Is Innovation Increasing Capital Intensity in Europe?

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Abstract

Using data on 14 EU countries from 1980-2007, this paper measures the role innovation has had in increasing capital intensity in Europe. A supply side system of the normalised CES production function and its two first order conditions are used to estimate the parameters using NLSUR. The results show innovation has not been capital biased, instead it has mitigated the rise of capital intensity in the region and improved the share of labour in production.

JEL: C22, E23, E25, 030, 051

1 Introduction

Since the 1970s, the share of income from labour has declined relative to capital in the EU (European Commission, 2007). Owing to the concentrated ownership of capital assets, this divergence in capital and labour is believed to be supporting a rise in income inequality in the developed world (Piketty, 2014). Karabarbounis and Neiman (2013) and others have cited the rise of cheap labour in Asia, the decline in the cost of capital, development of IT and computers and weaker unions as reasons why the capital share has risen relative to labour in output. Another possible cause is a bias of innovation in production, where new techniques developed to produce goods are creating more productive capital relative to labour. This paper studies this effect, whether innovation in Europe is contributing to higher capital intensity and hence income inequality in the region.

The impact of inequality at the social level has been clearly documented[1], however, new theory studying its impact on economic growth shows a link between higher inequality and weaker, less sustainable growth. For example, the theory of secular stagnation revived by Summers (2013) argues that the higher savings rate of the wealthy and higher inequality act to subdue economic activity if savings are higher than productive investment. Other examples such as Kumhof et al. (2015) and Rajan (2012) argue that inequality leads to a credit boom, which then raises the chances of financial crisis.

To study whether innovation in production is itself contributing to the rise in capital intensity, innovation for capital and labour are estimated. For the period of 1980-2007, the evolution of capital and labour intensity are measured, with changes attributed to changing volumes of the inputs, or technical progress. As an addition from previous literature, production functions for the primary, secondary, tertiary and quaternary industries are estimated to better understand where the evolution of technical bias has occurred.

This paper uses the constant elasticity of substitution (CES) production function to estimate innovation for the four sectors of the economy. A three equation supply side model is developed based on the first order conditions (FOCs) and production function of the EU economy. The production function will also be normalized, to allow for a more accurate interpretation of the parameters measured. The results show that innovation is not capital biased, in fact, innovation has been capital saving between 1980 and 2007. This result rejects the hypothesis that innovation has acted to increase capital intensity in the region, instead, it has acted to mitigate it. Estimates are consistent across each sector of the economy, however, the functional forms of innovation for capital and

[1] See Molinas (1998) for the impact of inequality on community solidarity, Wilkinson (2006) for its impact on health and longevity and Duncan and Murnane (2011) on its impact on education and job opportunity.

labour differ. In the primary sector, innovation is constant, in the secondary, tertiary and quaternary sectors, innovation follows an exponential functional form.

In section 2 the CES production function is introduced and theories of technical innovation are discussed. Section 3 reviews previous empirical findings of innovation. Section 4 introduces the model behind the analysis and section 5 discusses the source of the data and the development of the dataset used for analysis. Section 6 examines the results of the paper and section 7 provides some robustness checks for the model used. Section 8 discusses the broader implications of this analysis and avenues for further research. Finally, section 9 draws conclusions for the paper.

2 Theoretical Background

Innovation in this paper is measured by technical change in production, which is consistent with Binswanger and Ruttan (1978). It is defined as a change in the techniques of production at the individual firm, industry or economy level caused by developments from learning by doing, or through research and development.[2] There is a cost to innovation but once completed, the dissemination of the innovation is relatively costless. To measure the bias of technical change Hicks (1963) uses a more instructive definition for estimation - the response of the share of an input in the value of output to a change in the level of technology.

This paper aggregates factors to a two factor production function; labour and capital, where labour is the human contribution to output and capital accounts for the goods used in production, such as a hammer used in the production of pins. Technical change is therefore biased towards labour (capital) if the focus of the technique is labour (capital) intensive. For example, a new managerial technique that improves the productivity of workers in a manufacturing company is a labour augmenting technical change. It is important to note however, that although technical change may be biased in one direction, in reality, technical change tends to save both capital and labour simultaneously. This section discusses a formal exposition of technical change, before discussing theories of technical bias based on either market power, or perfect competition.

2.1 A Normalised CES Production Function

In a production function, a firm's output is separated into the factor inputs and technical progress. In this case, output is a function of capital, labour and technical change for capital and labour.

[2] R&D creates new blueprints, new seeds etc.

$$Y = F(A^K K, A^L L) \tag{1}$$

Where output is Y, K is capital, L is labour and technical change for capital and labour are defined as A^K and A^L. A function which allows for a broad estimate of the EU's production is the CES production function developed by Arrow et al. (1961). This production function assumes a constant elasticity of substitution between capital and labour, but technical change can take various forms. The elasticity defines the rate of substitution between factors, depending on a change in their prices and ranges from 0 to ∞. An elasticity of less than unity means factors are gross complements, which means a rise in the cost of one input leads to a decline in the use of both inputs. An elasticity above unity means factors are gross substitutes, which means a rise in the cost of one input leads to a reduction in the use of that input and an increase in the use of the other input. In a CES production function, this rate of substitution remains fixed and production can be written as follows:

$$Y = C\left[\pi(A^K K)^{\frac{1-\sigma}{\sigma}} + (1-\pi)(A^L L)^{\frac{1-\sigma}{\sigma}}\right]^{\frac{\sigma}{1-\sigma}} \tag{2}$$

Where C is the efficiency parameter of the factor inputs and determines how efficiently factors are used in production, π is the capital share of output, which lies between 0 and 1 and σ is the elasticity of substitution between capital and labour.

A development in estimating the CES production function has been to normalise the equation. The elasticity of substitution is estimated as a point elasticity, where factors substitute for one another in production at a given rate at a given time. So to be able to compare the other parameters with this elasticity of substitution, the entire production function is fixed at a benchmark point too. De La Grandville (1989) shows that there is a point of tangency across a family of CES production functions where the only parameter that differs, is the elasticity of substitution. It is therefore preferable to estimate at this point of tangency so that the technical change of labour in a certain period is comparable to technical change in capital and the elasticity of substitution in that same period. To estimate from this tangency, or benchmark point, the variables of the production function must be normalised. The normalisation requires a benchmark point for capital deepening (K_0) and a given level of production (Y_0), which are both averages of the capital and production time series. On top of this, a benchmark capital share in output is required (π_0), where π_0 is defined by the following equation.

$$\pi_0 = \frac{r_0 K_0}{p_0 Y_0} \tag{3}$$

Where r_0 is the benchmark rental rate of capital and p_0 is the benchmark price for output for the sample.

In this exposition the functional form of technical progress is assumed and technical progress is proxied by time. It is assumed that technical change develops from year to year and hence progress in technical change can be measured as progress through time. For the initial exposition, it is assumed factor augmenting technical progress is constant and takes the following form.

$$A_t^K = A_0^K e^{\gamma_K (t-t_0)} \tag{4}$$

$$A_t^L = A_0^K e^{\gamma_L (t-t_0)} \tag{5}$$

Where γ_K is technical progress for capital, γ_L is technical progress of labour and t represents time and t_0 is the average time over the sample, used to normalise technical change. At the benchmark point, technical progress of both capital and labour are 0.

Following Klump and de La Grandville (2000), for technical progress to have the same fixed point as the elasticity of substitution, it must also be normalised with respect to the corresponding output and factor input average.

$$A_0^K = \frac{Y_0}{K_0}\Big(\frac{1}{1-\pi_0}\Big)^{1/C} \tag{6}$$

$$A_0^L = \frac{Y_0}{K_0}\Big(\frac{1}{\pi_0}\Big)^{1/C} \tag{7}$$

The resulting production function, takes the following form if we assume the benchmark output level is the efficiency parameter.

$$Y_t = Y_0 \left[\pi_0 \Big(\frac{e^{\gamma_K (t-t_0)} K_t}{K_0} \Big)^{\frac{1-\sigma}{\sigma}} + (1-\pi_0) \Big(\frac{e^{\gamma_L (t-t_0)} L_t}{L_0} \Big)^{\frac{1-\sigma}{\sigma}} \right]^{\frac{\sigma}{1-\sigma}} \tag{8}$$

This production function studies the factor inputs in production, the technical bias of production and the complementarity or substitutability of the factors in production.

The FOCs are derived to create the three equation system. This system of equations has two distinct advantages over a single equation approach to estimating technical change. Firstly, by using the FOCs, firms are assumed to be optimising agents, which is an assumption of the data (León-Ledesma et al., 2010). Secondly, cross-equation parameter constraints are imposed when the system is regressed, this should result in more accurate estimates of the parameters.

$$\frac{\partial Y_t}{\partial K_t} = \pi_0 \left(\frac{Y_0}{K_0} e^{\gamma_K (t-t_0)} \right)^{\frac{\sigma-1}{\sigma}} \left(\frac{Y_t}{K_t} \right)^{\frac{1}{\sigma}} \tag{9}$$

$$\frac{\partial Y_t}{\partial L_t} = (1-\pi_0)\left(\frac{Y_0}{L_0}e^{\gamma_L(t-t_0)}\right)^{\frac{\sigma-1}{\sigma}}\left(\frac{Y_t}{L_t}\right)^{\frac{1}{\sigma}} \tag{10}$$

At this point, the impact of technical change can be demonstrated, through its impact on the marginal products of inputs. The clearest way of understanding the effect of technical change is by looking at the relative marginal product of capital to labour, which can be defined as follows:

$$\frac{MP_K}{MP_L} = \frac{1-\pi_0}{\pi_0}\left(\frac{L_0}{K_0}e^{(\gamma_K-\gamma_L)(t-t_0)}\right)^{\frac{\sigma-1}{\sigma}}\left(\frac{L_t}{K_t}\right)^{\frac{1}{\sigma}} \tag{11}$$

From this equation, it is clear that the impact of technical change of either capital or labour depends on the elasticity of substitution, therefore normalising the system to compare the parameters in each period is key for interpreting the results. If σ is greater than unity (factors are substitutes), then an increase in technical progress of capital for example, increases the relative marginal product of capital. On the other hand, if σ is below unity (factors are complements), then an increase in technical change reduces the relative marginal product of capital. In the case where σ is 1, then technical change has no impact on the relative marginal products of either capital or labour.

Where $\sigma < 1$ capital augmenting technical improves the relative marginal product of labour. This counter intuitive result is caused by the complementarity of factors. The rise in the productivity of capital leads to a rise in demand for labour that is larger than the rise in demand for capital. As a result of this higher demand, the marginal product of labour increases more than the marginal product of capital. Therefore a rise in capital augmenting technical change actually increases the relative marginal product of labour (Acemoglu, 2002). When $\sigma < 1$, capital augmenting technical change also reduces the income share of capital.[3]

The interpretation is therefore as follows, if the elasticity of substitution is above unity then if $\gamma_i > 0$ the technical change is factor augmenting and if $\gamma_K > \gamma_L$ and $\gamma_K > 0$ then technical change is capital biased. In the alternative case, where $\sigma < 1$, a positive technical change is factor saving and biased towards the other factor. Finally, when $\gamma_i < 0$, with a below unity σ, technical progress is biased towards that factor. It is therefore clear that capital augmenting technical change does not necessarily lead to a capital bias in technical change. Only when the elasticity of substitution is above unity does positive technical change of capital lead to a capital bias.

Equation (11) also shows that an increase in the relative volume of capital reduces the relative marginal product of capital. This is a common finding that creates the downward sloping demand curve for factor inputs.

The system of equations assumes profit maximisation so the second order conditions

[3]The same reasoning is used and is discussed in detail in León-Ledesma et al. (2010).

are checked to make sure the estimates will correspond to a maximum, rather than a minimum. This is done by differentiating the partial derivatives again, the following result occurs:

$$\frac{\partial^2 Y_t}{\partial K_t^2} = -\frac{1}{\sigma}\pi_0 \left(\frac{Y_0}{K_0} e^{\gamma_K (t-t_0)} \right) \left(\frac{Y_t}{K_t} \right)^{\frac{1}{\sigma}} K^{-1} \tag{12}$$

$$\frac{\partial^2 Y_t}{\partial L_t^2} = -\frac{1}{\sigma}(1-\pi_0) \left(\frac{Y_0}{L_0} e^{\gamma_L (t-t_0)} \right) \left(\frac{Y_t}{L_t} \right)^{\frac{1}{\sigma}} L^{-1} \tag{13}$$

All variables in these second order conditions are positive values, as a result, the values of the equation are necessarily negative. This means the estimated values represent maximums, consistent with profit maximisation of the firm.

2.2 Theories of Technical Bias

This section discusses the development of the theory of factor biased technical change. The theory began with Hicks in the 1930s and developed slowly over the 20th Century before being revived by Acemoglu in 2002. Capital augmenting technical growth can now be fitted into neoclassical growth theory models, which have traditionally relied on labour augmenting technical change only to allow markets to clear.

Hicks (1963) first proposition was that technical innovation occurs to minimise the cost of the relatively expensive factor in production. A profit maximising company will innovate to reduce its use of the relatively scarce factor inputs in production, due to the high cost and instead, use the lower cost factor input more abundantly in production. For example, if wages presented a higher cost than the user cost of capital, the firm would look for new innovation that reduces the use of labour relative to capital, to reduce their costs of production. This cost minimization approach is consistent across the theories that follow.

The next step was the theory of induced technical change of the 1960s and 70s, with Drandakis and Phelps (1966) formalising the role of factor saving technical bias caused by the price of capital and labour. A paper by Kennedy (1964) introduced the idea of the innovation possibilities frontier, which determined the direction of the technical change based on the factor shares in production. If for example, the labour share rose, innovation would occur until the factor shares returned to a previous equilibrium. Binswanger and Ruttan (1978) summarises the theory, where a finite set of resources are used to invest in either capital or labour saving research projects by the firm. The finite set of resources assumption is key as it creates a trade off between research for capital or labour augmenting technical change. The share of investment in capital or labour augmenting research projects depends on the benefits expected to be derived from the projects - the discounted sum of cost savings caused by the innovation in each year of its use (Binswanger and Ruttan, 1978). Where the cost saving is the savings of factor inputs in production, multiplied by the price of the factor. Research in technical innovation is therefore a function of the price of inputs, but crucially, it is also a function of the volume of inputs used in production. The theory was however criticized due to the lack of reasoning as to why firms would enact technical progress and whether innovation was exogenous or endogenous to firms. For example, Salter (1966) argued firms were interested in cost reductions overall, not reductions specific to a factor. The solution to these issues only developed in endogenous growth models such as Romer (1989) later in the 1980s and 90s, using the formal introduction of market power.

2.2.1 Theories with Market Power

Directed technical change theory (Acemoglu, 2002) is currently the predominant theory of technical change and developed the previous theory by using concepts from endogenous growth models. The theory uses the assumption of market power from Romer (1989) to justify the cost of R&D investment for firms. Market power allows for a markup over costs and so innovation is therefore countered by higher profits caused by the innovation.[4] As with previous theory finite resources and internal development of technical change are also assumed.[5]

In this framework, two forces drive technical change for a profit-maximising firm: the price effect and the market size effect. Firstly, the price effect occurs if there is an increase in the price of one of the inputs. For example, if the user cost of capital rose by 10% in a year relative to wages in a firm, the higher cost of the capital input would provide an incentive for the firm to invest in innovation that improves the productivity of capital. This technical change therefore reduces the amount of capital required in production, reducing the cost of production for the firm. Secondly, the market size effect creates a bias of technical progress towards the input that is used most in production. For example, if the firm's production requires 125 units of capital and 100 units of labour and the price of each good is equal, then the firm has an incentive to improve the productivity of the relatively more abundant good: capital. In this case a 1% improvement in the productivity of capital has a larger impact on overall productivity than the same rise in productivity of labour. In the real world, of course, technical progress is caused by a combination of these effects and so interpretation is less clear cut.

[4] Technical change would reduce the costs of production, while not affecting prices, allowing for a markup to arise and hence higher profits.

[5] This is consistent with Pavitt (1984) who finds that in the majority of industrial sectors, within firm innovation is dominant, as the innovation is specific to the production process of the firm.

Acemoglu shows that the elasticity of substitution defines which of the two effects dominates in production. When the elasticity of substitution between capital and labour is low, the price effect dominates, when the elasticity of substitution is larger, the market size effect dominates. A number of results are borne out of this model, the first is what is termed the"weak induced bias hypothesis" where irrespective of the value of the elasticity of substitution[6], an increase in the abundance of a factor will create some technical bias towards that factor. The"strong induced bias hypothesis" states that with a sufficiently large elasticity of substitution - breaching a threshold that is between 1 and 2 - demand for the abundant factors can become upward sloping, due to the increasing returns to scale caused by the non rivalry nature of technical change. In this case, technical change can create a bias in production which persistently increases the income share of that factor. This is an important result, as it means technical change may lead to an ever increasing capital share of income and mean technical progress will contribute to a higher income share for capitalists.

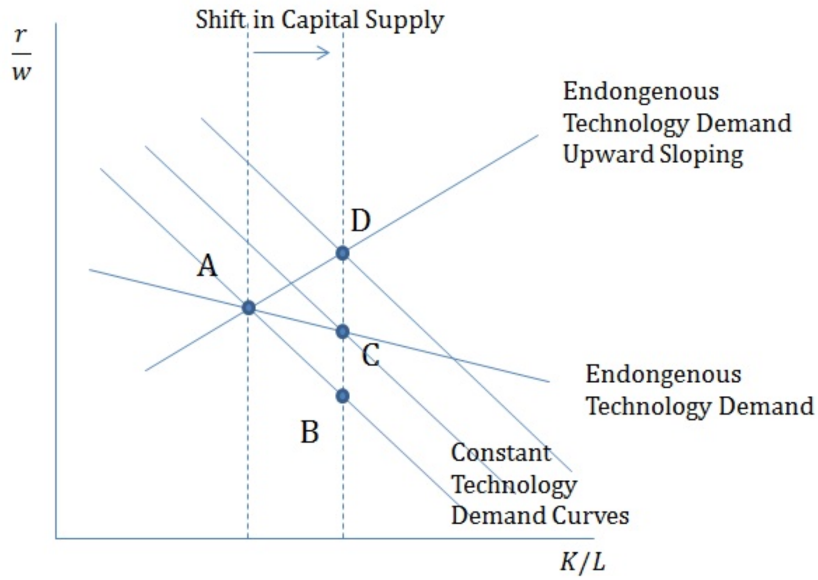
The two hypothesis of directed technical change are represented in figure 1, where σ is assumed to be greater than 1. Without endogenous technical change, a shift in the capital abundance relative to labour, pushes the economy from point A to point B, the marginal product of capital (r) declines, shifting the equilibrium downwards. However, with endogenous technology, the weak induced bias hypothesis leads to technical change which favours capital, this shifts the constant (short term) technology demand curve outwards, mitigating some of the decline in the user cost of capital and shifting production to point C, creating a flatter long term endogenous technology curve. In the case of the strong induced bias, technical progress of the factor is sufficient to move the economy from A to D, causing an upward sloping technology curve. At this point, the return on this factor rises.

Basing theory on directed technical change, Acemoglu embeds short term capital biased technical change into the neoclassical growth theory in an alternative paper (Acemoglu, 2003). In this paper, he argues that in the long run, technical change remains labour augmenting only and that capital augmenting technical change is a transitory phenomenon not present when the economy is on its balanced growth path (BGP).[7] In the neoclassical model, capital deepening and labour augmenting technical growth combine to maintain a consistent capital and labour income share in production, allowing the economy to achieve a BGP. A crucial assumption made by the author is that capital and labour are complements, that $\sigma < 1$. As a result, Acemoglu argues an increase in the user cost of capital, or a rise in the supply of capital causes technical

[6]As long as the elasticity of substitution between capital and labour differs from unity.

[7]Where the balanced growth path of the neoclassical growth model is defined as growth that is consistent with the Kaldor facts of a constant capita-output ratio and capital, labour share in national output (Solow, 1956).

Figure 1: Technical Change



Source: Acemoglu (2002)

change which brings the economy back to the BGP and balanced factor shares.

Acemoglu further argues that there two avenues through which capital intensity rises; via capital augmenting technical change and capital accumulation, while labour intensity only rises through technical change, as a labour stock cannot be accrued. Therefore, the author argues there is a natural bias in technical change towards labour. It is then argued that this bias means in the long run, technical change is purely labour augmenting and that capital augmenting technical change is a transitory phenomenon.

2.2.2 Theory with perfect competition

Previous theory on technical change has relied on market power to justify the high sunk cost of investment. However, a paper by Boldrin and Levine (2008) introduces a model where price taking firms justify innovation due to capacity constraints. The capacity constraints create a cost to disseminating information, creating a scarcity of the new innovation in initial periods of its use, this creates an advantage to innovating firms in their market. The authors cite a number of examples in the paper that are consistent with this theory, include the USA's agricultural innovation in the 1950s and the 1960s, where new plant varieties and animal species were not patentable and the seed nurseries were highly decentralised, innovation remained high and spurned the Green Revolution in the 1970s. Another example is the Indian pharmaceuticals industry, which does not recognize many patents from the western world. Even with these issues, Indian reproduction of the patented drugs is still delayed due to production and market constraints.

The theory of technical change depends on a set of conditions, which include internal innovation, scarce resources and in some cases, a below unity elasticity of substitution. Research from Pavitt (1984) has proven these assumptions to be consistent with reality, while the estimates of the elasticity of substitution are also consistent with the theory and discussed below.

3 Literature Review

Measurement of technical bias has developed largely along two lines; estimation using the CES production function or the translog production function. Attempts have been made to use varying elasticity of substitution models and other production functions[8], however results have been less robust. The two main approaches are therefore discussed in turn.

3.1 CES Production Function Estimates

Since Arrow et al. (1961) developed the CES production function, it has been used to estimate technical change. This approach uses either the production function itself, the FOCs with respect to capital and labour, or a combination of the two to estimate technical bias. This model is useful as the constant elasticity of substitutions allows for a clear interpretation of the technical bias for capital and labour. However, as mentioned above, the constant elasticity of substitution between capital and labour is an assumption that abstracts away from the real world.

A system of equations has been used in the majority of recent analysis to measure technical change. First of all, Antras (2004) uses a six equation specification using both a CES production function and the FOCs, as well as the three reverse equations to measure the elasticity of substitution between capital and labour and the bias of technical change. The paper uses private sector aggregate data for the USA between 1948 and 1998 from the National Income and Production Accounts and both labour and capital are measured in real terms. The author first estimates the elasticity of substitution with neutral technical change that does not augment either capital or labour, however, the author finds that without variable technical change, the elasticity of substitution is biased towards one. Alternatively, the functional form of the technical bias is assumed to be exponential for both labour and capital. The results of technical bias shows a negative technical change coefficient for capital and a positive one for labour. This means technical change is labour saving and capital using with an elasticity

[8] See Zellner (1962) as an example.

of substitution below one. As a result, the author estimates an annual capital bias in technical progress of approximately 3%.

The system of equations was augmented by the normalisation procedure. Klump et al. (2007) introduced the normalised CES production function for a more accurate analysis of the elasticity of substitution. This model is discussed in the theoretical background section of this paper, but two important empirical findings are made regarding the USA. Using a system of equations that includes the markup for imperfectly competitive markets and non-linear seemingly unrelated regressions (NLSUR), technical change is found to be largely labour augmenting. Labour augmenting technical change is estimated to be 1.5% compared to a capital augmenting technical change of just 0.4%. With an elasticity of substitution of less than one, this means technical change is more labour saving than capital saving. The second is that in their model they use a flexible form of the factor augmenting technical growth, using a Box-Cox formulation. Using this model they find capital biased technical progress follows a hyperbolic form and labour biased technical progress is exponential. This is consistent with Acemoglu's theory that capital biased technical change is a transitory phenomenon.

For the European Union, Klump et al. (2008) uses a slightly altered normalized CES production function from Klump et al. (2007) with perfect competition to derive a three equation system. This paper uses quarterly statistics from the Area Wide Model and Eurostat, these statistics are economy wide aggregates only and cannot be broken down to the industry level. Using NLSUR to estimate the system, they find technical change is predominantly capital augmenting, with a 1.0% technical change value and a 0.3% labour augmenting value, while the elasticity of substitution is estimated to be 0.6. As a result, technical change has a labour bias in the case of the EU. The Box-Cox transformation is not instructive in this case, so the functional form of technical change is assumed. The authors however identify a structural break in the statistics in 1997, after which, capital augmenting technical progress accelerates.

All of the papers discussed find an elasticity of substitution between capital and labour that is below unity. Jalava et al. (2006) on the other hand uses a much longer time period for Finland - between 1902 and 2003 - and find the production function is Cobb-Douglas[9] in the very long term. Only in a shorter period - between 1945 and 2003 – is the elasticity of substitution below unity. In this paper, only the FOCs are used, however, this allows them to use an error correction model to deal with cointegration of the variables, they also impose AR(2) on the model to deal with autocorrelation. Results show technical change is capital using and labour saving, with values of -0.3% for capital augmenting technical change and 4% for labour. This is relatively consistent with neoclassical theory due to the small capital bias and large bias for labour in

[9] Where the elasticity of substitution is 1 and the factor shares in production are constant.

technical change.

Estimates of capital and labour bias in technical innovation are not consistent across papers. This is in part due to the different approaches used, however, the technical bias parameters seem highly sensitive to the different time periods used in each paper. León-Ledesma et al. (2010) analyses the appropriate model to use in estimating technical change by testing the different models using Monte-Carlo simulations. They take a CES production function and measure the accuracy of the estimations using single equation estimations, a two equation FOC estimation and finally the full three system, normalised approach. They report that the single and two equation models deliver poor estimates and are not robust, suffering from non convergence issues when the value of the coefficients are not restricted. On top of this, non-normalized systems have a strong tendency to estimate an elasticity of substitution that is unity, affecting the technical bias estimates. This may have been one of the issues with Jalava's analysis, as the equations in this model are not normalised. The paper concludes that the normalised system of equation model provides the most accurate and robust results.

3.2 Translog Production Function Estimates

The translog price function summarised in Jorgenson et al. (2005) uses an alternative functional form of production that allows for many factor inputs to be included in production. The strength of these models is that the technical bias can be measured, as well as the deceleration of technical change, which shows whether the rate of technical change is decelerating, or accelerating. It is important to note however, that the translog price function is not a measure of induced technical change, rather a myopic maximisation function. On top of this, León-Ledesma et al. (2010) argues that considerable issues arise in the calculation of the time varying elasticity of substitution, which are compounded when including technical progress.

The introduction of the multifactor translog production function was developed by Binswanger (1974) to measure the technical bias of as many inputs in production as available. Using factor augmenting technical change and constant returns to scale, the author derives a set of time series matrices of the FOCs. With these FOCs, which are estimated using generalized least squares, the author can measure the technical bias of production. In the paper, the author measures technical change in agriculture in the USA between 1948 and 1964 with five factor inputs – fertilizer, land, labour, machinery and other. In his analysis, he finds that fertilizer and machinery are the two factors that rise at the largest rate when controlling for price changes. Between the period of 1948 and 1964, Binswanger estimates that the factor share in production for machinery rose by between 6.9 percentage points and 8.5 percentage points as a result of technical change. Technical change towards labour on the other hand is negative at a rate between 15.1 and 11.4 percentage points. This means, technical change was capital biased.

A paper by Jin and Jorgenson (2010) introduced a new approach to modeling technical change using the translog price function and a Kalman filter for the USA for 35 industries.[10] Between 1960 and 2005, heavy industry, such as coal mining and petroleum refining had the highest capital augmenting technical change, which peaked at 0.25 for coal mining Unsurprisingly, services had a marginally negative technical change for capital. Conversely, food products and textile and paper production had high labour augmenting technical change, with coal mining having the largest negative change, the range of technical change was between -0.1 and 0.1. The majority of industries therefore had a capital bias in technical change. On top of this, the authors find the impact technical change had on changing the factor's share in output was similar to the impact prices had on factor shares. A benefit of the Kalman filter is that it can be used to make future predictions, as such the paper concludes by arguing future technical change is likely to be capital biased.

As mentioned, the results of previous research differ significantly depending on the region analysed, time period and model estimated. Although the bias of technical change remains unclear, the elasticity of substitution for the aggregate economy has been consistently below unity using these two approaches.

4 Methodology

The normalised CES production function is the starting point of this analysis. It is favoured over the translog or varying elasticity of substitution functions to allow for more accurate estimates and interpretation of technical progress. On top of this, the CES function allows the functional form of the technical progress to be changed easily. The methodology used here is similar to the methodology applied by Klump et al. (2007) and León-Ledesma et al. (2010), but this system assumes perfect competition. Reliable estimates of the markup for the EU economy and each sector of the economy are not available, so this is a simplifying assumption to fit the statistics. The three other major assumptions of the system are that the elasticity of substitution does not change over the sample period, that technical change can be proxied by time and that labour and capital are perfectly elastic - that inputs can be changed in each period.

The system uses the log linearised CES production function of equation (8) in per capita form, as well as slightly altered log linearised FOCs that account for the use of nominal values of output and factor inputs.[11]

[10] These are consistent with the ISIC sector and subsector.

[11] See appendix I for a full transformation of CES function into the three equation model.

The geometric means of the variables are used to normalise the system. The geometric mean is used because the variables are not independent of one another; output or wages in one year are not independent from output or wages in other years. It also measures the central tendency of the parameters (Almkvist and Berndt, 1988), so appropriate for normalization. As such, the normalised parameters are transformed to averages (e.g. $\bar{\pi}$) and the system of equations takes the following form:

$$\begin{aligned} log\left(\frac{Y_t}{L_t}\right) &= \beta_0 + log\left(\frac{\bar{Y}}{\bar{L}}\right) + \gamma_L(t-\bar{t}) \\ &\quad - \frac{\sigma}{1-\sigma} log\left[\bar{\pi} e^{(\gamma_L-\gamma_K)(t-\bar{t})}\left(\frac{K_t/\bar{K}}{L_t/\bar{L}}\right)^{\frac{1-\sigma}{\sigma}} + (1-\bar{\pi})\right] + \varepsilon_t \end{aligned} \tag{14}$$

$$log\left(\frac{w_t L_t}{p_t Y_t}\right) = \beta_1 + log(1-\bar{\pi}) + \frac{1-\sigma}{\sigma}\left[log\left(\frac{Y_t/\bar{Y}}{L_t/\bar{L}}\right) - \gamma_L(t-\bar{t})\right] + \varepsilon_t \tag{15}$$

$$log\left(\frac{r_t K_t}{p_t Y_t}\right) = \beta_2 + log(\bar{\pi}) + \frac{1-\sigma}{\sigma}\left[log\left(\frac{Y_t/\bar{Y}}{K_t/\bar{K}}\right) - \gamma_K(t-\bar{t})\right] + \varepsilon_t \tag{16}$$

The FOCs of the model measure changes in capital and labour intensity by the volume of each of the inputs, the volume of output and a time trend. The time trend then corresponds to technical change of the factor. The rest of the variables included are constants and can collapse into the constant term of β_1 and β_2.

The NLSUR approach is used to estimate the resulting system, with cross equation restrictions imposed on variables present in more than one equation. The NLSUR approach is more efficient than OLS if the error terms are believed to be correlated (Zellner, 1962), which is the case in this system, so this method is preferred. The system is estimated using constant technical progress as shown in equation (15)[12] and also estimated with an exponential functional form. The exponential form is based on the Box-Cox transformation of Klump et al. (2007) and takes the following form.

$$A_t^i = A_0^i exp^{\frac{\gamma_i \bar{t}}{0.5}\left[\left(\frac{t}{\bar{t}}\right)^{0.5}-1\right]} \tag{17}$$

This equation replaces the constant technical progress of equations (4) and (5) and so replaces the functional form of the exponential in equation (14), as well as replacing the technical change parameters of equations (15) and (16). The full specification is defined in the appendix I. The parameter changes the relationship between technical

[12] Technical progress is defined as $\gamma_K(t-\bar{t})$

progress and the share of the factor in output. In the exponential case, technical change follows an exponential form and so the impact of technical change accelerates over time. This differs from the interpretation of the constant technical progress, which means technical change has a constant impact on the share of the factor in production.

There are a number of issues that need to be addressed in the system. Firstly, the variables of this model have a unit root and are I(1) stationary. Phillips and Durlauf (1986) show that simultaneous equation bias or measurement error bias arise for non stationary regressors. If regressions include non stationary variables, the estimates of their effects are spurious, unless cointegration - which means variables have the same long term trend - is present. If cointegration is present, estimators are super consistent and they converge more rapidly to the true value as the number of observations increases, so the biases disappear (Phillips and Durlauf, 1986).

In theory, cointegration should be present between the variables of this system, therefore two tests for cointegration are undertaken. The first is the Johansen test for cointegration, a test that can be done prior to estimation of the system.[13] The Johansen test tests if there is a linear combination of the regressors which sum to zero (Johansen, 1988). If there are combinations which are zero, then these regressors are cointegrated. The Johansen test is highly sensitive to the lag structure of the estimation and is affected significantly by small sample sizes, as the confidence intervals are based on an asymptotic distribution (Cheung and Lai, 1993). This means the more cointegrating relationships being tested, the worse it performs, as each additional relationship adds restrictions to the test and so takes up degrees of freedom. The entire system is therefore not tested at once, rather cointegration is tested for in each of equations (14)-(16) separately. The system shows cointegration consistently in all but the labour FOC and although this may be an issue, it may just be a failure of the test. Therefore the Engle-Granger test for cointegration is also checked to make sure cointegration is present once the system of equations is regressed. This is a test that can be completed after the system is estimated. For this test, regressors must be I(1) and the error terms of the estimated system must be stationary, if this is the case cointegration is present (Engle and Granger, 1987).

Although cointegration is present in this system, in small samples, convergence may still be an issue and biases may still arise (Dolado et al., 1990). Due to the severity of autocorrelation in this system, AR(2) terms are imposed on the equations.[14] This improves the stability of the model and convergence is more rapid in this case.

The presence of cointegration means the statistics for measuring the stationarity of the error terms include nuisance terms (MacKinnon, 2010), as such, the standard critical values don't apply for the augmented Dickey-Fuller test. Critical values from

[13]See table 3 in appendix II for results.

[14]See appendix I for model specification including the AR(2) variables.

MacKinnon (2010) are therefore used to measure the significance of cointegration results.[15]

Finally, the system of equations can include priors to direct the estimation. Convergence does not occur consistently if the elasticity of substitution and technical change take extreme values, therefore priors are used. Klump et al. (2007) note that their system converges at more than one point, depending on the priors of the elasticity of substitution. This implies there are local maxima. As a result, a range of values of the elasticity are used as priors for each estimation of this system[16] to check if the system also has local equilibrium points. In addition, in some cases where convergence is affected by technical growth parameters, the FOCs are estimated alone as a first stage of the regression to adjust the priors, after which, the full system is estimated.

5 Data

To analyse the model of (14)-(16), statistics for each variable are taken from the EU KLEMS database. The database takes statistics from each country's statistics office and then harmonises and aggregates across countries at the industry level. The benefit of these statistics is that they can be aggregated up to the primary, secondary, tertiary and quaternary sectors.[17] The statistics are annual and the time series runs between 1980 and 2007; the time period is restricted to the period in which capital volumes are calculated for all fourteen countries.[18] Finally, the statistics are aggregates of EU countries that have growth accounting statistics available, which excludes newer members.[19][20] Labour and capital compensation, equivalent to wL and rK are available at the ISIC industry and division level, output (pQ) is taken as gross value added and finally the labour volume is also available in the dataset.

The capital volume index (K) and value added volume index (Q) are calculated by aggregating the ISIC industry level statistics to the sector level. To compute the sector level values of K and Q, the volume indexes of each industry are weighted depending

[15] the values are noted in table 6 in the appendix II.

[16] $\sigma = 0.1, 0.5, 1.5, 2.0$

[17] The classifications are derived from the three sector measurement of the ISIC classification and quaternary industries are separated from the tertiary sector using Kenessey (1987) classification.

[18] Although this a relatively short time period, amounting to 27 observations León-Ledesma et al. (2010) show that using a system of equations improves the accuracy of estimations and as a result, estimations are relatively unaffected by sample size variation, with the confidence intervals, rather than estimates benefiting from higher numbers of observations in the model.

[19] Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, United Kingdom.

[20] In 2007, according to Eurostat, these countries accounted for 93.0% of the GDP of the European Union and so estimations are a relatively good approximation of the EU as a whole.

on the value size of each industry in the following way.

$$\text{Volume Index} = \frac{\sum_{i=1}^{n} \text{Volume Index}_i \cdot \text{Compensation}_i}{\sum_{i=1}^{n} \text{Compensation}_i} \qquad i = 1, ..., n \tag{18}$$

Where in this illustration, i represents each industry included in the sector, numbered from 1 to n.[21] For example, n represents the 12 industries in the tertiary sector. $Compensation$ is measured as rK for the capital volume index and pQ for the measure of output volume.

Total hours worked by persons engaged is the volume index of labour used in estimation. For the labour input measurement, the number of hours worked is preferred to persons engaged, as job sharing and part time working means persons engaged may overestimate labour input in production. There are also two choices for hours worked in the database, hours worked by persons engaged is preferred over hours worked by employees because hours worked by persons engaged includes informal labour, completed outside of contracted employment. An example of the discrepancy in an industry is in "private households with employed persons", where hours worked by employees was 30% that of hours worked by persons engaged in 2007.

Measurement of self-employed individual's incomes creates an issue in the statistics because all income is counted as labour income. To improve the accuracy of labour and capital compensations, the distribution of income is altered for the industry "private households with employed persons". This changes the income distribution for the tertiary sector and total economy. There are two common ways in which this is done; the first is by using the hourly wage for the rest of the services sector as a shadow wage for wages of this industry, which then accounts for labour income when multiplied by hours worked (Klump et al., 2007). However, this methodology does not work for this set of statistics as the average hourly wage of services is consistently too high, hence it overestimates labour compensation to the point where it exceeds total compensation for the industry in some years of the sample. As a result, a simpler approach is used, where two thirds of compensation are distributed to labour and one third to capital, consistent with historical distribution of capital and labour compensation.[22]

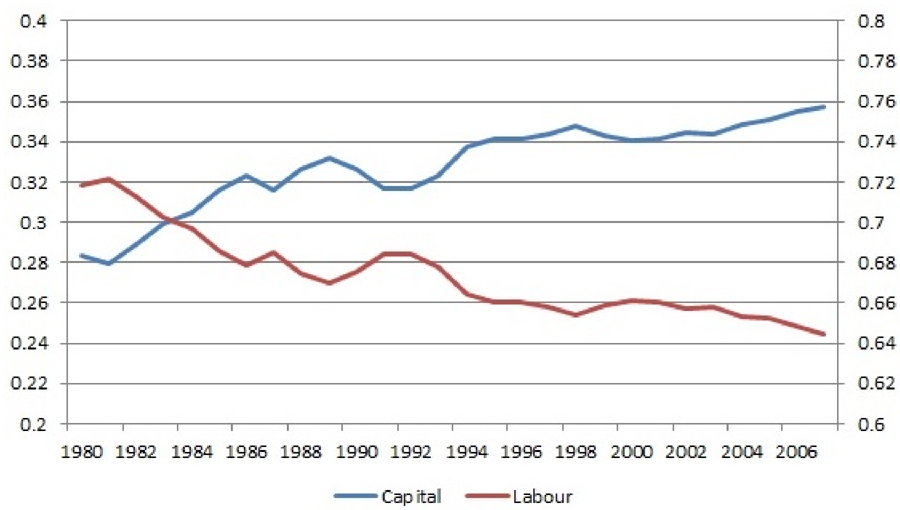
Figure 2 shows the capital share of income on the left hand axis and the labour share of income on the right hand axis, it is clear that the shares have diverged, with capital intensity rising in Europe over the sample period. Without a trend variable in the equation, both capital and labour share are non-stationary when tested using the Augmented Dickey Fuller (ADF) test, but are integrated to order 1. This differs from

[21] see Appendix II for list of industries per sector

[22] This is consistent with previous literature (Klump et al., 2007)

the assumptions of many theoretical growth models, including the model of Acemoglu (2003), as the Kaldor condition of constant income shares between capital and labour is violated.

Figure 2: Capital and Labour Share in Output



Source: EU KLEMS

The capital share in output averaged 32.8% over the sample period for the total economy and the highest capital intensity is present in the quaternary sector, followed by the tertiary sector. This is due to the proliferation of ICT capital in these sectors, which led to rapid increases in the volume of capital used. The capital share of income increased by an average by 7.4 percentage points and rose in every sector between 1980 and 2007. Although capital intensity is highest in the services sectors, the increase was the most pronounced in the primary sector, where the share of capital rose from 19.5% in 1980 to 33.5% in 2007.

The rise in capital intensity is the result of the rapid increase in the volume of capital compared to labour, not the marginal products of the inputs. Wages increased by 145.8% for the total economy, compared to only a 53.1% rise in the user cost of capital. The increase in wages was largest in manufacturing. This industry has developed to produce high tech products requiring high skilled production, while heavier, lower skilled manufacturing has been exported to Eastern Europe and other regions of the world (Veugelers, 2013). In nominal terms, wages increased in this sector by 222.6% between 1980 and 2007, while hours worked fell by 35.2%. According to the theory of directed technical change, the weak induced bias should lead to capital augmenting technical change, while the price effect could cause some incentive for labour augmenting technical change.

Hours worked in the total economy rose by 8.4%, a small amount relative to capital volume growth, however, the trends differed significantly across sectors. Hours worked declined in both the primary and secondary sectors, by 49.1% and 35.2% respectively. The tertiary and quaternary sectors on the other hand saw a rise in hours worked. This should mean labour-augmenting technical change differs across the sectors, as the abundance of labour rose or fell.

It is clear for the total economy, that the rise in the capital share, combined with the market size effect points towards capital augmenting technical progress. However, the rise in wage costs may mean the price effect impacts on technical progress for labour, this is particularly important for industries that have a relatively low elasticity of substitution, as Acemoglu (2002) notes that the price effect has a larger impact on technical progress if the elasticity of substitution is low.

6 Results

Tables 1 and 2 show the estimates for exponential technical growth and constant technical growth respectively. Each table includes the elasticity of substitution, technical growth for capital and labour and the average capital intensity. On top of this, the ADF test for a unit root for each of the three equations is summarised. Finally, the speed of convergence is also included in the tables. Column T represents the total economy, column 1, 2, 3, 4 represent the primary, secondary, tertiary, quaternary sectors of the economy respectively.

The ADF test is undertaken on the residuals of each of the equations to test for cointegration between the variables. The ADF test tests whether the lagged values of the dependent variable are able to explain the dependent variable, after the difference of the dependent variable is controlled for (Stock and Watson, 1988). The null hypothesis in this test is that the lagged values have no explanatory power of the dependent variable and hence the time series has a unit root. If this is rejected, the time series is stationary. If the ADF test rejects the null, cointegration is present and means estimations are not spurious. The results show that in almost all cases, cointegration is present.

For the total economy, technical change is capital saving and labour using. Taking constant technical change as an example, the interpretation is as follows; with annual capital augmenting technical change of 3.0% and an elasticity of substitution of 0.589, the capital share of income declines by 2.1% thanks to capital augmenting technical change[23], *ceteris paribus*. Technical change for labour on the other hand is negative, which means technical change for labour has improved the labour share of income. The elasticity of substitution is below unity in both the constant and exponential function case for the total economy, with technical change differing marginally across the two

[23]The decline in the income share is calculated in the following way: $(-0.030) * \left(\frac{1-0.589}{0.589}\right)$

Table 1: CES Production Function with Exponential Technical Growth

Parameter	T	1	2	3	4
σ	0.589***	0.890***	0.638***	0.611***	0.458***
	(0.015)	(0.040)	(0.015)	(0.011)	(0.012)
γ_K	0.030***	0.057***	0.020***	0.036***	0.013***
	(0.021)	(0.005)	(0.003)	(0.002)	(0.005)
γ_L	-0.024***	-0.008**	-0.033***	-0.021***	-0.017***
	(0.001)	(0.004)	(0.005)	(0.001)	(0.001)
π	0.328	0.293	0.278	0.338	0.380
Stationarity					
ADF_{FOC_K}	-3.451*	-4.527***	5.044***	-4.849***	-5.121***
ADF_{FOC_L}	-5.546***	-4.233***	4.838***	-5.222***	-4.920***
$\text{ADF}_{Y/L}$	-3.796**	-5.486***	4.823***	-5.128***	-4.579***
Convergence					
(No. of iterations)	Yes (26)	Yes (508)	Yes (21)	Yes (19)	Yes (26)

Note: standard errors in parentheses: *** p <0.01, ** p <0.05, * p <0.1
Critical values of ADF adjusted to MacKinnon (2010)

forms. Convergence is rapid in both cases, implying stability within the system of equations. An important note for the total economy with constant technical growth is that the ADF test for the FOC of capital cannot be rejected at the 5% or 10% level. Although the Johansen test shows integration is present, interpretation should be done with caution in this case.

The objective of this paper is to see whether capital biased technical change is present in the EU, which requires a positive γ_K and crucially, an above unity elasticity of substitution. The central finding of these estimates is therefore that capital biased technical change is not present and is not exacerbating inequality between factors of production.

In three of the four economic sectors, the estimates of exponential technical progress converge more consistently and more rapidly, so this form of progress is favoured. On top of this, no local maxima are found for any of the sectors of the economy. For the majority of the sectors of the economy, the elasticity of substitution is below unity, technical change is capital saving thanks to the positive γ_K and labour using thanks to the negative γ_L. Technical change is most capital saving in the primary and tertiary industry and labour using at the highest rate in the quaternary industry. These results are consistent with the weak induced bias hypothesis of Acemoglu (2002), as the rise in the capital share of income has resulted in technical change that is acting to reduce capital intensity.

Table 2: CES Production Function with Constant Technical Growth

Parameter	T	1	2	3	4
σ	0.818***	1.214***	0.558***	-	0.974***
	(0.030)	(0.046)	(0.008)		(0.024)
γ_K	0.030***	-0.093***	0.013***	-	-0.015
	(0.006)	(0.010)	(0.002)		(0.111)
γ_L	-0.024***	0.002	-0.029***	-	0.007
	(0.004)	(0.002)	(0.001)		(0.068)
π	0.328	0.293	0.278		0.380
Stationarity					
ADF_{FOC_K}	3.312	-4.874***	4.771***	-	-4.730***
ADF_{FOC_L}	4.025**	-4.793***	-5.393***	-	-4.633***
$\text{ADF}_{Y/L}$	4.395***	-5.155***	-5.679***	-	-5.164***
Convergence					
(No. of iterations)	Yes (22)	Yes (62)	Yes (10)	No	No

Note: standard errors in parentheses: *** p <0.01, ** p <0.05, * p <0.1
Critical values of ADF adjusted to MacKinnon (2010)

The estimates for each sector are relatively consistent, except in the case of the primary sector. This sector is the only one to have more stable estimates in the constant technical progress case. On top of this, the elasticity of substitution is 1.2, so a 1% increase in the marginal product of an input leads to a 1.2% increase in the total share of output. Although the sector differs, technical progress is biased towards labour here too. This is consistent with the theory, as producers are mitigating the rise in the capital share with technical progress that increases labour intensity.

Disentangling the price effect and market size effect for each of the sectors is difficult and the following examples are only a partial comparison of the sector estimates. However, the market size effect can be seen when the tertiary and quaternary sectors are compared. Both industries saw similar growth in the user cost of capital and wages, but the relative growth in the volume of capital was larger in the tertiary sector. The theory would then argue the tertiary sector should show technical change which is more capital saving, this is the case, with technical change for capital of 2.3% and 1.5% respectively.

The price effect on the other hand is less obvious from these results. The best comparison is between the secondary and quaternary industry, the relative change in the volume of capital to labour is similar in both sectors, but wage growth is much more pronounced relative to the user cost of capital in the case of the secondary industry. As a result, the price effect should mean technical change is significantly more labour saving in the case of the secondary industry, as the elasticity of substitution is relatively low in both cases. Technical change in the secondary industry is less labour using than the quaternary sector, however, the difference is small, perhaps due to the larger volume effect in the secondary sector, as hours worked declined by half.

To conclude, the hypothesis that technical change is capital biased is rejected, due to the below unity elasticity of substitution. Therefore technical progress is not one of the causes of growing capital intensity in the EU. The results are consistent with the theory of directed technical change and are similar across each industry. However, the market size effect seems to have been larger than the price effect in these estimates. These findings are tested for robustness in the following section.

7 Robustness Checks

Table 7 in appendix II includes additional robustness checks to measure the sensitivity of the estimates to alternative measures of labour, capital, alternative functional forms, as well as to different periods of time. For brevity, the robustness checks are undertaken on the total economy only, with the favoured exponential functional form of technical growth.

The first robustness check takes an alternative value of labour that measures hours worked by employees, rather than hours worked by persons engaged. The statistics for hours worked by employees are more accurately reported by statistics offices, so the changes in the volume of labour each year should be more accurate in this case. However, it assumes only employees contribute to output, a strong assumption. This alternative measure differs only slightly from the previous, so the impact on estimates should be relatively small. The estimates are marginally different, the elasticity of substitution changes by a small amount and technical change becomes slightly less capital saving.

A second test changes the user cost of capital to alter the volume of capital used in production. The user cost of capital is measured in two ways, either *ex-ante* using data from outside statistics and *ex-post*, where the user cost is estimated within sample, using the assumption that the sum of returns is equal to total profits (Schreyer and Pilat, 2001). The *ex-post* approach is preferred (Oulton, 2007) and used for the EU KLEMS statistics, however, it assumes perfect foresight of producers. The alternative cost of capital uses an *ex-ante* approach, using statistics that are available to firms during the period where investment decisions are completed. This measure does however have drawbacks, as the expected cost is not necessarily the real cost that is paid. The new user cost is calculated in the following way:

$$r = \frac{i + \delta}{1 - \tau} \tag{19}$$

Where i is the nominal interest rate, δ is the depreciation rate and τ is the corporate tax rate.[24] This new user cost of capital alters the volume of capital variable for the system, while total compensation remains the same. Due to volatility of the user cost of capital, the volume of capital becomes highly volatile, which tests the assumption of perfectly elastic capital volumes to the extreme. Convergence of the full system cannot be achieved, but the results from the FOCs alone are shown.[25] The system estimates the Cobb-Douglas production function, with technical change being insignificantly different from zero. León-Ledesma et al. (2010) show that estimating the FOCs only creates a bias in the elasticity of substitution towards unity, which is borne out in these results.

The assumptions of constant and exponential technical progress of the system is consistent with previous empirical literature. However, a functional form of technical progress is also tested that is consistent with the theoretical model of Acemoglu (2003). In this theory, technical change for capital is transitory, so is defined as following a log form[26], while technical change for labour is exponential. In this case, the system does not converge, as capital augmenting technical change does not follow a log form. Consistent with Klump et al. (2008), this result means capital augmenting technical change is not simply transitory.

Finally, the assumption of the same functional form of technical progress over the entire period is tested by looking at the fit of exponential and constant growth in different periods. Klump et al. (2008) note a structural break in the statistics for the EU in the year 1997. This date is tested as it coincides with the convergence of eurozone country currencies to the euro, which is likely to have affected access to capital as investor confidence rises for eurozone countries, 11 of which are in this sample. It must be stressed that the short time periods and the insignificant ADF values means any interpretation of the truncated time period estimates should be taken with caution.

In both periods, the exponential form of technical progress is preferred, as constant technical progress estimates do not converge fully. As a result, only the exponential forms are shown in the results. Modifying the sample period does however lead to different estimates of technical progress. The elasticity of substitution remains below unity so the interpretation of the technical change coefficients remains the same, but technical change is larger between 1980 and 1997. The difference between estimates is the result of higher inflation between 1980 and early 1995, which has led to a larger price effect in the first period. The rapid rise in the cost of capital during the 1980s is likely to have been one of the causes of the larger technical bias, while a more steady

[24]The long term interest rate is taken from Eurostat's real time database and is an aggregate across the European Union, as country specific interest rates are not available for the full time period. The depreciation rate - taken from EU KLEMS - is assumed to be constant over time and across countries. The tax rate is taken from the OECD tax database.

[25]Estimation using the FOCs along are used in a number of papers see León-Ledesma et al. (2010) and Binswanger and Ruttan (1978) for examples, and is instructive for assessing the performance of the system.

[26]Technical progress for capital takes the following form: $A_t^K = A_0^K e^{\frac{\gamma_K \bar{t}}{0.001}\left[(\frac{t}{\bar{t}})^{0.001} - 1\right]}$

rise in wages across the period means its relative price fell. This is consistent with the weak induced bias hypothesis of directed technical change.

8 Discussion

The central result of this paper is that capital augmenting technical growth has not supported the rise in the capital income share in output. As a result, technical progress is not leading to more inequality of inputs in the production of goods. The result holds across all sectors of the economy. These findings are consistent with the theory of directed technical change and previous empirical literature on Europe.[27] Apart from the total economy, the error terms are stationary in all cases, which means cointegration is present and hence the results are not spurious.

These results have implications for the discourse on capital intensity and inequality. Piketty (2014) argues that the rise in capital accumulation is self reinforcing, an increase in the stock of capital owned by the wealthy leads to higher returns on their capital as the return on capital outstrips the growth in the economy. However, the results of this paper show that the rise in capital intensity leads to technical change that mitigates the rise in inequality, improving the share of income in labour at the expense of capital. Only if the elasticity of substitution is above unity, would Piketty's argument hold. Therefore a continued rise in capital intensity would only occur if the trends affecting capital and labour continue, IT capital must continue to proliferate, trade union power must continue to deteriorate or competition for labour outside of Europe must continue to rise for capital intensity to continue to grow.

Neoclassical growth theory is also impacted by the results of this paper. The use of the Cobb-Douglas production function is inconsistent with estimates of production in Europe. Therefore the broader CES function, with both capital and labour augmenting technical progress should be preferred in general equilibrium models due to the below unity elasticity of substitution found in empirical analysis. The results of this paper also have implications in solving endogenous growth models, which rely on a production function with only labour augmenting technical growth, or transitory capital augmenting technical growth to be solved (Romer and Chow, 1996). Supporting previous empirical literature, this research shows capital augmenting technical progress is present in the economy over the longer term, so the assumption used in growth theory is questionable.

The methodology of this paper is consistent with previous analysis and theory, however, the supply side system used does have a number of drawbacks. The first is the constant elasticity of substitution between capital and labour over the sample

[27] See Klump et al. (2008), McAdam and Willman (2013) for examples.

period, a major assumption which may cause bias in the results. The other assumption made for this analysis is perfect competition in the markets. The number of firms present in the EU is large, however, market power in some of the primary industries and especially in industries such as energy - where production is government run in many cases - means this assumption may break down. On top of this, the imposition of the autoregressive structure to deal with the issue of autocorrelation does affect the structural nature of the estimates.

The results show that technical change itself has not supported a rise in capital intensity, however, the growth in the tertiary and quaternary sectors will. These sectors have the highest capital intensity of the economy, therefore as output shifts to these sectors, capital intensity in the total economy will also rise.

8.1 Further Research

The natural progress for the estimation of technical change would be to introduce estimation methods with a time varying elasticity of substitution between capital and labour. It may be the case that the elasticity of substitution differs at different points of the business cycle, with a larger elasticity of substitution and more labour biased technical growth during periods when the economy is at capacity and a smaller elasticity of substitution and less labour biased technical growth after downturns in the economy. A model like this may provide some insight into the rise of inequality that has occurred in the USA and Europe after the financial crisis of 2007 and 2008. It would also improve understanding of how production impacts the recovery and whether production exacerbates or mitigates the jobless recoveries that have occurred since 1990 in the USA and elsewhere (Schreft et al., 2003).

An implicit assumption when using the CES production function is that capital is perfectly elastic; that it can be changed in each period. Further research into the firm level production function, with a modified FOC for capital could be made that includes more inelastic capital. For example, a vintage model of capital accumulation (Boucekkine et al., 2011) may improve modeling of the investment decisions and how technical change develops for each factor.

Another alternative would be to study how regulation is affecting the technical bias in production. For example, whether the persistently low interest rates imposed in 2007/08, after the financial crisis in Europe and the USA has impacted production. Or how the lower financial regulation in the western world since the 1970s has affected production in the economy. The second question would be particularly interesting to study as banking regulation tightens with the introduction of Basel III.

9 Conclusion

This paper estimates the bias of technical change in the EU and asks whether it is exacerbating the rise in inequality of factor income shares or not. Using a normalised CES production function and its two FOCs, estimates of factor augmenting technical change over the period of 1980-2007 show that it is not capital biased. The estimates show that technical change is capital saving and labour using, which means technical change has acted to mitigate the rise in capital intensity in the EU, rather than worsen it. This result contributes to the literature on technical change as it looks at production functions for each sector of the economy. Even in the sectors with the largest rise in the capital share, technical progress has acted to reduce capital intensity. An elasticity of substitution below unity confirms previous research and shows using Cobb-Douglas production functions in theoretical models is inaccurate.

Using a normalised production function has augmented the results of this analysis. The normalisation provides more meaningful estimations, allowing the parameters to be properly compared with one another. The results are robust, significant and are consistent with the theory of directed technical change, but not with neoclassical endogenous growth theory. Estimates for each economic sector are also consistent, with the exponential functional form of technical progress favoured in all cases but the primary sector.

The rise of capital intensity in the EU is an issue for policy makers concerned with income inequality in the region. The rise in capital incomes and the squeezing of labour income will worsen the rising inequality of the developed world. However, technical change is acting to reduce the difference in factor income shares, rather than worsen it.

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A Appendix I: Derivation of log linearised system of equations

Firms are assumed to be profit maximising, so the FOCs with respect to capital and labour are the marginal products of capital and labour:

$$\frac{\partial Y_t}{\partial K_t} = \pi_0 \left(\frac{Y_0}{K_0} e^{\gamma_K (t-t_0)} \right)^{\frac{\sigma-1}{\sigma}} \left(\frac{Y_t}{K_t} \right)^{\frac{1}{\sigma}} \tag{20}$$

$$\frac{\partial Y_t}{\partial L_t} = (1-\pi_) \left(\frac{Y_0}{L_0} e^{\gamma_L (t-t_0)} \right)^{\frac{\sigma-1}{\sigma}} \left(\frac{Y_t}{L_t} \right)^{\frac{1}{\sigma}} \tag{21}$$

In neoclassical theory and under perfect competition, the marginal product of labour and capital is the real wage and real user cost of capital respectively. Using the nominal wage and nominal user cost of capital, the marginal products are the following:

$$\frac{\partial Y_t}{\partial K_t} = \frac{r_t}{p_t} \tag{22}$$

$$\frac{\partial Y_t}{\partial L_t} = \frac{w_t}{p_t} \tag{23}$$

Where r is the nominal user cost of capital, w is the nominal wage and p is the price level. Combining equations (20) with (22) and multiplying both sides by K_t/Y_t and combining (21) with (23) and multiplying both sides by L_t/Y_t leads to the final FOCs that are represented as the labour and capital share in output. By transforming the FOCs so that they are based on the capital and labour share of output, EU KLEMS data can be used without the need for calculating the price level. This specification is consistent with Klump et al. (2008).

$$\frac{r_t K_t}{p_t Y_t} = \pi_0 \left(\frac{Y_0}{K_0} e^{\gamma_K (t-t_0)} \right)^{\frac{\sigma-1}{\sigma}} \left(\frac{Y_t}{K_t} \right)^{\frac{1-\sigma}{\sigma}} \tag{24}$$

$$\frac{w_t L_t}{p_t Y_t} = (1-\pi_) \left(\frac{Y_0}{L_0} e^{\gamma_L (t-t_0)} \right)^{\frac{\sigma-1}{\sigma}} \left(\frac{Y_t}{L_t} \right)^{\frac{1-\sigma}{\sigma}} \tag{25}$$

These FOCs are log linearised and the CES production function is transformed to a log linear, per capita function as shown below. Log linearisation is done to create an additive, rather than multiplicative relationship between the technical change parameter and other parameters in the equation, this simplifies estimation.

$$Y_t = \bar{Y} \left[\bar{\pi} \Big(\frac{e^{\gamma_K (t-\bar{t})} K_t}{\bar{K}} \Big)^{\frac{1-\sigma}{\sigma}} + (1-\bar{\pi}) \Big(\frac{e^{\gamma_L (t-\bar{t})} L_t}{\bar{L}} \Big)^{\frac{1-\sigma}{\sigma}} \right]^{\frac{\sigma}{1-\sigma}} \tag{26}$$

If we then log linearise and factorise with respect to $\left(\frac{e^{\gamma_L(t-\bar{t})}L_t}{\bar{L}}\right)^{\frac{1-\sigma}{\sigma}}$ the following equation is derived

$$log(Y_t) = log(\bar{Y}) - log\left(\frac{L_t e^{\gamma_L(t-\bar{t})}}{\bar{L}}\right) - \left(\frac{\sigma}{1-\sigma}\right) log\left[\bar{\pi}\left(\frac{e^{\gamma_K(t-\bar{t})}K_t}{\bar{K}}\right)^{\frac{1-\sigma}{\sigma}} \Big/ \left(\frac{e^{\gamma_L(t-\bar{t})}L_t}{\bar{L}}\right)^{\frac{1-\sigma}{\sigma}} + (1-\bar{\pi})\right] \tag{27}$$

Taking the $log(L_t)$ to the right hand side, the log linearised form is derived.

$$log\frac{Y_t}{L_t} = log\left(\frac{\bar{Y}}{\bar{L}}\right) + \gamma_L(t-\bar{t}) - \frac{\sigma}{1-\sigma}\left[\bar{\pi}e^{\frac{\sigma-1}{\sigma}\left[\gamma_L(t-\bar{t})-\gamma_K(t-\bar{t})\right]}\frac{K_t/\bar{K}}{L_t/\bar{L}}^{\frac{1-\sigma}{\sigma}} + (1-\bar{\pi})\right] + \varepsilon_t \tag{28}$$

These equations define the log linearised system of equations.

A.1 System with exponential functional form of technical progress

$$\begin{aligned} log\left(\frac{Y_t}{L_t}\right) &= \beta_0 + log\left(\frac{\bar{Y}}{\bar{L}}\right) + \frac{\gamma_L\bar{t}}{0.5}\left[\left(\frac{t}{\bar{t}}\right)^{0.5} - 1\right] \\ &- \frac{\sigma}{1-\sigma} log\left[\bar{\pi}e^{\left(\frac{\gamma_L\bar{t}}{0.5}\left[\left(\frac{t}{\bar{t}}\right)^{0.5}-1\right] - \frac{\gamma_K\bar{t}}{0.5}\left[\left(\frac{t}{\bar{t}}\right)^{0.5}-1\right]\right)}\left(\frac{K_t/\bar{K}}{L_t/\bar{L}}\right)^{\frac{1-\sigma}{\sigma}} + (1-\bar{\pi})\right] + \varepsilon_t \end{aligned} \tag{29}$$

$$log\left(\frac{w_tL_t}{p_tY_t}\right) = \beta_1 + log(1-\bar{\pi}) + \frac{1-\sigma}{\sigma}\left[log\left(\frac{Y_t/\bar{Y}}{L_t/\bar{L}}\right) - \frac{\gamma_L\bar{t}}{0.5}\left[\left(\frac{t}{\bar{t}}\right)^{0.5} - 1\right]\right] + \varepsilon_t \tag{30}$$

$$log\left(\frac{r_tK_t}{p_tY_t}\right) = \beta_2 + log(\bar{\pi}) + \frac{1-\sigma}{\sigma}\left[log\left(\frac{Y_t/\bar{Y}}{K_t/\bar{K}}\right) - \frac{\gamma_K\bar{t}}{0.5}\left[\left(\frac{t}{\bar{t}}\right)^{0.5} - 1\right]\right] + \varepsilon_t \tag{31}$$

A.2 System with AR(2) structure

$$\begin{aligned} log\left(\frac{Y_t}{L_t}\right) &= \beta_0 + log\left(\frac{\bar{Y}}{\bar{L}}\right) + \gamma_L(t-\bar{t}) - \frac{\sigma}{1-\sigma} log\left[\bar{\pi}e^{\gamma_L(t-\bar{t})-\gamma_K(t-\bar{t})}\left(\frac{K_t/\bar{K}}{L_t/\bar{L}}\right)^{\frac{1-\sigma}{\sigma}} + (1-\bar{\pi})\right] \\ &+ \beta_1 log\left(\frac{Y_{t-1}}{L_{t-1}}\right) + \beta_2 log\left(\frac{Y_{t-1}}{L_{t-1}}\right) + \varepsilon_t \end{aligned} \tag{32}$$

$$log\left(\frac{w_t L_t}{p_t Y_t}\right) = \beta_3 + log(1-\bar{\pi}) + \frac{1-\sigma}{\sigma}\left[log\left(\frac{Y_t/\bar{Y}}{L_t/\bar{L}}\right) - \gamma_L(t-\bar{t})\right] + \beta_3 log\left(\frac{w_{t-1}L_{t-1}}{p_{t-1}Y_{t-1}}\right) + \beta_4 log\left(\frac{w_{t-2}L_{t-2}}{p_{t-2}Y_{t-2}}\right) + \varepsilon_t \quad (33)$$

$$log\left(\frac{r_t K_t}{p_t Y_t}\right) = \beta_5 + log(\bar{\pi}) + \frac{1-\sigma}{\sigma}\left[log\left(\frac{Y_t/\bar{Y}}{K_t/\bar{K}}\right) - \gamma_K(t-\bar{t})\right] + \beta_6 log\left(\frac{r_{t-1}K_{t-1}}{p_{t-1}Y_{t-1}}\right) + \beta_7 log\left(\frac{r_{t-2}K_{t-2}}{p_{t-2}Y_{t-2}}\right) + \varepsilon_t \quad (34)$$

B Appendix II: Tables

B.1 Methodology

Table 3: Johansen test for cointegration

	Cointegration (lag structure)				
Equation	T	1	2	3	4
FOC_K	Yes (2)	Yes(5)	Yes(1)	Yes(1)*	No
Trace Statistic	0.583	3.761	3.256	1.721	-
FOC_L	Yes(2)	No	Yes(2)	No	Yes(4)
Trace Statistic	2.610	-	3.751	-	0.310
CES	Yes (3)	Yes(5)	Yes(3)	Yes(1)	Yes(5)
Trace Statistic	3.021	0.442	0.609	3.138	1.171

Note: 5% value of trace statistic for cointegration : 3.842
*cointegration found at the 10% level only

B.2 Data

Table 4: Industry Breakdown

ISIC Code	Industry Level
A-C	Primary
A	Agriculture and Hunting
B	Forestry and Fishing
C	Mining and Quarrying
D	Secondary - Manufacturing
E-I	Tertiary
E	Electricity, Gas and Water Supply
F	Construction
G	Wholesale and Retail Trade
H	Hotels and Restaurants
I	Transport and Storage and Communication
J-P	Quaternary
J-K	Finance, Insurance, Real Estate and Business Services
L-Q	Community Social and Personal Services
P	Private Households with Employed Persons

Table 5: Summary Statistics

Sample Period: 1980-2007	T	1	2	3	4
Average Capital Share (π)	0.33	0.29	0.28	0.34	0.38
Capital share growth (pp)	7.42	15.82	5.65	9.37	4.16
r growth (%)	53.10%	20.74%	45.39%	54.78%	59.84%
Capital volume growth (%)	145.78%	59.32%	90.28%	162.05%	161.93%
w growth (%)	146.80%	67.61%	222.68%	125.69%	127.31%
Hours worked growth (%)	8.40%	-49.10%	-35.19%	12.77%	53.98%

B.3 Results

Table 6: McKinnon Critical Values for ADF

Significance Level	Critical Value
1%	4.294
5%	3.741
10%	3.452

B.4 Robustness Checks

Table 7: Robustness Checks: Total Economy

Parameters	Hours worked employees	Alt User Cost#	Log K#	1980-1997	1998-2007
σ	0.586***	1.001***	1.103***	0.712***	0.550***
	(0.020)	(0.003)	(0.146)	(0.031)	(0.070)
γ_K	0.029***	0.070***	3.914	-0.060	0.026***
	(0.003)	(11.824)	(0.094)	(0.017)	(0.009)
γ_L	-0.022***	9638.710	-1.954	-0.028***	0.023
	(0.001)	(58244.07)	(2.810)	(0.002)	(0.043)
π	0.328	0.328	0.328	0.328	0.328
Stationarity					
ADF_{FOC_K}	-2.898	-3.654*	-3.675**	-2.804	N/A
ADF_{FOC_L}	-4.659***	-3.669*	-4.430***	-2.662	N/A
$\text{ADF}_{Y/L}$	-3.897*	N/A	N/A	-2.797	N/A
Convergence					
(No. of iterations)	Yes(57)	Yes(22)	Yes(18)	Yes(14)	Yes(19)

Note: standard errors in parentheses: *** p <0.01, ** p <0.05, * p <0.1
Critical values of ADF adjusted to MacKinnon (2010),
Insufficient observations for ADF test between 1998-2007
System of FOCS estimated only