{MP_L}}{\partial T}\right|_{K/L} > 0 \tag{1}$$

where B stands for bias, T represents an index of technology and MP_K and MP_L are the marginal products of capital and labour respectively. In the case of two inputs, a capital-using bias is by construction labour saving. Conversely, if the expression is negative, or if MP_K / MP_L in the numerator is replaced by MP_L / MP_K, technological progress is said to be biased towards labour, or labour using and capital saving.

When the marginal product of capital increases relative to that of labour at given factor proportions, the rental rate of capital rises relative to the wage rate assuming perfectly competitive factor markets. Consequently, the share of capital in total cost increases while that of labour falls, as noted by Hicks (1932, p.122): "*In every case, a labour-saving invention will diminish the relative share of labour in the national dividend. Exactly the same holds,* mutatis mutandis*, of a capital-saving invention.*" This led Binswanger (1974a) to formulate a definition of the factor bias in terms of changes in the share of inputs in total cost due to technological

7 See also Acemoglu (2002) for a definition along these lines.

change. He points out that changes in factor cost shares that are observed in the data can be caused not only by biased technological change as described above, but also by changes in factor demand due to factor price changes. Therefore, when using data on cost shares to isolate the bias, relative factor prices must be held constant in order to control for such price-induced factor substitution. This implies the following definition of capital-biased technological change:

$$B = \frac{\partial \ln s_K}{\partial T}\bigg|_{r/w} > 0 \tag{2}$$

where s_K is the share of capital in total cost, r is the rental rate of capital and w is the wage rate. Hence an increase in the (log of the) share of capital at given relative factor prices due to technological change implies that the latter is capital-using, which in the two-input case is again equivalent to labour-saving technological change. If the expression is negative, or if s_K is replaced with s_L in the numerator, technological change is biased towards labour, or labour using and capital saving. When there are more than two inputs, the cost share approach has the advantage that it yields a separate measure of the bias for each input, since the definition in (2) is not a relative expression in terms of any two of them. By contrast, the definition in (1) defines the bias relative to the n^{th} input, so that biases are only measurable for n-1 inputs.

The cost share approach to measuring the bias of technological change was formalised by Binswanger (1974a, 1974b), starting from a minimised cost function based on the duality of production theory. Every production function has as its dual a cost function that expresses the minimum cost of production as a function of input prices, the level of output and technology. Using Shephard's lemma, the input shares in total cost can be obtained as the elasticities of the cost function with respect to the price of each input. Assuming a cost function of the translog form, simple expressions for the factor bias of technological change can then be derived from the estimated cost share equations.

When implementing the cost share approach, the way technology is modelled plays a key role. Binswanger and other early studies (e.g. Stevenson, 1980) use a simple time trend to proxy the level of technology at each point in time. We do this in our baseline specification. Sato (2013) also takes this route in analysing the factor bias for Japanese industries from 1973 to 2008. He finds that technological change was capital using, labour saving, electricity using and non-electricity energy saving. On the other hand, Jin and Jorgenson (2010) assume that the cost function and associated share equations represent a state-space model where technology and factor biases are latent state variables that they recover with the Kalman filter. Their findings for US industry data from 1960 to 2005 suggest that technological change was capital using, labour and materials saving, energy using before 1980 and energy saving afterwards.

Cost share equations derived from a translog function have also been employed in the empirical literature on skill-biased technological change and labour market polarisation. For example, Michaels, Natraj and Van Reenen (2014) add ICT capital to the cost function as a quasi-fixed input and then investigate the relationship between ICT and the cost shares of low-, middle- and highly educated workers.[8] We pursue a similar approach to integrate patent stocks into the cost function. Based on data for the US, Japan and nine EU countries between 1980

[8] Other studies in this tradition using a similar approach are Berman et al (1994) and Machin and Van Reenen (1998).

and 2004, Michaels et al. (2014) estimate that industries with rising ICT capital also registered a substantial increase in the share of highly educated workers and a decline in the share of middle-educated workers, with no significant effect on the least educated. After analysing the task content of occupations held by workers with different education levels, the authors conclude that ICT complements highly skilled workers performing non-routine cognitive tasks and substitutes medium-skilled workers carrying out routine tasks, while not affecting the low-skilled, whose non-routine manual tasks have so far been less easy to automate.

The main alternative to the cost share approach is the primal approach of assuming a production function with factor-augmenting technological change. A common choice in the literature is the constant elasticity of substitution (CES) function, which in the two-input case may be written as follows (e.g. Acemoglu, 2002):

$$Y = [\, \gamma \, (A_L L)^{\frac{\sigma-1}{\sigma}} + (1-\gamma)\, (A_K K)^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}} \, , \qquad (3)$$

where σ is the elasticity of substitution between labour and capital. Based on (3), Kalt (1978) and Doraszelski and Jaumandreu (2014) estimate the factor demand functions implied by firms' optimising behaviour and use them to recover the rates of factor-augmenting technological change, i.e. the rates of change over time in the technology levels A_L and A_K. Setting these in relation to each other yields an indication of the factor bias using the definition in (1) that depends on the magnitude of the elasticity of substitution. As established by Acemoglu (2002), in the two-input case, labour-augmenting technological change is biased towards labour if $\sigma > 1$, i.e. when labour and capital are gross substitutes in production. If $\sigma < 1$ (gross complements), labour-augmenting technological change is biased towards capital. Hence estimates of σ must be obtained to infer the bias from rates of factor-augmenting technological change. Doraszelski and Jaumandreu (2014) assume a CES production function with the inputs capital, labour and materials and allow for capital- and labour-augmenting as well as Hicks-neutral technological change. Using firm-level data for Spain from 1990 to 2006, they find that the rate of labour-augmenting technological change was larger than that of capital-augmenting technological change, together with $\sigma < 1$. Following the discussion above, this suggests that technological change is biased towards capital and therefore labour saving in their sample. The bias with respect to materials is not separately examined.

The main drawback of the primal approach is that assuming a production function imposes restrictions on the technology parameters. For example, the CES function assumes that the elasticity of substitution is identical for all input pairs (Uzawa, 1962; McFadden, 1963), which is problematic in the case of more than two inputs. It is also contradicted by empirical findings based on functional forms that allow substitution patterns to differ between inputs, like the translog form. For example, Kratena and Wüger (2012), who use the cost share approach to investigate the impact of technological change on energy demand in Europe, find a variety of substitution patterns between inputs across industries. In the translog cost share approach, elasticities of factor substitution between each pair of inputs are derived as simple functions of the estimated coefficients (Binswanger,1974b). Verschelde et al. (2014) attempt to overcome this limitation of the primal approach by using nonparametric methods to fit production functions to the data locally instead of specifying a one-size-fits-all production function a priori. Based on firm-level data for Belgian manufacturing between 1996 and 2010, their estimates suggest that technological change was low-skilled labour saving in many sectors and materials and capital using in a few. However, their data do not allow them to differentiate between high- and medium-skilled labour and energy is not considered as a separate input.

2.2 Induced innovation and directed technological change

The literature on induced innovation and directed technical change also takes its cue from Hicks (1932), who refers to the rising price of labour relative to capital as the main reason behind the predominance of labour-saving innovations (p.125-126): *"A change in the relative prices of the factors of production is itself a spur to invention, and to invention of a particular kind - directed to economising the use of a factor which has become relatively expensive ... Let us call these 'induced' inventions."* Accordingly, one key focus of empirical work in this area has been the role that factor prices can play in stimulating innovation and inducing technological change to take a desired direction. Governments can affect prices through taxes and subsidies, thus providing incentives for inventors and firms to develop ways to save on some inputs and use others. A higher price of fossil energy, for example, can be expected to spur innovative activity in technologies that lower the cost of energy input by raising energy efficiency or finding cheaper alternative sources (Lanzi and Sue Wing, 2010). Similarly, measures that lower the relative price of labour could be expected to reduce incentives for innovative activity directed towards saving labour. Hence compared to the first part of the empirical analysis in this paper, where we hold factor prices constant to examine the bias of technological change, in the second part we allow prices to vary as one way of shifting the bias or redirecting technological change. Besides relative prices, another policy lever that can provide incentives for innovative activity is government support for R&D investment in particular technologies. A notable recent example is the quite considerable government support for renewable energy technologies in some European countries in the last decades, for example in Germany.

On the other hand, the evolutionary view of technological change emphasises its path-dependent, cumulative nature and regards the effects of the incentives provided by prices and R&D support as limited since firms' response in terms of their innovative activity is determined by and occurs within the current technological regime or trajectory (Dosi, 1988). In this view, technological change is not just seen as reacting passively to market demand and signals like relative prices or as an exogenous by-product of scientific discoveries,[9] but also as endogenously driven by firms' continual search for improved techniques given their current knowledge. Price and demand signals can play a role in bringing about new technological regimes in the longer term by influencing firms' choices between alternative technologies (e.g. between fossil and renewable energy sources). Overall therefore, factors beyond relative prices and R&D support are likely to play a role in determining the direction of technological change. We account for the level of technological knowledge currently available for inventors to build on, which also features in theories of endogenous growth like Romer (1990), where increasing returns to knowledge make innovation less costly the higher the existing knowledge stock.

[9] These two views correspond respectively to the "market/demand-pull" and "science/technology-push" hypotheses regarding the drivers of innovation and technological change.

On induced energy-saving innovation, two related empirical studies employing a similar framework are Popp (2002) and Kruse and Wetzel (2014). Both investigate the role of energy prices, government R&D and the stock of energy-related patents on patenting activity, the former for the US and the latter for 26 OECD countries. Popp (2002) finds that while energy prices and the patent stock have sizeable positive effects on patenting in energy-saving fields, the effect of government energy R&D is either insignificant or negative. Kruse and Wetzel (2014) estimate separate models for 11 energy technologies from the World Intellectual Property Office's Green Inventory using panel data on 26 OECD countries from 1982 to 2009. Their most consistent finding across technologies is a strong positive effect of the patent stock, while the sign and significance of the energy price and government R&D are heterogeneous. Estimating the model for all technologies combined yields an insignificant coefficient on the energy price and an only marginally significant but positive coefficient on R&D. We adopt a similar empirical model as Popp (2002) and Kruse and Wetzel (2014) but analyse the effect of the energy tax rate separately from the energy price.

Regarding induced labour-saving innovation, Alesina, Battisti and Zeira (2015) investigate the effect of labour regulations that raise the wage of low-skilled workers relative to high-skilled ones on labour productivity and on high- and low-skill-intensive innovation. Their model predicts that labour regulation should induce more innovation - which is assumed to be labour-saving - in low-skill-intensive sectors and thus lead to higher labour productivity of low-skilled workers, with the opposite effect on high-skilled sectors and productivity. This is tested empirically using panel data for up to 42 countries on productivity and on patent applications in research- ("high-skill") and non-research-intensive ("low-skill") technology fields. Labour regulation as measured either by an index of employment protection legislation or by union density indeed turns out to be positively related to low-skilled labour productivity and to patenting in low-skill technologies, and negatively to high-skill productivity and patenting. We share with Alesina et al. (2015) the underlying idea that wages by skill level affect innovation, but in contrast to them, we establish empirically the labour-saving nature of our innovation measure rather than simply assuming it.

3. Empirical framework and estimation methods

This section first outlines the cost share approach to measuring the bias of technological change using a translog cost function. In subsection 3.2, we derive the factor bias for our baseline specification where the level of technology at each point in time is proxied with a time trend. This implies that technological change is exogenous and takes place at a constant annual rate. Subsection 3.3 then introduces our preferred specification, which models the level of technology using both stocks of knowledge in energy- and labour-saving fields and a time trend capturing knowledge in remaining fields. Expressions for the factor bias of both representations of technology are derived. This sets the stage for the models of induced technological change presented in subsection 3.4, which relate technological change in energy- and labour-saving fields to policy variables that could shift the bias away from saving labour towards saving energy. Modelling the determinants of energy- and labour-saving technological change in this way allows us to endogenise both its rate and its direction regarding energy and labour.

3.1 The translog cost share approach to measuring the bias

Let output be produced with a production function $Y = f(\mathbf{x}, T)$, where **x** is the vector of inputs and *T* represents an index of technology. Assuming perfect competition in the factor markets, a profit-maximising firm produces a given level of output with the choice of inputs that leads to the minimum possible cost of production. Hence dual to the production function, there exists a minimum cost function given by

$$C = C\,(\boldsymbol{p}, Y, T) = \textstyle\sum_i p_i\, x_i^*, \tag{4}$$

where **p** is the vector of input prices, x_i^* are the optimal factor input demands resulting from cost minimisation, and in our case, $i = \{K, L_L, L_M, L_H, E, M\}$ representing capital, low-, medium- and high-skilled labour, energy and non-energy intermediates (materials for short). Production and cost functions are equivalent in that all the information contained in one can be recovered from the other. We assume constant returns to scale, in which case the cost function can be shown to take the form $C = p_Y(\mathbf{p},\ T) \cdot Y$, where $p_Y(\mathbf{p},\ T)$ is the so-called output price function giving the price of one unit of output. Therefore, equation (4) becomes

$$p_Y(\boldsymbol{p},\ T) \cdot Y = \textstyle\sum_i p_i x_i^*, \tag{5}$$

so that the sum of the value of inputs exhausts the value of output $p_Y \cdot Y$.

The factor input shares in total cost are obtained from the cost function by making use of Shephard's lemma, according to which the optimal input demands x_i^* are derived by differentiating the cost function with respect to each input price. Given constant returns to scale, this implies $x_i^* = Y \cdot \partial p_Y(\mathbf{p}, T)/\partial p_i$. The factor cost shares can then be obtained as the elasticities of the output price function with respect to the factor price (Jorgenson, 2000):

$$s_i = (p_i x_i^*)/(p_Y Y) = \partial\, ln\, p_Y(\boldsymbol{p}, T)/\partial\, ln\, p_i. \tag{6}$$

We assume a price function $p_Y(\mathbf{p}, T)$ of the translog form, a very flexible functional form that approximates any twice-differentiable function to the second order and allows for a variety of substitution patterns between inputs (Christensen, Jorgenson and Lau, 1973). It consists of the sum of the levels and interactions of the logs of all elements in the function, that is in our case:

$$ln\, p_Y = \alpha_0 + \textstyle\sum_i \alpha_i\, ln\, p_i \;+\; \alpha_t T \;+\; \frac{1}{2} \sum_{i,j} \gamma_{ij}\, ln\, p_i \cdot ln\, p_j + \frac{1}{2}\, \alpha_{tt} T^2 \;+ \sum_i \rho_{ti}\, ln\, p_i \cdot T, \tag{7}$$

where $i, j = \{K, L_L, L_M, L_H, E, M\}$ and symmetry $(\gamma_{ij} = \gamma_{ji})$ is imposed. From (7), the factor cost share equations are derived according to (6). The output price function is assumed to be homogeneous of degree one in input prices, which requires imposing the following restrictions:

$$\textstyle\sum_i \alpha_i = 1,\ \sum_i \sum_j \gamma_{ij} = \sum_i \gamma_{ij} = \sum_j \gamma_{ij} = \sum_i \rho_{ti} = 0. \tag{8}$$

These imply that the derived cost share equations sum to one, so that in estimation, one share equation is dropped and the input prices on the right-hand side of the five remaining ones (see below) are defined relative to the price of the dropped input. Without loss of generality, we exclude the cost share of high-skilled labour, and given the restrictions in (7), its parameters can be recovered from the estimates of the remaining equations.

3.2 The bias of exogenous technological change

In the baseline case, we assume that the index of technology *T* in (7) takes the form of a time trend *t*, so that technological change occurs at a constant exogenous rate. This implies the following system of cost share equations, which we estimate using panel data for 25 EU countries over the period from 1995 to 2009:

$$\begin{aligned} s_{K,c,t} &= \alpha_K + \textstyle\sum_i \gamma_{Ki} \ln\left(\frac{p_i}{p_{LH}}\right)_{c,t} + \rho_{tK} t + \eta_{K,c} + \varepsilon_{K,c,t} \\ s_{LL,c,t} &= \alpha_{LL} + \textstyle\sum_i \gamma_{LLi} \ln\left(\frac{p_i}{p_{LH}}\right)_{c,t} + \rho_{tLL} t + \eta_{LL,c} + \varepsilon_{LL,c,t} \\ s_{LM,c,t} &= \alpha_{LM} + \textstyle\sum_i \gamma_{LMi} \ln\left(\frac{p_i}{p_{LH}}\right)_{c,t} + \rho_{tLM} t + \eta_{LM,c} + \varepsilon_{LM,c,t} \\ s_{E,c,t} &= \alpha_E + \textstyle\sum_i \gamma_{Ei} \ln\left(\frac{p_i}{p_{LH}}\right)_{c,t} + \rho_{tE} t + \eta_{E,c} + \varepsilon_{E,c,t} \\ s_{M,c,t} &= \alpha_M + \textstyle\sum_i \gamma_{Mi} \ln\left(\frac{p_i}{p_{LH}}\right)_{c,t} + \rho_{tM} t + \eta_{M,c} + \varepsilon_{M,c,t} \end{aligned} \tag{9}$$

where the subscripts *c* and *t* denote countries and time respectively. $\eta_{i,c}$ represents a country-specific fixed effect and $\varepsilon_{i,c,t}$ is a mean-zero error term. This system is estimated using Zellner's (1962) seemingly unrelated regression (SUR) estimator, which allows $\varepsilon_{i,c,t}$ to be correlated across the five cost share equations. This is likely to be relevant for (9), given that demand for all factors of production is determined simultaneously by firms' choice of the cost-minimising input combination producing a desired level of output. In this case, the SUR estimator leads to more efficient estimates compared to equation-by-equation (OLS) estimation, assuming that all regressors are exogenous. This last assumption may not hold in our case, since prices and factor demands and therefore cost shares are jointly determined by labour demand and supply. Hence the system in (9) is also estimated using GMM with lagged relative prices as instruments (in progress). Industry-level results are obtained by estimating (9) separately for each industry.

The bias of (exogenous) technological change for each input *i* is derived from the cost share equations according to definition (2):[10]

$$\partial \ln s_{i,c,t} / \partial t = \rho_{ti} / s_{i,c,t} \tag{10}$$

which we obtain using the estimated ρ_{ti}-coefficients in (9) together with information on $s_{i,c,t}$, the cost share of input *i* per country and time period. For high-skilled labour, ρ_{tLH} is obtained residually given the restriction that the ρ-coefficients must sum to 0.

As established by Binswanger (1974b), in the case of a translog cost function, Allen partial elasticities of factor substitution between each input pair $i \neq j \in \{K, L_L, L_M, L_H, E, M\}$ can be computed based on the parameter estimates of γ_{ij} in (9) as follows:

$$\sigma_{ij} = \sigma_{ji} = \gamma_{ij} / s_i s_j + 1 \tag{11}$$

Own- and cross-price elasticities of factor demand are given by $\varepsilon_{ii} = \gamma_{ii}/s_i + s_i - 1$ and $\varepsilon_{ij} = (\gamma_{ij} + s_i s_j)/s_i$. The results of the baseline specification (9) with purely exogenous technological change are discussed in section 5.1.

3.3 The bias of endogenous technological change

Introducing endogenous technological change in energy- and labour-saving fields is a preliminary step to modelling policy instruments that can direct it towards saving energy and

[10] Note that this approach also allows estimating the rate of Hicks-neutral technological change or total factor productivity growth, $\alpha_t + \alpha_{tt} t$, by including the price equation (7) in the system of equations to be estimated.

using labour in the next subsection. Thus we extend our specification of the level of technology beyond a simple time trend and complement it with stocks of knowledge in energy- and labour-saving technologies, T_{ESAV} and T_{LSAV}. The time trend t now captures any other kind of technology that we do not explicitly model and its rate of change remains exogenous. Overall therefore, we have $T = \{t, T_{ESAV}, T_{LSAV}\}$. The knowledge stock in technology field k is assumed to accumulate as a function of all current and past innovative activity,

$$\dot{T}_k = f(P_k, T_k) \tag{12}$$

where $k = \{ESAV, LSAV\}$ and P_k denotes the flow of patent applications, our proxy for innovative activity. A simple example for (11) is the perpetual inventory model, according to which $\dot{T}_k = P_k - \delta T_k$, with δ the rate of knowledge obsolescence or decay.

The knowledge stocks enter the cost function as quasi-fixed inputs that firms take as given in the short run, which means that under constant returns to scale, they enter the price function in (7) relative to output:[11]

$$\ln p_Y = \alpha_0 + \sum_i \alpha_i \ln p_i + \alpha_t t + \frac{1}{2}\sum_{i,j} \gamma_{ij} \ln p_i \cdot \ln p_j + \frac{1}{2}\alpha_{tt} t^2 + \sum_i \rho_{ti} \ln p_i \cdot t + \sum_k \beta_k \ln \frac{T_k}{Y}$$
$$+ \frac{1}{2}\sum_k \gamma_{kk}\left(\ln \frac{T_k}{Y}\right)^2 + \sum_{i,k} \rho_{ki} \ln p_i \cdot \ln \frac{T_k}{Y} + \sum_k \rho_{tk} \cdot t \cdot \ln \frac{T_k}{Y}$$

where, as above, $i,j = \{K, L_L, L_M, L_H, E, M\}$ and $k = \{ESAV, LSAV\}$. This price function implies the following system of cost share equations for our panel of 25 EU countries from 1995 to 2009:

$$\begin{aligned}
s_{K,c,t} &= \alpha_K + \textstyle\sum_i \gamma_{Ki} \ln\left(\frac{p_i}{p_{LH}}\right)_{c,t} + \rho_{tK} t + \textstyle\sum_k \rho_{kK} \ln\left(\frac{T_k}{Y}\right)_{c,t-5} + \eta_{K,c} + \varepsilon_{K,c,t} \\
s_{LL,c,t} &= \alpha_{LL} + \textstyle\sum_i \gamma_{LLi} \ln\left(\frac{p_i}{p_{LH}}\right)_{c,t} + \rho_{tLL} t + \textstyle\sum_k \rho_{kLL} \ln\left(\frac{T_k}{Y}\right)_{c,t-5} + \eta_{LL,c} + \varepsilon_{LL,c,t} \\
s_{LM,c,t} &= \alpha_{LM} + \textstyle\sum_i \gamma_{LMi} \ln\left(\frac{p_i}{p_{LH}}\right)_{c,t} + \rho_{tLM} t + \textstyle\sum_k \rho_{kLM} \ln\left(\frac{T_k}{Y}\right)_{c,t-5} + \eta_{LM,c} + \varepsilon_{LM,c,t} \\
s_{E,c,t} &= \alpha_E + \textstyle\sum_i \gamma_{Ei} \ln\left(\frac{p_i}{p_{LH}}\right)_{c,t} + \rho_{tE} t + \textstyle\sum_k \rho_{kE} \ln\left(\frac{T_k}{Y}\right)_{c,t-5} + \eta_{E,c} + \varepsilon_{E,c,t} \\
s_{M,c,t} &= \alpha_M + \textstyle\sum_i \gamma_{Mi} \ln\left(\frac{p_i}{p_{LH}}\right)_{c,t} + \rho_{tM} t + \textstyle\sum_k \rho_{kM} \ln\left(\frac{T_k}{Y}\right)_{c,t-5} + \eta_{M,c} + \varepsilon_{M,c,t},
\end{aligned} \tag{13}$$

The baseline regression is again estimated using SUR, while GMM estimates are in progress. The knowledge stocks T_k are lagged by several years in estimation to allow for a time lag between an invention and its effect on factor shares. This should also alleviate endogeneity concerns regarding T_k. The factor bias of exogenous technological change remains as in (10). The bias of energy- and labour-saving technological change for each input is derived similarly:

$$\partial \ln s_i / \partial \ln(T_{ESAV}/Y) = \rho_{ESAV,i}/s_i \quad \text{and} \quad \partial \ln s_i / \partial \ln(T_{LSAV}/Y) = \rho_{LSAV,i}/s_i. \tag{14}$$

where country- and time subscripts are suppressed for ease of exposition. We are interested in the bias of T_{ESAV} with respect to energy and of T_{LSAV} with respect to low-, medium- and high-skilled labour. Results for the bias of both exogenous and endogenous technological change from our preferred specification (13) are reported in section 5.2, where we establish the energy-

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[11] See e.g. Kratena (2007). The aggregate stock of knowledge or level of technology can be considered as given in the short term assuming that the individual firm adds little to it but benefits from the spillovers it generates. For a similar approach to introducing a stock of energy-saving knowledge into a cost function, see Popp (2001).

saving nature of technological change in energy-saving fields and similarly for labour-saving fields. Therefore, we now turn to our models of induced innovation, which provide the framework for investigating policy variables that could spur more energy-saving and less labour-saving technological change and thereby shift its bias from energy to labour.

3.4 Shifting the bias of technological change

Given the accumulation equation for the knowledge stock in field *k* in (12), technological change $\dot{T}_k$ is a function of innovative activity P_k, which we proxy with the flow of patent applications. We specify separate models for energy- and labour-saving patents and investigate how to stimulate the former and attenuate the latter. The policy variables we consider are, following the literature on induced innovation, factor prices, which can be raised and lowered through taxation, and government R&D expenditures in energy- and labour-saving technologies. Two further drivers of innovative activity are included that both Popp (2002) and Kruse and Wetzel (2014) have shown to be important. The first is the patent stock that accumulates until the end of the previous period, $T_{k,t-1}$, to measure the level of technological knowledge available to inventors at time *t*. The second is the total number of patent applications per country and year, $P_{c,t}$, to control for country-level trends in patenting brought about, for example, by changing propensities to patent. All explanatory variables enter in lags to reduce endogeneity concerns.

Hence, we postulate the following general model of innovative activity in field *k* and country *c* at time *t*:

$$P_{k,c,t} = f\left[p(\tau)_{j,c,t-1}, R\&D_{k,c,t-1}, T_{k,c,t-1}, P_{c,t-1}\right] \tag{15}$$

where $p(\tau)_{j,c,t-1}$ is the price of input *j* (energy or labour), which depends on the respective tax rate τ, and $R\&D_{k,c,t-1}$ denotes government R&D expenditures in field *k*. Equation (15) implies that the knowledge accumulation function (12) may be rewritten as $\dot{T}_k = f\left\{P_k\left[p(\tau)_j, R\&D_k\right], T_k\right\}$. This formulation will be used in a subsequent deliverable to derive the impact of changes in the policy variables on factor demand via their impact on innovation, thereby linking the two parts of the analysis in this paper and quantifying the effects of shifting the bias of technological change.

The dependent variable in (15), $P_{k,c,t}$, consists of fractional counts of patent applications that are either positive or zero. In this case, count data models are appropriate, among which the Poisson model is a common choice (Wooldridge, 2002). It implies the following exponential specification for the relationship in (15):

$$P_{k,c,t} = \exp\left[\beta_{p_j} \ln p(\tau)_{j,c,t-1} + \beta_{r\&d_k} \ln R\&D_{k,c,t-1} + \beta_{T_k} \ln T_{k,c,t-1} + \beta_P \ln P_{c,t-1} + \mu_{k,c} + \lambda_{k,t}\right] + \nu_{k,c,t} \tag{16}$$

where $\mu_{k,c}$ and $\lambda_{k,t}$ are country- and period-specific fixed effects and $\nu_{k,c,t}$ is a mean-zero error term. The exponential functional form ensures that the values of $P_{k,c,t}$ predicted by the model are non-negative. Poisson regression assumes that the conditional variance of the process in (16) equals the conditional mean, while in practice the variance for count data is often larger (overdispersion). This is also what our estimates suggest, so we report results from a negative binomial model, a standard generalisation of the Poisson model that allows for overdispersion.

Since the previous period's knowledge stock $T_{k,c,t-1}$ contains lagged values of the dependent variable, correlation between it and the unobserved country-specific fixed effects $\mu_{k,c}$ leads to inconsistent estimates. To counter this, Blundell, Griffith and Windmeijer (2002) propose the so-called pre-sample mean estimator for dynamic count data models. It relies on the availability of observations on the dependent variable prior to the estimation sample period, which is satisfied in our case. Implementing the estimator involves including the log of the country-specific time average of these pre-sample observations on the right-hand side of (16) to proxy for $\mu_{k,c}$. This additional regressor takes the form $\ln \bar{P}_{k,c,p} = \ln\left[(1/TP)\sum_{r=0}^{TP-1} P_{k,c,0-r}\right]$, where TP denotes the number of pre-sample observations available. The underlying assumptions for the procedure to be valid are that the pre-sample mean is correlated with the dependent variable $P_{k,c,t}$ but not with the error term $\nu_{k,c,t}$ and that it captures (much of) the unobserved country-specific time-invariant shocks to patenting that $\mu_{k,c}$ represents.

4. Data and variables

This study employs three sets of data. First, we compute the factor cost shares and prices in specifications (9) and (13) using data from the World Input-Output Database (WIOD), which provides industry-level data for the EU countries from 1995 onwards. Second, data on patent applications by technology field, which enter equation (16) and from which we construct the patent stocks in (13), are taken from the patent databases of the OECD. Third, data on taxes and government R&D in (16) are drawn from Eurostat and the OECD. Table I in the Appendix provides a list of the main data sources.

Overall, our analysis covers 25 EU member states - the EU-27 excluding Romania and Bulgaria - from 1995 to 2009. The factor bias of technological change is measured both at the level of countries as well as industries, which are classified according to NACE revision 1.1. Of the original 35 industries available in the WIOD, four are dropped due to missing data.[12] Thus the panel dataset employed to estimate factor biases is balanced. The induced innovation equations are estimated only at the country level due to data availability on the policy variables and because patents are more easily assigned to countries than to industries. While the patent data cover the EU-25 from 1980 onwards, government R&D is less consistently available, so the resulting panel dataset is unbalanced.[13]

4.1 Factor cost shares and prices

The factor cost shares are constructed according to equation (6), that is, by dividing the nominal input values $p_i x_i$ through by nominal gross output $p_Y Y$. For this purpose, we take from the Socio-Economic Accounts (SEA) of the WIOD the series on nominal gross output, capital compensation $(p_K K)$ and labour compensation. Combining the latter with the shares of low-, medium- and high-skilled workers in total labour compensation yields compensation by skill group $(p_{LL} L_L, p_{Lm} L_M$ and $p_{LH} L_H)$, where skill type reflects the level of educational attainment according to the ISCED classification.[14] To derive the nominal value of energy intermediates

[12] These are leather products and footwear (NACE 1.1 sector 19); coke, refined petroleum and nuclear fuel (23); water transport (61); and private households with employed persons (P). The industries are listed in Appendix Table II.

[13] There are no data for Cyprus, Latvia, Lithuania and Malta as well as missing values for the remaining countries.

[14] Low-skilled workers are those who have completed at most ISCED levels 1 and 2, medium-skilled workers have completed at most levels 3 and 4 and high-skilled workers at most levels 5 and 6.

$p_E E$, we combine data on gross energy use in terajoule, available by energy commodity in the Environmental Accounts (EA) of the WIOD, with information on industry energy prices by energy commodity from the International Energy Agency (IEA)'s Energy Prices and Taxes Statistics database. The energy commodities entering E are coal and oil and their derivatives, gas, electricity and heat products, but not renewables like biomass, solar, geothermal, hydroelectric or wind energy, whose energy flow does not have a price. Non-energy intermediate inputs (or materials) $p_M M$ are computed by subtracting $p_E E$ from the nominal value of total intermediate inputs, available in the SEA.

The WIOD is also the primary source of data on prices. From the SEA, we take the price level of gross output p_Y as well as the information required to construct the prices of low-, medium- and high-skilled labour (p_{LL}, p_{Lm} and p_{LH}) as hourly labour compensation by skill type. The price of energy intermediates comes from the IEA as described above, and the price of non-energy material inputs p_M is obtained using data from the World Input-Output Tables (WIOT).[15] The price of capital is computed as the user cost of capital according to $p_K = p_I(r + \delta)$, where p_I is the price level of gross fixed capital formation from the SEA, r is the real rate of return on capital and δ is the depreciation rate of the capital stock.[16] All prices are in index form with 1995=1.

For the analysis at the country level, we aggregate the industry-level input shares derived from the WIOD by simply summing the nominal values of inputs and output over industries for each country and year. The price indices are aggregated using a Divisia index, so that for example the price of energy for country c at time t is given by $\ln(p_{E,c,t}) = \sum_s \frac{(p_E E)_{s,t}}{(p_E E)_t} \ln(p_{E,s,t})$, where s denotes sector or industry and the weights are the industry shares in the country-level nominal value of energy input. Summary statistics are contained in Table III in the Appendix.

Figure 1 and Figure 2 depict the average annual rates of change in factor cost shares and relative prices for the EU-25 countries, which serves to gain some indication of the factor bias of (exogenous) technological change. Following the definition in equation (2), a decline in the cost share of an input whose price remains relatively constant would be suggestive of a factor-saving bias. This is the case for medium-skilled labour in several countries (Austria, Denmark, Ireland and Poland). For the remaining countries, both relative price and factor share of medium-skilled labour change over our sample period, and the direction of change is rather heterogeneous. Inspection of country patterns reveals a relationship with levels of development and structural change: in general, the share of medium-skilled labour declined in the more advanced countries from Western and Northern Europe, while it increased in countries from Southern and Eastern Europe, often from low initial levels compared to low-skilled labour (not shown; examples include Greece, Portugal, Spain, Italy).

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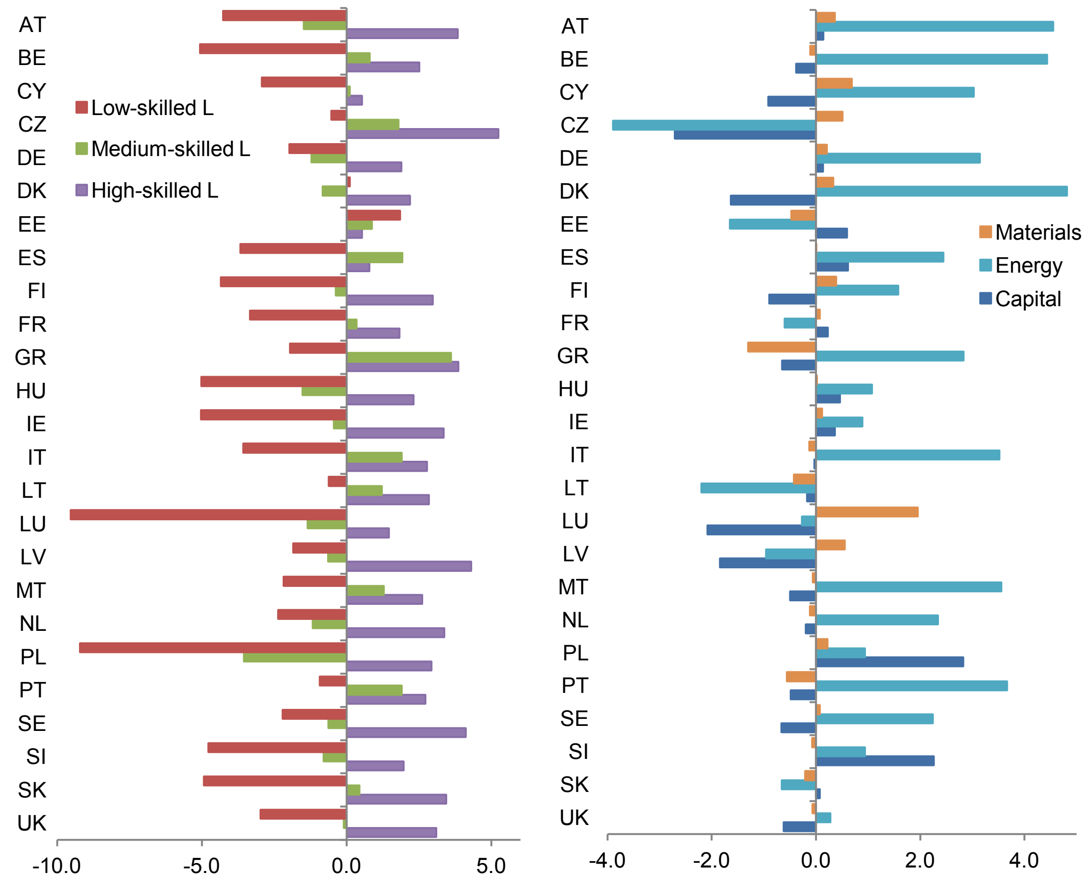
[15] The WIOT are available at current as well as previous years' prices in the WIOD. Kratena and Wüger (2012) describe how this dataset allows for calculating the prices of all intermediate deliveries in the dimension (users and countries)*(users and countries).

[16] r is derived as the interest rate on treasury bills in the secondary market (from the IMF) deflated by the gross output price level p_Y. To compute δ, we use information on asset-specific depreciation rates and the industry-specific asset composition of the capital stock, both from EU KLEMS.

Meanwhile, low-skilled labour has been in retreat almost everywhere, with a decline in its cost share of 3.25% on average across countries and time. Its relative price also fell, but by less (on average by 2.7% per year). In contrast, there is not a single country in our sample that has not seen its share of high-skilled labour increase (at a given relative price), indicating that exogenous technological change has been biased towards high-skilled labour. Finally, the cost share of energy increased by more than its relative price on average, while the cost share of capital declined by considerably less.[17] The share of non-energy intermediates, or materials for short, rose very slightly while their relative price declined by more than 2% annually on average across countries and time. The parameter estimates of the translog cost share system will provide a clearer picture by isolating the factor biases while holding all relative prices constant.

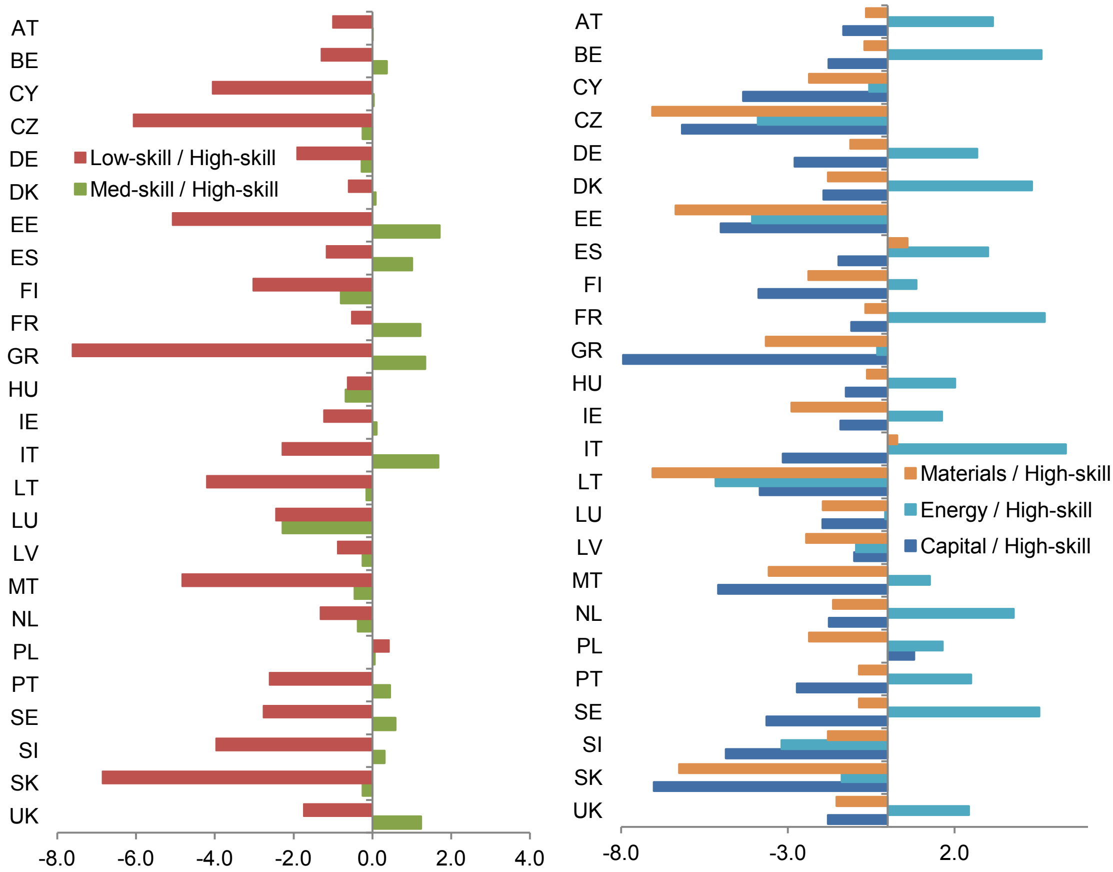
Figure 1 **Average annual rates of change in factor cost shares, 1995-2009**



Source: Own calculations based on WIOD (February 2012 release), IEA *Energy Prices and Taxes*, EU KLEMS, IMF.

[17] The average annual increase in the cost share of energy was 1.44% compared to a price increase of 1.15%. For capital, the corresponding figures are -0.24% and -3.06% per year.

Figure 2 **Average annual rates of change in relative factor prices, 1995-2009**



Source: Own calculations based on WIOD (February 2012 release), IEA *Energy Prices and Taxes*, EU KLEMS, IMF.

4.2 Patent applications and patent stocks

To measure innovation and the stock of knowledge in energy- and labour-saving technology fields, we use data on citation-weighted patent applications to the European Patent Office (EPO) recorded by priority date from the OECD REGPAT and Citations databases. Although patent applications can only be considered an intermediate measure of innovation output, since they measure inventions rather than their successful introduction into the market, they have the advantage that they are widely available across countries and time. In addition, applications to the EPO indicate a certain degree of confidence on the part of the inventor regarding the commercial success of the patent since they are costly and the review process is internationally standardised according to the European Patent Convention. Patent applications to the EPO have also been classified into technology fields according to the International Patent Classification (IPC) based on information provided in the patent documents. We make use of this property to measure innovation and knowledge stocks in energy- and labour-saving fields.

Patent applications are weighted by the citations they receive in subsequent applications to increase the likelihood of capturing high-quality patents, as patent citations have been shown to correlate strongly with the market value of the original patent (Hall, Jaffe and Trajtenberg, 2005). The data are fractional counts, since in the case of several applicants from different countries, patents are divided equally among these to avoid double counting. We consider patent applications by country of residence of the applicant rather than the inventor since the level of technology enters as an input into production in the cost share approach outlined in section 3. Hence we wish to assign patents to those industries or countries where they are used in production, which is more closely reflected by place of residence of the applicant, who will hold the intellectual property over the invention after the patent is granted. For the industry-level analysis, patent stocks constructed at the country level are employed. While it would be preferable to use a concordance like Schmoch et al. (2003) to map patents by technology areas to industries, the latter coincide with industry of manufacture rather than industry of use of the technology in most available concordances. Hence we focus on the country-level results.

To identify patent applications in energy-saving technology fields, we combine information from the OECD's classification of environment-related technologies (ENV-Tech) with the World Intellectual Property Office's Green Inventory, which lists so-called environmentally sound technologies.[18] Our aim is to select technologies with the potential to save energy input as defined in section 4.1, i.e. mostly from fossil sources. Thus, we combine patents in the following two types of technology fields:

- Renewables: from the OECD classification, we use "Energy generation from renewable and non-fossil sources", which includes wind, solar, geothermal, marine and hydro energy as well as biofuels and fuel from waste. From the WIPO Green Inventory, we use "Alternative energy production", which in addition to the fields contained in the OECD classification also comprises natural heat and producing mechanical power from muscle energy.
- Technologies that have the potential to improve energy efficiency in general: from the OECD, we use the fields incineration and energy recovery; technologies for improved output efficiency; technologies for improved input efficiency; energy storage; hydrogen technology; fuel cells; fuel efficiency in transportation; and energy efficiency in buildings and lighting. From the WIPO classification, we add the field energy conservation, which includes power supply circuitry and measurement of electricity consumption, among others.

Although a patent may belong to more than one of these technology fields, we use the IPC codes assigned to each patent and field to ensure that the patents are counted only once when generating our variable on energy-saving patent applications.

Since there are no classifications of labour-saving or -using technologies that we are aware of, labour-saving technologies are proxied with patent applications in ICT and advanced manufacturing technologies. On the one hand, this reflects findings from the literature on skill-biased technological change, which suggests that the rise of ICT has gone hand-in-hand with declining employment of unskilled workers. On the other, it allows us to test whether current technological advances, e.g. in robotics, are as labour saving as some authors have predicted. ICT patents are collected using a classification developed at the OECD that comprises the subgroups telecommunications; consumer electronics; computers and office machinery; and other ICT. Advanced manufacturing technologies consist of robotics; computer-integrated manufacturing; machine tools; and measuring, controlling and regulating of industrial processes.

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18 For the sources of all technology classifications, see Appendix Table I.

The citation-weighted number of patent applications in ICT and advanced manufacturing is generated both as separate variables to investigate their effects on factor shares individually and as a combined variable for the analysis of induced innovation since we find that they were both labour saving overall.

Figure 3 compares the time series on citation-weighted patent applications in energy- and labour-saving fields to the total number of applications (top line, right scale) per country. The number of patents in ICT and advanced manufacturing (middle line, left scale) generally exceeds that in energy-saving fields (bottom line, left scale), sometimes considerably so (Finland, France, Sweden, UK). It also tends to develop in line with the total number of applications over time. In several countries, energy-saving patents exhibit an upward trend since the early 2000s, and in Denmark, they even exceeded labour-saving patents in 2009.

Based on the patent data, the knowledge stocks T_{ESAV} and T_{LSAV} are constructed according to one of two specifications consistent with the general model in (12), with which we experiment in estimation to establish robustness of the results. The first is the perpetual inventory model, which describes the period-*t* knowledge stock of country *c* in field *k* as

$$T_{k,c,t} = P_{k,c,t-1} + (1-\delta)T_{k,c,t-1} \tag{17}$$

where $k = \{ESAV, LSAV\}$. We assume that patent applications P_k do not add to the knowledge stock immediately but after a time lag of one year, given that the EPO publishes the patent documents 18 months after application. The depreciation rate δ is set to equal 15%.[19] The initial-period knowledge stock is computed as $T_{k,c,1980} = P_{k,c,1980}/(\delta + g_{k,c})$, where $g_{k,c}$ is the country-specific average annual growth rate of patent applications in technology field *k* between 1980 and 2009. The entire available time series on patent applications is used to construct patent growth since the patent stock series will be sensitive to the initial knowledge stock and hence to a mismeasured growth rate. Given that the influence of $g_{k,c}$ on the patent stock series declines over time, any measurement error associated with the initial value should be small by 1995, when estimation of (13) begins.

The alternative specification for the knowledge stock we employ follows Popp (2001) in allowing for knowledge diffusion in addition to knowledge decay:

$$T_{k,c,t} = \sum_{s=1}^{\infty} P_{k,c,t-s} \cdot e^{-\delta_1(s)}(1 - e^{-\delta_2(s)}) \tag{18}$$

where *s* is the number of years before the current year *t* going back to 1980, δ_1 is the rate of knowledge depreciation and δ_2 is the rate of diffusion. That is, the patent stock at time *t* consists of the weighted sum of all previous periods' patent applications, where the overall weight of older patents declines over time since obsolescence reduces the knowledge stock by more than diffusion raises it.[20] This specification also implies a time lag of one year until a patent enters the knowledge stock. As above, we assume a rate of decay of 15%. For the rate of diffusion, we assume 3% but check robustness against 0.2%, both values estimated by Popp (2001, 2002)

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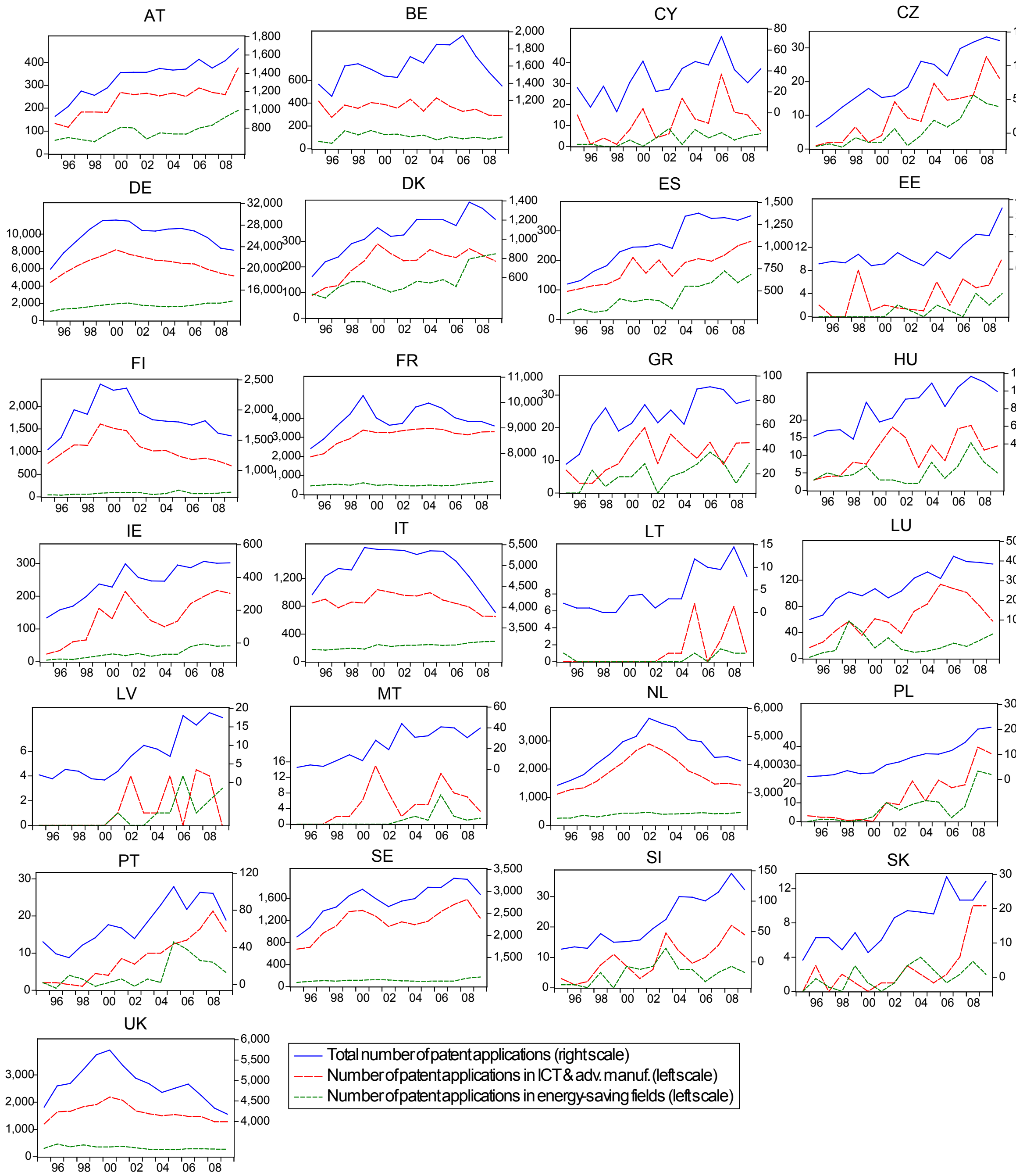
[19] A rate of knowledge obsolescence between 10% and 15% on average across technology fields and industries is often assumed or estimated in the literature (e.g. Park and Park, 2006). In high-tech fields, it is likely to be on the higher side (Roper and Hewitt-Dundas, 2011). Since all our empirical specifications contain country-specific fixed effects, the choice of δ should not affect the results as long as it remains relatively constant over time per country.

[20] Note that the expression involving δ_2 is smaller than that involving δ_1.

for energy-saving technologies in US manufacturing industries. Overall, the specification chosen for the knowledge stock does not make a difference to our empirical results, so in section 5.2, we present results based on equation (18) to allow for knowledge diffusion as well as decay.

Figure 3 **Patent applications total, labour- and energy-saving fields, 1995-2009**



Notes: Figures shown are citation-weighted patent counts.

Source: OECD REGPAT and Citations databases, WIFO calculations based on technology classifications by OECD, WIPO and Centre for European Economic Research and TNO (2010, 2012).

4.3 Policy variables

The prices of energy and labour that we use for $p(\tau)_{j,c,t-1}$ in equation (16) may or may not already include taxes. Firms pay less energy tax than households - much less in some countries - so in addition to the industry energy price p_E, we also include the implicit energy tax rate from Eurostat. This equals total energy tax revenues divided by final energy consumption and is measured in constant Euros per tonne of oil equivalent. On the other hand, p_{LL}, p_{Lm} and p_{LH} from the WIOD comprise wages and salaries gross of income tax as well as social security contributions payable by employers. Hence we do not add an additional variable for labour taxes.

Data on government R&D expenditures in energy-saving technology fields are taken from the IEA Energy Technology RD&D Statistics database. In line with the technologies chosen for energy-saving patents, we sum expenditures on the total public-sector RD&D budget, measured in constant Euros, over the following technology categories: energy efficiency, renewable energy sources, hydrogen and fuel cells, and other power and storage technologies. Fossil fuels and nuclear energy are excluded. For government R&D expenditures in ICT and advanced manufacturing, we use OECD data on government budget appropriations or outlays for R&D (GBAORD) by socioeconomic objective according to the NABS 2007 classification.[21] Among these objectives, two are relevant for us: “industrial production and technology”, which relates to improving the manufacturing processes of industrial products and which we use to proxy R&D in advanced manufacturing; and “general advancement of knowledge”, under which the largest amounts of public ICT R&D tend to fall in the EU countries (Stancik and Rohman, 2014). We sum GBAORD, measured in constant Euros, in these two objectives. Summary statistics on all indicators that appear in equation (16) are given in Table IV in the Appendix.

5. Results and discussion

5.1 The bias of exogenous technological change

This section reports the results of estimating the system of factor cost share equations in (9) using SUR.[22] Technological change is exogenous, i.e. the level of technology is represented by a time trend. Instead of reporting the coefficients for all variables, we focus on the factor biases of technological change with respect to the inputs capital, labour by skill level, energy and non-energy materials. Since the bias calculated according to equation (10) above varies across countries and over time, we present the median to reduce the influence of outliers. Table 1 shows country-level estimates for our balanced panel of 25 countries over 15 years, while Table 2 provides a breakdown at the industry level obtained by estimating system (9) separately for 31 industries. The figures multiplied by 100 can be interpreted as the annual percent change in factor cost shares due to exogenous technological change, holding relative prices constant. Significant factor-saving biases are highlighted in green and significant factor-using ones in red.

[21] NABS stands for “nomenclature for the analysis and comparison of scientific programmes and budgets”.

[22] Initial results using GMM with lagged relative prices as instruments are similar albeit less significant, which is not uncommon with instrumental variables techniques. They are available upon request.

Table 1 **Bias of exogenous technological change: country-level estimates of system (9)**

COUNTRIES (Median bias)	bias_t_K (ρ_{tK}/s_K)	bias_t_LL (ρ_{tLL}/s_{LL})	bias_t_LM (ρ_{tLM}/s_{LM})	bias_t_LH (ρ_{tLH}/s_{LH})	bias_t_E (ρ_{tE}/s_E)	bias_t_M (ρ_{tM}/s_M)
T = time trend t	0.0018	**-0.0582**	**-0.0100**	**0.0273**	*0.0074*	**0.0038**
	(0.0012)	(0.0032)	(0.0016)	(0.0025)	(0.0038)	(0.0007)
Country fixed-effects: Yes		Observations: 375		Average adjusted R^2: 0.915		

Notes: System (9) estimated on country-level data using seemingly unrelated regressions (SUR); estimation period 1995-2009; significant factor-saving biases given in green, factor-using biases in red; figures in bold font are significant at the 1% level, underlined figures at the 5% level, figures in italics at the 10% level; standard errors (in parentheses) robust to cross-equation correlation.

Table 2 **Bias of exogenous technological change: industry-level estimates of system (9)**

NACE 1.1 SECTORS (Median bias)		bias_t_K (ρ_{tK}/s_K)	bias_t_LL (ρ_{tLL}/s_{LL})	bias_t_LM (ρ_{tLM}/s_{LM})	bias_t_LH (ρ_{tLH}/s_{LH})	bias_t_E (ρ_{tE}/s_E)	bias_t_M (ρ_{tM}/s_M)
Agriculture	AtB	-0.0050	**-0.0384**	-0.0036	**0.0674**	**0.0187**	**0.0094**
Mining, quarrying	C	**0.0412**	**-0.0767**	**-0.0531**	**-0.0310**	**0.0171**	**-0.0022**
Food, beverages	15t16	**0.0135**	**-0.0382**	**-0.0065**	**0.0329**	0.0014	*-0.0009*
Textiles	17t18	**-0.0211**	**-0.0278**	-0.0004	**0.0573**	**0.0176**	**0.0028**
Wood and cork	20	-0.0113	**-0.0461**	-0.0011	**0.0346**	**0.0176**	**0.0030**
Pulp, paper	21t22	-0.0050	**-0.0437**	**-0.0099**	**0.0364**	*0.0104*	**0.0043**
Chemicals	24	**0.0079**	**-0.0423**	**-0.0228**	**0.0220**	-0.0023	**0.0026**
Rubber, plastics	25	-0.0031	**-0.0453**	-0.0069	**0.0425**	**0.0204**	**0.0029**
Non-metallic minerals	26	**-0.0137**	**-0.0420**	-0.0021	**0.0446**	0.0023	**0.0059**
Basic metals	27t28	**-0.0143**	**-0.0546**	**-0.0121**	**0.0390**	**0.0262**	**0.0058**
Machinery	29	-0.0031	**-0.0456**	0.0015	**0.0467**	**0.0216**	0.0006
Electrical equipment	30t33	**-0.0157**	**-0.0702**	**-0.0093**	**0.0424**	**0.0385**	**0.0067**
Transport equipment	34t35	0.0062	**-0.1055**	**-0.0139**	**0.0259**	-0.0080	**0.0061**
Other manufacturing	36t37	0.0039	**-0.0459**	**-0.0132**	**0.0388**	**0.0231**	**0.0040**
Electricity, gas, water	E	*-0.0045*	**-0.0969**	**-0.0408**	0.0125	**0.0254**	-0.0029
Construction	F	0.0035	**-0.0370**	*-0.0024*	0.0117	0.0102	**0.0039**
Sale of motor vehicles	50	-0.0061	**-0.0367**	-0.0013	**0.0206**	0.0035	**0.0080**
Wholesale trade	51	-0.0009	**-0.0374**	**-0.0054**	**0.0322**	0.0139	**0.0047**
Retail trade	52	-0.0074	**-0.0389**	**-0.0044**	**0.0335**	0.0135	**0.0097**
Hotels, restaurants	H	0.0003	**-0.0266**	**0.0098**	**0.0214**	*-0.0099*	0.0008
Land transport	60	-0.0059	**-0.0375**	**-0.0154**	**0.0484**	**0.0342**	**0.0067**
Air transport	62	-0.0141	**-0.0847**	**-0.0262**	**0.0380**	**0.0307**	**0.0100**
Other transport activ.	63	-0.0099	**-0.0357**	0.0016	**0.0494**	0.0191	0.0025
Post, telecoms	64	-0.0086	**-0.0770**	**-0.0340**	**0.0447**	*0.0180*	**0.0239**
Financial intermed.	J	0.0013	**-0.1535**	**-0.0388**	**0.0205**	-0.0188	**0.0152**
Real estate activities	70	-0.0072	-0.0075	**0.0097**	**0.0272**	**0.0783**	**0.0142**
Other business activ.	71t74	-0.0140	**-0.0403**	**-0.0047**	**0.0186**	-0.0154	0.0038
Public administration	L	0.0000	**-0.0678**	**-0.0086**	**0.0256**	0.0034	0.0037
Education	M	-0.0076	**-0.0441**	**-0.0098**	**0.0073**	0.0156	**0.0024**
Health	N	0.0001	**-0.0431**	**-0.0099**	**0.0108**	0.0034	**0.0112**
Social, personal serv.	O	*0.0038*	**-0.0500**	**-0.0097**	**0.0198**	0.0047	**0.0056**
Country fixed-effects: Yes			Observations: 375		Average adjusted R^2: 0.835		

Notes: System (9) estimated separately for 31 NACE 1.1. industries using seemingly unrelated regressions (SUR); estimation period 1995-2009; significant factor-saving biases given in green, factor-using biases in red; figures in bold font are significant at the 1% level, underlined figures at the 5% level, figures in italics at the 10% level; standard errors (available upon request) robust to cross-equation correlation.

The most sizeable biases in Tables 1 and 2 are those with respect to labour: exogenous technological change was clearly low- and medium-skilled labour saving and high-skilled labour using, both at the aggregate country level and for individual sectors. On aggregate, holding relative prices constant, the cost shares of low- and medium-skilled labour declined at annual rates of 5.8% and 1% respectively, while that of high-skilled labour rose by 2.7% per year. Taken together, these figures imply an annual labour-saving bias of 4% for exogenous technological change. The industry-level estimates in Table 2 reveal that the low-skilled labour-saving bias was largest in financial intermediation (15% per year) and manufacture of transport equipment (11%). Increases in the shares of high-skilled labour were generally larger in manufacturing, transport services and post and telecommunications than in other industries, although agriculture registered the biggest annual increase (6.7%). The medium-skilled labour-saving biases tend to be smaller but are still substantial in mining (5.3%) and financial intermediation (about 4%).

Regarding energy and non-energy intermediate inputs (materials), the results suggest that exogenous technological change was factor-using. The aggregate country-level biases are small, at 0.7% and 0.4% per year respectively, and only marginally significant in the case of energy. However, at the industry level, technological change was significantly energy-using in agriculture and mining, most manufacturing industries, transport services, and electricity, gas and water supply, with the energy factor share increasing by between 1% and 3% annually. The bias with respect to capital is insignificant at the country level. At the industry level, there are both significant capital-using biases (4% per year in mining) and capital-saving ones (between 1.4 and 2% in several manufacturing industries), but many are insignificant.

On the whole therefore, our estimates indicate that exogenous technological change for the EU-25 from 1995 to 2009 was skill-biased but labour saving overall, as well as energy and materials using.

5.2 The bias of endogenous technological change

In this section, we present the results of estimating system (13), where the level of technology is represented both by patent stocks in energy- and labour-saving fields, T_{ESAV} and T_{LSAV}, as well as an exogenous time trend *t* to capture all other types of knowledge not explicitly modelled. We refer to the factor bias with respect to the patent stocks as the bias of endogenous technological change given that we model their determinants in the next section. These biases also give an indication of the direction of technological change regarding energy and labour in our data. Patent stocks in ICT and advanced manufacturing technologies are included separately to test their individual relationships with factor shares, and all patent stocks are lagged by five years (recall that they are available since 1980) to account for the fact that inventions are likely to take some time before affecting cost shares. Table 3 contains estimates of the median country-level biases computed according to equations (10) and (14). Since patents are less easy to assign to industries than to countries, industry-level results are relegated to Table V in the Appendix.

The factor biases of exogenous technological change in the top third of Table 3 retain their signs and significance levels compared to Table 1. All significant biases decline slightly but not significantly so in absolute values, except for the bias with respect to energy which doubles in size but is also less precisely estimated. Factor biases of endogenous technological change are shown in the middle and bottom thirds of the table. The estimates indicate that technological change as measured by the change in the ICT patent stock was medium-skilled labour saving and high-skilled labour using, while the bias with respect to low-skilled labour is not significantly different from zero. This is consistent with the findings of Michaels, Natraj and Van Reenen (2014) and adds to the existing empirical evidence on the skill bias of ICT. The sector-level results for ICT in Appendix Table V are mostly in line with this, although some heterogeneity is noticeable across sectors. In particular, several industries are characterised by a low-skilled labour-saving bias, especially in services. For the ICT-producing industries, where ICT would be expected to be labour-using, this can only be confirmed at the 10% significance level for highly skilled labour in post and telecommunications (NACE industry 64). In optical and electrical equipment manufacturing (30-33), the biases are correctly signed but not significant, while the latter also holds for industries 71-74, which contain computer services (72). The last grouping may be too broad to correctly capture the effect of computer services.[23]

Given equation (14), the factor biases of endogenous technological change have the interpretation of elasticities, so their size is not directly comparable to the biases of exogenous technological change at the top of the table. The figures for ICT imply that over our sample period, the cost shares of medium- and high-skilled labour respectively declined by 0.64% and rose by 0.34% for every 10% increase in the ICT patent stock relative to output. Since the latter actually grew by close to 10% per year on average, -0.64% and 0.34% are approximately the annual cost share changes due to technological change in ICT. These percentages are smaller than the corresponding biases of exogenous technological change, but for medium-skilled labour they are only marginally more than two standard deviations away from each other.

Table 3 **Bias of endogenous technological change: country-level estimates of system (13)**

COUNTRIES (Median bias)	**bias_t_K** (ρ_{tK}/s_K)	**bias_t_LL** (ρ_{tLL}/s_{LL})	**bias_t_LM** (ρ_{tLM}/s_{LM})	**bias_t_LH** (ρ_{tLH}/s_{LH})	**bias_t_E** (ρ_{tE}/s_E)	**bias_t_M** (ρ_{tM}/s_M)
T = time trend t	0.0020 (0.0013)	**-0.0414** (0.0040)	**-0.0099** (0.0016)	**0.0223** (0.0026)	*0.0141* (0.0082)	**0.0036** (0.0037)
	bias_ict_LL ($\rho_{ICT,LL}/s_{LL}$)	**bias_ict_LM** ($\rho_{ICT,LM}/s_{LM}$)	**bias_ict_LH** ($\rho_{ICT,LH}/s_{LH}$)	**bias_am_LL** ($\rho_{AM,LL}/s_{LL}$)	**bias_am_LM** ($\rho_{AM,LM}/s_{LM}$)	**bias_am_LH** ($\rho_{AM,LH}/s_{LH}$)
+ T_{LSAV}	-0.0041 (0.0086)	**-0.0640** (0.0103)	0.0341 (0.0156)	-0.0021 (0.0087)	*0.0101* (0.0060)	*-0.0150* (0.0078)
	bias_esav_E ($\rho_{ESAV,E}/s_E$)	Country-specific fixed effects: Yes Observations: 375 Average adjusted R^2: 0.937				
+ T_{ESAV}	0.0020 (0.0037)					

Notes: System (13) estimated on country-level data using seemingly unrelated regressions (SUR); estimation period 1995-2009; significant factor-saving biases given in green, factor-using biases in red; figures in bold font are significant at the 1% level, underlined figures at the 5% level, figures in italics at the 10% level; standard errors (in parentheses) robust to cross-equation correlation.

[23] As discussed in section 4.2, since due to data constraints we use country-level patent stocks, the sector-level results should not be overemphasised.

Technological change as measured by the change in the stock of patents in advanced manufacturing ("am") technology fields was medium-skilled labour using and high-skilled labour saving, with no significant effect on low-skilled labour. The results therefore suggest that not even highly skilled labour is immune from the adverse employment effects of new technologies. This also holds for some individual industries, as the last three columns of Table V in the Appendix show.[24] The labour-using biases in machinery manufacturing (NACE industry 29, which contains machine tools) and electrical and optical equipment (30-33) are consistent with advanced manufacturing technologies representing product innovations in these industries that dominate any labour-saving effects. This could be one reason why our results contrast with the predictions of Frey and Osborne (2013) and Brynjolfsson and McAfee (2014). Another possible explanation is that we are relying on the within-country variation over time to identify the coefficients. As Figure I in the Appendix shows, in contrast to the ICT patent stock, the advanced manufacturing patent stock declines over time or remains flat in several countries, which could be driving its negative correlation with the high-skilled labour share. A related final point is that our data may be too aggregate to identify the expected effects. On the one hand, robotics is only a subcategory of advanced manufacturing technologies.[25] On the other, our skills measure is based on educational attainment, so the data do not allow a detailed differentiation of the task content of occupations as in Frey and Osborne (2013). In general, our estimated biases are small and only marginally significant.[26] Taken together, they indicate that advanced manufacturing was labour saving overall.

The factor bias of technological change in energy-saving fields is not significant at the country level, which could be due to an amalgamation of effects in industries where energy-saving technologies are more likely to be employed and thus have an impact with industries were they are less relevant. Indeed, the disaggregation to the industry level in Table V in the Appendix reveals that a significant energy-saving bias exists in several energy-intensive industries, among them electricity, gas and water supply (NACE sector E); pulp, paper, printing and publishing (21-22); chemicals and chemical products (24); and two transport services industries (60 and 63). Since the average annual growth rate of the stock of energy-saving patents was close to 6% from 1995 to 2009, the estimated biases (between -0.04 and -0.09) in these industries imply a reduction in their energy cost shares from 0.24% to 0.54% per year.

Finally, for use in the follow-up deliverable linking the two parts of this paper, Table VI in the Appendix shows the own-price elasticities of demand for all inputs. They are all negatively signed and of reasonable size. The elasticities of energy and labour will enter the calculations of the total effect of changes in the policy instruments, in particular the prices of energy and labour, on factor demand, including short-run substitution effects. For completeness, we also show the Allen partial elasticities of substitution for all inputs, computed according to equation (11).

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24 Significant biases are highlighted for agriculture, mining, manufacturing, electricity and construction, where these technologies are most likely to be produced and/or used.

25 For this reason, our results are not directly comparable to recent estimates by Graetz and Michaels (2015), who use data on industrial robots from the International Federation of Robotics and find a significant negative relationship between robots per hour worked and the share of low-skilled labour.

26 The elasticities in Table 3 imply that the cost shares of medium- and high-skilled labour respectively rose by 0.09% and fell by 0.13% per year.

In sum, the biases of endogenous technological change have the expected signs in the case of ICT and energy-saving technologies for some important industries, while the biases of exogenous technological change remain similar to section 5.1. Technological change in ICT was skill biased but labour saving overall, and the latter also holds for advanced manufacturing. Therefore, we use the combined series on patent applications in ICT and advanced manufacturing to proxy labour-saving innovation and technological change in the next section. Before moving on, it is worth briefly recapping the main finding of the empirical analysis so far, namely that technological change in the EU since 1995 has gone hand in hand with declining demand for low- and medium-skilled labour. Clearly, one key policy implication targeted at the (labour) supply side is the crucial importance of appropriate education and training measures to equip workers with the skills required to adapt as new technologies transform the world of work.

5.3 Shifting the bias of technological change

This section examines policy mechanisms that could shift the bias of technological change away from saving labour towards saving energy by stimulating energy-saving and attenuating labour-saving technological change. Results for induced energy-saving innovation, i.e. equation (16) estimated for energy-saving technologies, are reported in Table 4. Table 5 presents results for innovation in ICT and advanced manufacturing technologies combined. In both cases, we start with the baseline specification (16) in column (i) and then carry out several robustness checks in the remaining columns. The results are obtained from unbalanced panels of at most 25 countries and 14 years (due to the lagged explanatory variables) using the PSM estimator. The PSM terms $\ln \bar{P}_{k,c,p}$ consist of country-specific averages of patent applications between 1980 and 1994 and control for unobserved fixed effects. Given the functional form of equation (16), the parameter estimates can be interpreted as elasticities.

In our baseline specification for energy-saving innovation in column (i) of Table 4, of the three policy variables that we consider, only the implicit energy tax rate τ_E is statistically significant. Its coefficient is positive, indicating that a higher energy tax rate could stimulate energy-saving innovation. The estimate implies that a 10% increase in the tax is associated with a 2.1% increase in energy-saving patent applications. Popp (2002) finds a similarly-sized elasticity of US patenting with respect to the energy price, while our coefficient on the latter is insignificant. This should not be too much of a concern however, since the energy tax is the key policy lever affecting the final energy price, and our price measure excludes most energy taxes. In Kruse and Wetzel (2014)'s study of OECD countries, the effect of the energy price is also not significant when estimated over all 11 of their green energy technology fields combined, while the technology-specific regressions reveal substantial heterogeneity regarding its sign and significance across individual technologies.

As R&D is likely to affect patenting only after some time lag, we investigate whether this might cause its insignificant coefficient. In column (ii), we show the results of including R&D lagged by two years, which does not make a difference. The same holds when using lags three and four instead (not shown). Our measure of government energy R&D therefore does not seem to be an effective way to foster energy-saving patenting, which resembles the findings of Popp (2002) and Kruse and Wetzel (2014). Data on government energy R&D are unavailable for six of the 25 EU countries we consider, so it restricts our sample quite considerably. Hence in column (iii), we test the robustness of the results to excluding the R&D variable given that it is insignificant. The parameter estimates change somewhat in size but retain their significance levels. The implied effect of a 10% increase in the energy tax rate on energy patenting declines from 2.1% to 1.8%, but this difference is not statistically significant.

Table 4 **Induced innovation in energy-saving technologies**

Dependent Variable: $P_{ESAV,c,t}$	**(i) NegBin, PSM**	**(ii) NegBin, PSM**	**(iii) NegBin, PSM**	**(iv) Poisson, PSM**
$\ln p_{E,c,t-1}$	-0.1440	-0.1024	0.1065	0.0388
	(0.175)	(0.171)	(0.157)	(0.145)
$\ln \tau_{E,c,t-1}$	0.2106 **	0.2148 **	0.1797 **	0.0576
	(0.089)	(0.010)	(0.074)	(0.081)
$\ln R\&D_{ESAV,c,t-1}$	0.0071			0.0543 **
	(0.033)			(0.024)
$\ln R\&D_{ESAV,c,t-2}$		-0.0026		
		(0.053)		
$\ln T_{ESAV,c,t-1}$	0.9615 ***	0.9337 ***	0.6333 ***	1.4429 ***
	(0.152)	(0.191)	(0.101)	(0.117)
$\ln P_{c,t-1}$	0.3559 ***	0.3896 ***	0.4851 ***	0.2686 ***
	(0.083)	(0.127)	(0.055)	(0.056)
$\ln \bar{P}_{ESAV,c,p}$	-0.4212 ***	-0.4100 ***	-0.2261 ***	-0.7308 ***
	(0.089)	(0.098)	(0.064)	(0.081)
$\ln \alpha$	-2.5579	-2.5252	-2.3048	Deviance gof:
	(0.198)	(0.219)	(0.161)	1776 (0.000)
α	0.0775	0.0800	0.0998	Pearson gof:
	(0.015)	(0.018)	0.016)	2103 (0.000)
LR test of α = 0	1112 (0.000)	1026 (0.000)	1403 (0.000)	
Time dummies	Yes	Yes	Yes	Yes
Countries	19	19	25	19
Observations	199	185	318	199

Notes: Estimates in all columns are obtained using the NB2 model (Cameron and Trivedi, 1986), a commonly employed version of the negative binomial model where the variance of the dependent variable is assumed to be a function of the mean (instead of a constant, as in NB1); Huber-White standard errors (in parentheses) are robust to heteroskedasticity; *** and ** indicate significance at the 1% and 5% levels respectively.

Across columns (i) to (iii), the estimated elasticity for the stock of energy-saving patents T_{ESAV} is always positive and significant at the 1% level. A 10% increase in the knowledge stock is associated with an increase in energy-saving patent applications by 9.6% in our baseline specification in column (i), which is large and similar to the findings of Popp (2002) and Kruse and Wetzel (2014). The total patent count P_c, which controls for country-specific trends in patenting, is also always positive and highly significant.

In column (iv), the baseline model is re-estimated using a Poisson instead of a negative binomial specification. Here, government energy R&D has a significant positive effect, while the energy tax rate is insignificant. However, the goodness-of-fit tests shown in the second half of the table strongly reject this specification. Another way to see this is from the statistics on α in columns (i) to (iii). The Poisson model corresponds to $\alpha = 0$, that is, the conditional variance of the dependent variable equals its mean. This hypothesis is rejected everywhere.

Overall, the results in Table 4 indicate that a direct way for government policy to induce more energy-saving innovation could be to increase taxes on energy, while a more indirect one would be to raise the knowledge stock in energy-saving technologies available in an economy. The latter could be achieved with policy measures related to fostering domestic research and improving the framework conditions for the diffusion and absorption of new knowledge generated at home and abroad.

In our baseline specification for innovation in ICT and advanced manufacturing technologies in column (i) of Table 5, the coefficient on the compensation of low-skilled workers is positive and significant at the 1% level, suggesting that higher compensation of this skill group acts as a spur to patenting in technologies which our results in section 5.2 suggest are labour saving.[27] Hence, the compensation of low-skilled workers could be an instrument for government policy to attenuate labour-saving technological change. The size of the estimated elasticity implies that a 10% reduction in low-skilled labour compensation is associated with about a 5.1% decrease in patenting, which is large compared to the elasticity of energy-saving patenting with respect to the energy tax above. The other compensation variables are not statistically significant.

Government R&D expenditures in the NABS categories related to ICT and advanced manufacturing appear to be significantly negatively related to patenting in these fields. This also holds when using lags two, three or four of the R&D measure instead of lag 1 (not shown). The implied size of the effect is approximately a 1.4% reduction in patenting for every 10% increase in government R&D, which is not very large compared to the effect of low-skilled labour compensation. In column (ii), we split up $R\&D_{LSAV,c,t-1}$ into its two subcomponents, R&D in industrial production and technology ($R\&D_{IPT,c,t-1}$) and R&D in general advancement of knowledge ($R\&D_{GAK,c,t-1}$), which according to a recent study by Stancik and Rohman (2014) is the NABS category under which most public ICT R&D in the EU countries tends to be registered. The results in column (ii) indicate that it is this category that drives the significant negative coefficient. One interpretation could be that government ICT R&D crowds out private R&D, which is also what Popp (2002) finds regarding the effect of government energy R&D on energy-saving patenting. In column (iii), we investigate the robustness of the results to omitting the insignificant variables on labour compensation for medium- and high-skilled workers. The general conclusions from the previous two columns carry through.

In all columns, the coefficient on the stock of labour-saving patents T_{LSAV} is positive and significant at the 1% level. The estimate in column (i) suggests an 8.3% increase in patenting for a 10% increase in the patent stock, which rises only marginally when the insignificant compensation variables are dropped in column (iii). This is again a large effect, although it is slightly smaller than for energy-saving patents above. The coefficient on the total patent count P_c is also highly significant and positive. It is almost twice as large as in Table 4, indicating that a general increase in patenting at the country level is more strongly associated with an increase in ICT and advanced manufacturing patents than with energy-saving ones. Finally, column (iv)

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[27] This is consistent with the finding of Alesina et al. (2015) that more stringent labour market regulations that implicitly raise the low-skilled wage rate induce more innovation. However, their measure of innovation is patenting in “low-skill” technologies whose labour-saving nature is only assumed and not tested.

shows results from a Poisson instead of a negative binomial specification. The estimated coefficients differ substantially from the previous columns, but as in Table 4, the goodness-of-fit tests strongly reject this model.

Table 5 **Induced innovation in ICT and advanced manufacturing technologies**

Dependent Variable: $P_{LSAV,c,t}$	(i) NegBin, PSM	(ii) NegBin, PSM	(iii) NegBin, PSM	(iv) Poisson, PSM
$\ln p_{LH,c,t-1}$	-0.3067	-0.3255		-1.3443 ***
	(0.391)	(0.367)		(0.420)
$\ln p_{LM,c,t-1}$	0.5033	0.6231		1.0478 ***
	(0.393)	(0.407)		(0.381)
$\ln p_{LL,c,t-1}$	0.5063 ***	0.5436 ***	0.5145 ***	0.8819 ***
	(0.187)	(0.192)	(0.166)	(0.301)
$\ln R\&D_{LSAV,c,t-1}$	-0.1367 **		-0.1047 **	-0.2170 ***
	(0.055)		(0.043)	(0.052)
$\ln R\&D_{GAK,c,t-1}$		-0.1451 **		
		(0.063)		
$\ln R\&D_{IPT,c,t-1}$		-0.0197		
		(0.036)		
$\ln T_{LSAV,c,t-1}$	0.8254 ***	0.8038 ***	0.8427 ***	0.9258 ***
	(0.089)	(0.101)	(0.087)	(0.110)
$\ln P_{c,t-1}$	0.6475 ***	0.6900 ***	0.6040 ***	0.5900 ***
	(0.116)	(0.128)	(0.112)	(0.102)
$\ln \bar{P}_{LSAV,c,p}$	-0.3653 ***	-0.3548 ***	-0.3713 ***	-0.3744 ***
	(0.081)	(0.093)	(0.073)	(0.058)
$\ln \alpha$	-2.6990	-2.7711	-2.6735	Deviance gof:
	(0.277)	(0.249)	(0.267)	7059 (0.000)
α	0.0672	0.0626	0.0690	Pearson gof:
	(0.019)	(0.016)	(0.018)	8061 (0.000)
LR test of α = 0	6097 (0.000)	5864 (0.000)	7182 (0.000)	
Time dummies	Yes	Yes	Yes	Yes
Countries	21	21	21	21
Observations	244	244	244	244

Notes: Estimates in all columns are obtained using the NB2 model (Cameron and Trivedi, 1986), a commonly employed version of the negative binomial model where the variance of the dependent variable is assumed to be a function of the mean (instead of a constant, as in NB1); Huber-White standard errors (in parentheses) are robust to heteroskedasticity and serial correlation; *** and ** indicate significance at the 1% and 5% levels respectively.

In sum, the results from the induced innovation regressions for ICT and advanced manufacturing technologies suggest that one avenue for governments to attenuate our measure of labour-saving technological change is through the compensation rates of low-skilled workers. Reducing these could make them more attractive to hire and therefore contribute to moderating the considerable decline in demand for their labour they experienced since 1995 according to our estimates in section 5.1. To maintain their wage income, the reduction in compensation levels from the viewpoint of employers could be achieved by lowering the social security contributions the latter pay for them, which together with wages and salaries constitute total labour compensation.

6. Summary and outlook

This paper contributes to the empirical literature on measuring the factor bias of and directing technological change. In the first part of the analysis, we provide a comprehensive assessment of the bias with regard to capital, energy and non-energy intermediates as well as low-, medium- and high-skilled labour for 25 EU countries from 1995 to 2009. We are not aware of a similarly extensive Europe-wide investigation into this issue. Using the factor cost share approach, we measure the bias of both exogenous technological change, represented by a time trend, and of endogenous technological change in energy- and labour-saving fields, where the level of technology is represented by patent stocks. Here, we add to the existing literature by using patent stocks in ICT and advanced manufacturing as measures of labour-saving technology, which is supported by our empirical findings. In the second part of the analysis, we investigate policy instruments to redirect technological change away from saving labour towards saving energy. Based on the literature on induced innovation, we model energy- and labour-saving patenting as functions of factor prices and taxes, government R&D expenditures and lagged patent stocks.

Our results in the first part indicate that exogenous technological change had a substantial labour-saving bias, especially concerning low- and medium-skilled workers, and a smaller energy-using bias. The overall cost share of labour declined at annual rates of 3 to 4% due to exogenous technological change in the specifications with and without endogenous technological change. Disaggregating by skill level, the decline was particularly pronounced for low-skilled labour, at approximately 5% per year on average between the two specifications. On the other hand, the cost share of high-skilled labour rose by about 2.5% per year on average, while that of medium-skilled labour declined by 1%. This pattern of declining shares of low- and medium-skilled labour coupled with a rising share of high-skilled labour suggests that technological change in our sample was skill biased. The average increase in the cost share of energy due to exogenous technological change was close to 0.8% per year.

We also find that endogenous technological change as measured by changes in the patent stocks in ICT and advanced manufacturing technologies was labour saving overall in both cases. In particular, technological change in ICT was medium-skilled labour saving and high-skilled labour using, adding to the existing empirical evidence on the skill bias of ICT. The cost share of medium-skilled labour declined by 0.64% per year and that of high-skilled labour rose by 0.34%. In addition, technological change in energy-saving fields was energy saving in several energy-intensive industries, with annual reductions in the energy cost shares of at most 0.54%. These estimates, although smaller than the biases of exogenous technological change, suggest that the link between the two parts of the empirical analysis - our assumptions on what constitutes energy- and labour-saving technology fields - holds at least to some extent.

The results of the induced innovation regressions in the second part suggest that two policy instruments could be combined into a strategy to redirect technological change - at least the part that we measure and that is amenable to policy influence - towards saving more energy and less labour. First, a higher tax rate on energy could be implemented to stimulate energy-saving innovation. The estimates suggest that an increase in the energy tax rate by 10% raises patenting in energy-saving fields by 2.1%. Second, our measure of labour-saving innovation could be attenuated by reducing the compensation of low-skilled workers. Here, we find that a

10% reduction in the compensation of low-skilled workers lowers patenting in ICT and advanced manufacturing by 5.1%. To maintain the wage income of low-skilled workers, the reduction in their compensation from the point of view of employers can be achieved by subsidising the social security contributions the latter pay for them. By using the revenue generated through higher energy taxes to make up for the shortfall in social security receipts, governments could thus accomplish the shift in the bias of technological change away from saving labour towards saving energy in a budget-neutral fashion.

The overall aim of the suggested policy strategy is to influence the direction of technological change while leaving its rate unaffected. To this end, the changes in the policy instruments can be calibrated such that their overall impact on the rate of technological change is neutral. However, whether this can be achieved simultaneously with revenue neutrality, given the difference in the estimated innovation effects of changes in the policy instruments described above, depends on the energy tax base and the size of social security contributions. We will be better able to assess this in a follow-up paper, which links the two parts of the analysis in this study to derive the overall effects of changes in the energy tax rate and low-skilled labour compensation, via their impact on rates of energy- and labour-saving innovation, on employment and energy demand. For this purpose, the dynamic New Keynesian (DYNK) model in Kratena and Sommer (2014a) will be used, which is a complete model of the economy that takes into account feedback effects of policy changes throughout the economy.[28] While Kratena and Sommer (2014a) simulate only the effect of shifting the bias of exogenous technological change, based on the results in this paper we will be able to quantify the effects of shifting the bias endogenously through changes in the policy instruments.[29]

The analysis in this paper has been concerned with factor demand and how to incentivise it to take a desired direction. Regarding labour however, the pronounced decline in demand for workers with low and intermediate skill levels relative to the highly skilled that emerges from our analysis highlights the importance of policies targeted at raising the supply of appropriately skilled labour. If we really are facing a “third industrial revolution” (The Economist, 2014), where ICT, computer algorithms and robotics combined make human labour redundant more quickly than in the past, it will be crucial for workers to be able to adapt equally quickly by acquiring the relevant skill set enabling them to take on the new roles that will certainly emerge for humans to fill. The policy implications are likely to differ across skill types. While for people without a secondary-school qualification, general upskilling is indispensable, medium-skilled workers may simply have to be trained to use new technologies in their jobs. In general, education and training policy will need to target disadvantaged groups and foster life-long learning in coordination with labour market policy. Policy-makers will need to be more forward-looking,

28 The DYNK model features a similar specification of the production side (firms) as this paper but also accounts for trade in intermediates. In addition, it contains specifications for private consumption (households), the labour market and the public sector. The model resembles a dual CGE model in most of its specifications but has the advantage that all key relationships are estimated rather than calibrated.

29 See also Kratena and Sommer (2014b), who use the DYNK model to simulate the effects of a green tax reform, i.e. higher taxes on energy and concomitantly reduced social security contributions. They find that energy use declines and employment rises, at least in the medium term. Using our model, these measures would be expected to have stronger effects, due to their additional impact on the bias of technological change.

reform-minded and capable of overcoming vested interests than in the past. The potential pay-offs, in terms of mitigating inequality and safeguarding political stability, are large.

Finally, we turn to the limitations of this paper and directions for future research. First, establishing the robustness of the results in the first part of the analysis to addressing remaining endogeneity concerns is work in progress, although initial estimates indicate that the main results carry through. Second, regarding our approach to directing technological change away from saving labour, it would have been preferable to identify labour-using technologies and look for policy instruments to stimulate them. However, whether an invention uses or saves labour is generally difficult to measure. It is not as clear from patent documents as is the case for energy-saving technologies and can often only be inferred with a time lag. Instead, using insights from the academic and policy literature on ICT and robotics, we were able to add to the empirical evidence on their labour-saving nature. Lastly, since our estimates of the factor biases of endogenous technological change are small compared to the biases of exogenous technological change, only part of the overall bias can be shifted by means of the policy instruments we identify in this paper. For future research, this calls for modelling other sources of endogenous technological change which in this study remain part of its exogenous component. A related more general point is that factors other than government policy instruments play a role in shaping the direction of technological change. For example, the statistical significance of the cumulated patent stock in labour- and energy-saving fields in the patent regressions highlights the importance of past innovative activity as well as the path-dependent nature of technological change.

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Appendix

Table I **Data sources**

DATASET	SOURCE
WIOD	http://www.wiod.org/new_site/home.htm
IEA Energy Prices and Taxes Statistics Database	http://www.oecd-ilibrary.org/energy/data/end-use-prices_ene-pric-data-en
OECD patent databases	http://www.oecd.org/sti/inno/oecdpatentdatabases.htm
Classifications of energy-saving technology fields	http://www.oecd.org/env/consumption-innovation/indicator.htm http://www.wipo.int/classifications/ipc/en/est/
OECD ICT classification	http://www.oecd.org/sti/inno/40807441.pdf
Classification of advanced manufacturing technology	Centre for European Economic Research, and Idea Consult. 2012. *Exchange of Good Policy Practices Promoting the Industrial Uptake and Deployment of Key Enabling Technologies*. Report for the European Commission, DG Enterprise and Industry. http://ec.europa.eu/enterprise/sectors/ict/files/kets/ex_of_practice_ket_final_report_en.pdf. Centre for European Economic Research, and TNO. 2010. *European Competitiveness in Key Enabling Technologies*. Background Report for European Commission, DG Enterprise. http://www.manufuture.org/manufacturing/wp-content/uploads/Final__report_07.06.10_KETs_Background_Report_2010_05_28.pdf.
IEA Energy Technology RD&D Statistics database	http://www.oecd-ilibrary.org/energy/data/iea-energy-technology-r-d-statistics/rd-d-budget_data-00488-en?isPartOf=/content/datacollection/enetech-data-en
OECD GBAORD by NABS socio-economic objective	http://stats.oecd.org/Index.aspx?DataSetCode=GBAORD_NABS2007

Table II **NACE revision 1.1 industries in the WIOD**

NAME	NACE CODE
Agriculture, hunting, forestry and fishing	AtB
Mining and quarrying	C
Food, beverages and tobacco	15t16
Textiles and textile products	17t18
Leather, leather products and footwear	19
Wood and products of wood and cork	20
Pulp, paper, paper products; printing and publishing	21t22
Coke, refined petroleum and nuclear fuel	23
Chemicals and chemical products	24
Rubber and plastics	25
Other non-metallic mineral products	26
Basic metals and fabricated metal products	27t28
Machinery nec	29
Electrical and optical equipment	30t33
Transport equipment	34t35
Manufacturing nec; recycling	36t37
Electricity, gas and water supply	E
Construction	F
Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of fuel	50
Wholesale trade and commission trade, except of motor vehicles and motorcycles	51
Retail trade, except of motor vehicles and motorcycles; repair of household goods	52
Hotels and restaurants	H
Land transport	60
Water transport	61
Air transport	62
Supporting and auxiliary transport activities; activities of travel agencies	63
Post and telecommunications	64
Financial intermediations	J
Real estate activities	70
Renting of machinery and other business activities	71t74
Public administration and defence; compulsory social security	L
Education	M
Health and social work	N
Other community, social and personal services	O
Private households with employed persons	P

Table III **Summary statistics: Translog cost share system (country level)**

		Mean	Std. Dev.	Min	Max	Observations
Capital share (s_K)	overall	0.201	0.032	0.103	0.297	N = 375
	between		0.031	0.143	0.279	n = 25
	within		0.013	0.143	0.263	T = 15
Low-skilled labour share (s_{LL})	overall	0.062	0.045	0.004	0.214	N = 375
	between		0.044	0.007	0.183	n = 25
	within		0.012	0.027	0.111	T = 15
Medium-skilled labour share (s_{LM})	overall	0.152	0.049	0.047	0.282	N = 375
	between		0.048	0.056	0.250	n = 25
	within		0.013	0.104	0.198	T = 15
High-skilled labour share (s_{LH})	overall	0.075	0.022	0.024	0.132	N = 375
	between		0.020	0.034	0.121	n = 25
	within		0.010	0.049	0.119	T = 15
Energy share (s_E)	overall	0.040	0.018	0.011	0.119	N = 375
	between		0.017	0.014	0.084	n = 25
	within		0.008	0.021	0.075	T = 15
Materials share (s_M)	overall	0.470	0.054	0.327	0.642	N = 375
	between		0.053	0.364	0.580	n = 25
	within		0.016	0.366	0.532	T = 15
Relative price of capital (p_K/p_{LH})	overall	0.740	0.221	0.265	1.819	N = 375
	between		0.153	0.442	1.120	n = 25
	within		0.163	0.383	1.752	T = 15
Relative low-skilled labour compensation (p_{LL}/p_{LH})	overall	0.760	0.213	0.295	1.761	N = 375
	between		0.151	0.460	1.078	n = 25
	within		0.153	0.425	1.676	T = 15
Relative medium-skilled labour compensation (p_{LM}/p_{LH})	overall	1.008	0.082	0.724	1.285	N = 375
	between		0.064	0.815	1.119	n = 25
	within		0.053	0.888	1.201	T = 15
Relative price of energy (p_E/p_{LH})	overall	1.075	0.376	0.425	2.656	N = 375
	between		0.281	0.562	1.557	n = 25
	within		0.256	0.476	2.173	T = 15
Relative price of materials (p_M/p_{LH})	overall	0.846	0.176	0.357	1.187	N = 375
	between		0.140	0.542	1.087	n = 25
	within		0.110	0.534	1.322	T = 15
ICT patent stock rel. to output (T_{ICT}/Y)	overall	0.418	0.650	0	3.029	N = 375
	between		0.642	0.001	2.335	n = 25
	within		0.159	-0.949	1.175	T = 15
Advanced manufacturing patent stock rel. to output (T_{AM}/Y)	overall	0.079	0.110	0	0.477	N = 375
	between		0.109	0.000	0.445	n = 25
	within		0.027	-0.029	0.284	T = 15
Energy-saving patent stock rel. to output (T_{ESAV}/Y)	overall	0.104	0.138	0	0.650	N = 375
	between		0.138	0.000	0.494	n = 25
	within		0.024	0.009	0.260	T = 15

Table IV **Summary statistics: Induced innovation equations (country level)**

Energy-saving technologies		**Mean**	**Std. Dev.**	**Min**	**Max**	**Observations**
Patent count (P_{ESAV})	overall	155.5	354.6	0	2289.1	N = 375
	between		354.7	0.367	1727.3	n = 25
	within		68.0	-501.8	717.3	T = 15
Energy price (p_E)	overall	1.656	0.744	0.874	6.194	N = 375
	between		0.408	1.276	3.279	n = 25
	within		0.627	-0.623	4.571	T = 15
Implicit energy tax rate (τ_E)	overall	1.324	0.655	0.095	3.105	N = 371
	between		0.602	0.427	2.773	n = 25
	within		0.281	-0.158	2.507	T-bar = 14.8
Energy-saving govt R&D ($R\&D_{ESAV}$)	overall	64.9	70.7	0.038	403.2	N = 219
	between		55.5	0.488	182.6	n = 19
	within		44.9	-52.1	342.1	T-bar = 11.5
Energy-saving patent stock (T_{ESAV})	overall	154.5	346.2	0.001	1957.1	N = 375
	between		350.5	0.092	1645.9	n = 25
	within		40.4	-111.5	465.7	T = 15
Total patent count (P)	overall	2425.4	5339.5	0	28947.9	N = 375
	between		5412.4	4.833	25998.5	n = 25
	within		559.5	-3705	5374.9	T = 15
Pre-sample mean ($\bar{P}_{ESAV,P}$)	overall	140.7	316.9	0	1478.3	N = 375
	between		323.0	0	1478.3	n = 25
	within		0	140.7	140.7	T = 15

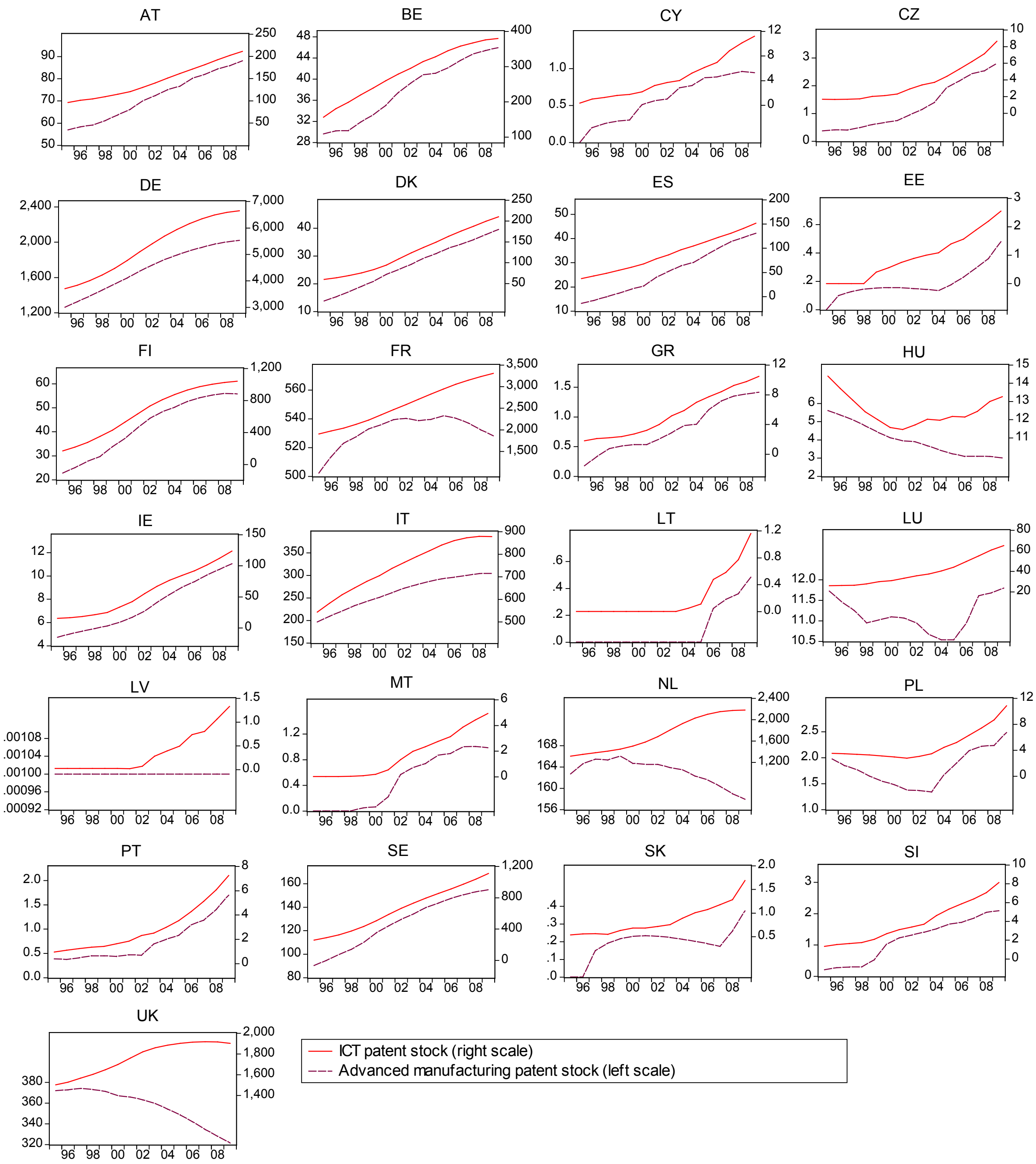
ICT and advanced manufacturing		**Mean**	**Std. Dev.**	**Min**	**Max**	**Observations**
Patent count (P_{LSAV})	overall	697.3	1428.8	0	8184.6	N = 375
	between		1430.9	1.256	6495.2	n = 25
	within		265.8	-1380	2386.7	T = 15
Low-skilled labour compensation (p_{LL})	overall	1.167	0.491	0.623	3.870	N = 375
	between		0.409	0.737	2.463	n = 25
	within		0.282	-0.296	2.872	T = 15
Medium-skilled labour compensation (p_{LM})	overall	1.640	0.766	1.000	6.010	N = 375
	between		0.541	1.111	3.102	n = 25
	within		0.553	-0.462	4.548	T = 15
High-skilled labour compensation (p_{LH})	overall	1.630	0.740	0.986	4.742	N = 375
	between		0.535	1.071	2.778	n = 25
	within		0.521	-0.148	3.798	T = 15
Labour-saving govt R&D ($R\&D_{LSAV}$)	overall	782.7	2081.9	0.991	19627.7	N = 271
	between		3108.8	4.388	14497.0	n = 21
	within		658.0	-5370.3	5913.4	T-bar = 12.9
Labour-saving patent stock (T_{LSAV})	overall	620.4	1322.8	0.001	7393.5	N = 375
	between		1320.8	0.211	5925.5	n = 25
	within		266.1	-1103.6	2088.3	T = 15
Total patent count (P)	overall	2425.4	5339.5	0	28947.9	N = 375
	between		5412.4	4.833	25998.5	n = 25
	within		559.5	-3704.7	5374.9	T = 15
Pre-sample mean ($\bar{P}_{LSAV,P}$)	overall	450.3	985.3	0	4377.0	N = 375
	between		1004.3	0	4377.0	n = 25
	within		0	450.3	450.3	T = 15

Table V **Bias of endogenous technological change: industry-level estimates of system (13)**

NACE 1.1 SECTORS	bias_t_K (ρ_{tK}/s_K)	bias_t_LL (ρ_{tLL}/s_{LL})	bias_t_LM (ρ_{tLM}/s_{LM})	bias_t_LH (ρ_{tLH}/s_{LH})	bias_t_E (ρ_{tE}/s_E)	bias_t_M (ρ_{tM}/s_M)	bias_ict_LL $(\rho_{ICT,LL}/s_{LL})$	bias_ict_LM $(\rho_{ICT,LM}/s_{LM})$	bias_ict_LH $(\rho_{ICT,LH}/s_{LH})$	bias_esav_E $(\rho_{ESAV,E}/s_E)$	bias_am_LL $(\rho_{AM,LL}/s_{LL})$	bias_am_LM $(\rho_{AM,LM}/s_{LM})$	bias_am_LH $(\rho_{AM,LH}/s_{LH})$
AtB	0.0051	**-0.0468**	-0.0024	**0.0547**	**0.0222**	**0.0071**	0.0482	-0.0357	0.0085	-0.0083	-0.0037	-0.0141	**-0.0776**
C	**0.0413**	**-0.0706**	**-0.0568**	-0.0285	0.0160	-0.0021	-0.0753	**-0.0551**	*-0.0603*	0.0511	**0.1473**	**0.1297**	**0.1306**
15t16	**0.0183**	**-0.0411**	**-0.0052**	**0.0366**	0.0028	**-0.0020**	**-0.0275**	**-0.0301**	0.0005	-0.0266	0.0158	0.0106	-0.0265
17t18	**-0.0269**	**-0.0283**	-0.0061	**0.0529**	-0.0034	**0.0066**	**0.0624**	**0.0516**	**0.0490**	0.0313	0.0151	-0.0050	-0.0475
20	0.0075	**-0.0504**	-0.0034	**0.0312**	**0.0139**	0.0010	-0.0036	-0.0087	0.0106	0.0526	0.0100	0.0204	-0.0063
21t22	-0.0063	**-0.0424**	**-0.0082**	**0.0419**	0.0137	**0.0037**	-0.0230	**-0.0450**	*0.0230*	-0.0590	0.0013	0.0183	-0.0134
24	-0.0018	**-0.0470**	**-0.0235**	**0.0312**	**0.0235**	**0.0037**	-0.0612	**-0.0660**	0.0060	-0.0607	**0.1188**	**0.0517**	0.0027
25	-0.0059	**-0.0376**	-0.0065	**0.0451**	0.0101	**0.0032**	-0.0177	-0.0321	-0.0061	0.0314	-0.0080	**0.0552**	0.0115
26	**-0.0126**	**-0.0429**	-0.0043	**0.0442**	0.0091	**0.0055**	-0.0007	*-0.0137*	0.0152	0.0332	0.0165	0.0122	-0.0229
27t28	**-0.0094**	**-0.0534**	**-0.0133**	**0.0386**	**0.0226**	**0.0052**	-0.0089	-0.0088	0.0300	0.0497	*0.0219*	0.0224	-0.0020
29	**-0.0073**	**-0.0523**	-0.0022	0.0417	**0.0226**	**0.0031**	0.0326	-0.0074	0.0086	-0.0163	**0.0662**	0.0072	*-0.0318*
30t33	**-0.0187**	**-0.0696**	-0.0073	**0.0426**	**0.0346**	**0.0069**	0.0133	0.0004	0.0171	**0.1337**	0.0270	*0.0221*	-0.0014
34t35	0.0057	**-0.0780**	**-0.0108**	**0.0255**	-0.0175	**0.0049**	**-0.0667**	**-0.0947**	0.0021	0.0394	-0.0511	*0.0211*	-0.0047
36t37	0.0033	**-0.0488**	**-0.0160**	**0.0385**	**0.0233**	**0.0052**	0.0024	-0.0136	0.0044	-0.0077	*0.0238*	**0.0352**	-0.0147
E	-0.0059	**-0.0603**	**-0.0435**	**0.0085**	**0.0273**	-0.0028	0.0582	**-0.0635**	0.0986	*-0.0423*	-0.0539	**0.0556**	-0.0197
F	0.0074	**-0.0351**	-0.0032	**0.0137**	0.0108	**0.0029**	-0.0572	0.0157	0.0017	**0.1039**	0.0144	-0.0065	0.0259
50	-0.0050	**-0.0371**	-0.0025	**0.0262**	0.0041	**0.0075**	**-0.0772**	0.0010	0.0159	0.0399	0.0341	0.0221	0.0096
51	**0.0071**	**-0.0405**	**-0.0076**	**0.0300**	0.0134	0.0023	-0.0093	0.0094	0.0092	0.0330	0.0387	0.0164	-0.0057
52	-0.0051	**-0.0406**	**-0.0058**	**0.0331**	0.0149	**0.0100**	-0.0299	0.0041	0.0065	*-0.0483*	0.0316	0.0149	-0.0065
H	**0.0067**	**-0.0260**	**0.0059**	**0.0325**	**-0.0171**	0.0002	**-0.1157**	**0.0315**	0.0167	0.0197	-0.0027	0.0049	-0.0285
60	-0.0030	**-0.0405**	**-0.0181**	**0.0400**	**0.0379**	**0.0064**	**-0.0936**	-0.0120	*0.0341*	*-0.0389*	-0.0156	0.0075	-0.0089
62	-0.0123	**-0.0717**	**-0.0310**	**0.0381**	**0.0303**	**0.0102**	-0.0146	0.0201	0.0042	0.0474	-0.0059	-0.0070	-0.0590
63	-0.0083	**-0.0366**	-0.0007	**0.0401**	**0.0241**	0.0024	-0.0337	-0.0165	0.0264	-0.0909	-0.0142	-0.0159	-0.0848
64	**-0.0078**	**-0.0718**	**-0.0353**	0.0462	0.0177	**0.0242**	**-0.1332**	0.0071	*0.0431*	0.0548	-0.0064	0.0186	0.0260
J	-0.0009	**-0.1043**	**-0.0383**	0.0218	-0.0231	**0.0159**	**-0.0968**	0.0070	0.0507	0.0763	-0.1244	0.0104	0.0222
70	**-0.0054**	-0.0017	**0.0095**	**0.0324**	0.0654	**0.0089**	-0.0401	**-0.0580**	-0.0505	0.0984	0.0537	0.0211	-0.0157
71t74	**-0.0140**	**-0.0393**	**-0.0048**	**0.0183**	-0.0123	**0.0038**	-0.0163	-0.0124	-0.0185	**0.1400**	0.0543	0.0111	0.0048
L	0.0008	**-0.0638**	**-0.0085**	**0.0222**	0.0072	**0.0042**	**0.0659**	-0.0115	0.0674	-0.0128	-0.0354	-0.0004	-0.0478
M	-0.0024	**-0.0462**	**-0.0113**	**0.0067**	**0.0247**	0.0024	0.0021	**0.0348**	0.0476	0.0173	0.0327	-0.0113	-0.0255
N	0.0027	**-0.0427**	**-0.0100**	0.0096	0.0056	**0.0108**	**0.0468**	0.0025	**0.0452**	0.0063	0.0180	-0.0080	-0.0558
O	**0.0077**	**-0.0360**	**-0.0090**	0.0192	0.0066	0.0015	0.0245	**-0.0222**	-0.0092	0.0316	-0.0493	0.0055	-0.0366

Notes: System (13) estimated separately for 31 NACE 1.1. industries using seemingly unrelated regressions (SUR); significant factor-saving biases given in green, factor-using biases in red; figures in bold font are significant at the 1% level, underlined figures at the 5% level, figures in italics at the 10% level; standard errors (available upon request) robust to cross-equation correlation. Significant factor biases of technological change in advanced manufacturing only highlighted for manufacturing industries.

Figure I **Patent stocks in ICT and advanced manufacturing technologies, 1995-2009**



Notes: Figures shown are patent stocks constructed according to equation (18).

Source: OECD REGPAT and Citations databases, WIFO calculations based on technology classifications by OECD and Centre for European Economic Research and TNO (2010, 2012).

Table VI **Elasticities of demand and substitution derived from estimates of system (13)**

Own-price elasticities of demand		Allen partial elasticities of substitution	
ε_{K}	-0.682	$\sigma_{K,LL}$	-1.518
ε_{LL}	-0.158	$\sigma_{K,LM}$	0.270
ε_{LM}	-0.271	$\sigma_{K,LH}$	0.887
ε_{LH}	-0.378	$\sigma_{K,E}$	0.904
ε_{E}	-0.231	$\sigma_{K,M}$	1.343
ε_{M}	-0.460	$\sigma_{LL,LM}$	1.272
		$\sigma_{LL,LH}$	1.891
		$\sigma_{LL,E}$	1.213
		$\sigma_{LL,M}$	-0.571
		$\sigma_{LM,LH}$	-1.655
		$\sigma_{LM,E}$	-1.921
		$\sigma_{LM,M}$	0.678
		$\sigma_{E,LH}$	-0.539
		$\sigma_{E,M}$	0.910
		$\sigma_{M,LH}$	0.949

Notes: Values reported are medians across countries and time. Allen substitution elasticities > 0 denote substitutes and < 0 complements. $\sigma_{ij} = \sigma_{ji}$.

Project Information

Welfare, Wealth and Work for Europe

A European research consortium is working on the analytical foundations for a socio-ecological transition

Abstract

Europe needs change. The financial crisis has exposed long-neglected deficiencies in the present growth path, most visibly in the areas of unemployment and public debt. At the same time, Europe has to cope with new challenges, ranging from globalisation and demographic shifts to new technologies and ecological challenges. Under the title of Welfare, Wealth and Work for Europe – WWWforEurope – a European research consortium is laying the analytical foundation for a new development strategy that will enable a socio-ecological transition to high levels of employment, social inclusion, gender equity and environmental sustainability. The four-year research project within the 7th Framework Programme funded by the European Commission was launched in April 2012. The consortium brings together researchers from 34 scientific institutions in 12 European countries and is coordinated by the Austrian Institute of Economic Research (WIFO). The project coordinator is Karl Aiginger, director of WIFO.

For details on WWWforEurope see: www.foreurope.eu

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Utrecht University	UU	Netherlands
Vienna University of Economics and Business	WU	Austria
Centre for European Economic Research	ZEW	Germany
Coventry University	COVUNI	United Kingdom
Ivory Tower	IVO	Sweden
Aston University	ASTON	United Kingdom