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October 2014 **No 266**

NationalBank
OF BELGIUM
Eurosystem

Editoral

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ISSN: 1375-680X (print)
ISSN: 1784-2476 (online)

A constrained nonparametric regression analysis of factor-biased technical change and TFP growth at the firm level *

Marijn Verschelde[†], Michel Dumont[‡], Bruno Merlevede[§], Glenn Rayp[¶]

Abstract

Using firm-level data for Belgium, we study the validity of Hicks neutrality in several sectors that cover the spectrum of knowledge intensity. We find that Hicks neutrality is clearly not supported by the data in different sectors. The results are not sensitive to altering the specification of the technology by including firm age and R&D into the analysis. We also reject Hicks neutrality for a balanced sample, pointing to 'within-firm' factor-biased technical change and we also find factor-biased technical change in the pre-crisis era, indicating that unobserved heterogeneity in demand does not drive the results. Overall, our results point towards low-skilled labour-saving and materials-using technical change. So far, this has received little attention and may be linked to offshoring and global value chain networks. Finally, we show that nonparametric estimates of TFP change that allow for factor biases support the evidence of the recent slowdown in TFP growth in many manufacturing sectors in Belgium. Estimations of TFP and technical change are shown to be sensitive to the estimation method and the specification of the factor bias of technical change.

Keywords: total factor productivity, factor bias, nonparametric estimation.

JEL classificaton: C35, D24, 030

*Financial support by the Belgian National Bank is gratefully acknowledged. We greatly appreciate the permission of the CFS-STAT commission to use firm-level R&D data and the help provided by Karl Boosten (Federal Public Planning Service Science Policy).

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1 Introduction

Despite decades of research, total factor productivity (TFP) - defined as the part of output that is not explained by measured inputs- remains what Abramovitz (1956) labeled as some sort of measure of our ignorance. Hulten (2001, 2009) enumerates problems that may result in TFP being a biased indicator of disembodied technical efficiency: for example, measurement errors; omitted variables; aggregation bias and model misspecification. Recent contributions tackle some of these problems, such as endogeneity and within-industry heterogeneity. A potential bias that appears to receive less attention is the fact that most calculations of TFP growth explicitly assume technological change to be Hicks-neutral.
Although Solow (1957) argued that technological progress over the period 1909-1949 was neutral, others have provided historical evidence that technological change has mostly not been factor-neutral. The data for the US, used by Sato (1970), indicate that technological progress was labour-saving over the period 1909-1960. Binswanger (1974) concluded that technological change was neutral before 1944 but was labour-saving (machinery-using) between 1944 and 1968. According to Abramovitz (1993), technology favoured physical capital in the 19th century. In the 20th century the bias shifted towards intangible capital (contribution of education and R&D). Acemoglu (2011) points out that in the late 18th and early 19th century technology favoured low-skilled workers whereas more recently evidence seems to bear out a bias in favour of high-skilled workers. Berman, Bound and Machin (1998) provide evidence of skill-biased technological change in most OECD countries for the 1970s and 1980s. Bessen (2008) concludes that most empirical studies reject the assumption of Hicks neutrality. Violante (2008) argues that to make sense of the rising skill premiums witnessed in most OECD countries- given the dramatic increase in the relative supply of college graduates- one must introduce factor-biased technological change.

Skill-biased technological change (SBTC) is often put forward as the major explanation for the weakened labour market position of the low-skilled (Bound and Johnson, 1992; Berman, Bound and Griliches, 1994; Autor, Katz and Krueger, 1998; Sanders and ter

Weel, 2000; Levy and Murnane, 2005; Autor, Katz and Kearney, 2008; Goldin and Katz; 2008; Brynjolfsson and McAfee, 2011) whereas the structural increase in the income share of capital, witnessed in many OECD countries is by some explained by capital-augmenting technological change (see, for example, Bentolila and Saint-Paul, 2003; Arpaia et al. 2009 and chapter 3 in OECD Employment Outlook 2012). In most studies, high-skilled labour is explicitly assumed or at least implied to be a complement to capital. However, a task-based view of the contribution of ICT (for example, Autor, Levy and Munrane, 2003) provides a less straightforward link between capital and skills.

The literature and empirical evidence on factor-biased technological change seems at odds with the explicit assumption of factor-neutral technological change of most estimations of TFP growth. There are relatively few studies that consider the impact of potential non-neutral technological progress on TFP estimates. Felipe and McCombie (2001), in their assessment of the stellar performance of East Asian NICs, conclude that accounting for factor-biased technological change tends to increase TFP estimates but only marginally. On the other hand, Murgai (1999) finds that accounting for factor-biased technological change, substantially raises estimates of TFP growth for the Punjab region in India and Bailey, Irz and Balcombe (2004) show that ignoring the bias in technological progress for UK agriculture over the period 1953-2000, results in a strong underestimation of TFP growth. Dupuy (2006) argues that investment in ICT after 1973 succeeded in maintaining the growth in the knowledge stock at its previous rate but the bias in technological progress explains the productivity slowdown of the 1970s and 1980s. Bessen (2008) replicates a number of previous studies. He concludes that ignoring the factor bias tends to underestimate the contribution of technological progress. For example, the conclusion by Kim and Lau (1994) and Young (1995) that economic growth of East Asian NICs was due to capital accumulation rather than due to (disembodied) technological progress results from ignoring the factor bias. In contrast with Felipe and McCombie (2001), his estimates suggest a far more substantial role for factor-augmenting technical change in East Asia. Antonelli and Quatraro (2010), using country-level data for 12 OECD countries over the period 1970-2003, provide indications of factor-biased technological change. A bias that favours the utilization of the relatively scarce production factors in a given country reduces the TFP growth of that country. Antonelli and Quatraro (2010) argue that ignoring the knowledge bias in recent technological progress may explain part of the perceived productivity slowdown in most OECD countries. Zhang (2014) points out that as recent technological change in China appears to be capital-saving, an assessment based on the assumption of Hicks neutrality will provide biased conclusions as to the contribution of technological change to economic growth in China.

This paper contributes to the literature on factor-biased technical change, first, by providing a general overview of factor biases in 14 manufacturing sectors in Belgium. While the existing literature on factor-biased technical change focuses on specific sectors, we test whether or not factor-biased technical change is pervasive in manufacturing. Second, besides focusing on skill and capital biases, we test for a materials bias, which received little attention so far in the literature and is expected to gain importance because of the increasing prevalence of offshoring and involvement in global value chains. Third, we provide insight into the robustness of factor biases when allowing for within-industry heterogeneity in technology by including firm-level R&D and firm age in the analysis. Fourth, we address factor biases in a fully nonparametric framework that is constrained to be consistent with micro-economic theory, implying that we make no a priori assumptions on the functional form of the production function (except monotonicity). Last, we suggest a fully nonparametric TFP change framework that does not impose Hicks neutrality.

The remainder of this paper is structured as follows. In section 2 we discuss the literature on TFP growth with factor-biased technical change. In subsection 2.1 we briefly discuss how ignoring the potential factor bias in technological progress affects estimates of total factor productivity growth. Subsection 2.2 provides an overview of the ways in the literature a factor bias is estimated or accounted for. In section 3, we discuss the nonparametric methodology to estimate technical change, factor-biased technical change and TFP growth. In section 4, we describe the used data on manufacturing in Belgium. In section 5 we discuss the results and section 6 concludes.

2 Total factor productivity growth with factor-biased technological change

2.1 Impact of factor-biased technological change on total factor productivity growth

The question whether technological change is neutral or biased is raised in the literature with respect to three main issues: the validity as such of the assumption of (Hicks-) neutral technical change[1], widely made in theoretical as well as applied research; the potential bias in the estimation of TFP when erroneously (Hicks-) neutral technical change is imposed and, finally, the impact of technical change on the factor shares (and hence income distribution).

The first issue is mainly an empirical question, for which we refer to the next section. How the second issue is formulated, depends on the framework that is used and the specific assumptions that are made. However, it can be easily illustrated in a standard neoclassical linear homogeneous production framework $Y = F(K, L, A(t))$ in which output Y is a function of two inputs (for example capital K and labour L). $A(t)$ reflects the shift in output for a given level of inputs, generally considered to reflect technological change[2]. The

[1] Neutral technological change is defined either as Hicks-, Solow- or Harrod-neutral. The usual definition is the first, in terms of which neutrality is defined as a time-constant marginal rate of substitution between the input factors. Harrod neutrality implies that the capital-output ratio remains constant at a given interest rate. Bessen (2008) points out that the assumption of Harrod-neutrality, necessary to assure a steady state solution in neoclassical growth theory (see Barro and Sala-i-Martin, 2004), is not supported by empirical evidence.

[2] Solow (1956) labelled A_t as an increasing scale factor and Solow (1957) stated that he used "technical change" as a shorthand expression for any kind of shift in the production function.

Solow residual is then defined in intensity terms[3] ($y = \frac{Y}{L}$; $k = \frac{K}{L}$) as $R_{Solow} = \widehat{y} - s\widehat{k^*}$ (with s denoting the output share of capital and k^* the profit-maximizing capital-labour ratio), i.e. the change in labour productivity that cannot be attributed to capital-deepening. Bessen (2008) shows that the Solow residual is only an accurate measure of technical change if the capital-labour ratio is independent from A, i.e. when technological change is Hicks-neutral. If the bias of technical change is defined as $B \equiv \frac{\frac{\partial^2 F}{\partial K \partial A}}{\frac{\partial F}{\partial K}} - \frac{\frac{\partial^2 F}{\partial L \partial A}}{\frac{\partial F}{\partial L}} \equiv \frac{F_{KA}}{F_K} - \frac{F_{LA}}{F_L}$, then Hicks-neutrality corresponds to $B = 0$. In general, k^* depends on the relative factor reward ($w \equiv \frac{w_L}{w_K}$) as well as on A and labour productivity growth is therefore equal to $\widehat{y} = s\sigma\left(\widehat{w} + B\right) + R_{Solow}$, where $\sigma = \frac{F_K F_L}{F F_{KL}}$ denotes the elasticity of substitution. It follows immediately that the Solow residual only captures the total effect of technical change ($R = \widehat{y} - s\sigma\widehat{w}$) conditional upon Hicks neutrality.

As regards the third issue, Ferguson (1968) showed in the same framework that the change in the income shares $(s, 1-s)$ are a function of σ, k^* and B :

$$\widehat{s} = (1-s)\left[B + (1 - \frac{1}{\sigma})\widehat{k^*}\right] \tag{1}$$

From (1) it is clear that Hicks capital-biased technical change ($B > 0$) does not necessarily imply a negative (positive) impact on the income share of labour (capital), as this also depends on the elasticity of substitution and the change in the capital-labour ratio. Ferguson points out that this may offer an alternative explanation to the Cobb-Douglas assumptions (Hicks-neutral technological change and $\sigma = 1$) for the fact that factor income shares appear to be relatively constant in the long run, as pointed out by Acemoglu (2003). Arpaia et al. (2009) and OECD (2012) report that the share of capital in national income increased substantially in recent decades in most OECD countries. This could be due to a strong capital bias in technological change or an elasticity of substitution larger than 1, combined with capital-deepening, or both.

[3] Where, as usual, $\widehat{TFP} = \frac{\frac{\partial TFP}{\partial t}}{TFP} = \frac{\dot{TFP}}{TFP}$

2.2 How to measure the factor bias of technological change?

The estimation methodology of the bias in technical change is closely linked to that of total factor productivity as such, in which following Diewert (1981) three main approaches can be distinguished: the nonparametric index approach, the econometric and the nonparametric linear programming approach. In the nonparametric index calculation of total factor productivity, one tries to take account of the factor bias by correcting the input factor shares that are used as weights of input factor growth. Total factor productivity growth, taken as the Solow residual, is measured by the Tornqvist-Theil approximation of the Divisia index of the difference between the growth of output and the factor share weighted growth of the input factors. As indicated in the previous section, when biased, technical change will be (partially) reflected by the change in factor shares and therefore the Solow residual must be corrected. The difference between the corrected and the Solow residual is then taken as an indicator of the factor bias. Bailey, Irz and Balcombe (2004) propose to estimate constant technology factor shares, assuming a translog revenue and cost function, from which output revenue and factor cost shares are derived. In these share functions, the bias of technical change is specified as a random walk with drift process, which is estimated and used to compute an adjusted TFP index. Felipe and McCombie (2001) use a computational approach to recover the constant technology factor shares. Bessen (2008) uses estimates of σ from the literature to estimate R $(= \widehat{y} - s\sigma\widehat{w})$.

The most common approach to measure factor bias of technological change is the econometric estimation, mostly of a flexible production or cost function, in which the factor bias of technical change is either taken into account by a time trend and interaction effects of time and other regressors or by a general index of technical change, additively and multiplicatively with other regressors. Christensen, Jorgenson and Lau (1973) allowed for a factor bias through the interaction of production factors with an index of technology. Using the dual translog cost function, Binswanger (1974) measured the factor bias by considering interaction terms of factor prices with time. Stevenson (1980) introduced a third order translog cost function in which second order coefficients can change over time. Although this substantially increases the number of coefficients to estimate, he argues that this model is more realistic and permits to test for price-induced factor biases and the assumption that large firms have a higher rate of technological progress than small firms. Estimating the factor bias from a translog cost function is also used more recently, amongst others, by Adams (1999), who allows for labour heterogeneity of the inputs and who considers R&D as the factor bias determinant and Betts (1997), who models the factor bias of technical change by a time trend.

As shown in Kumbhakar, Heshmati and Hjalmarsson (1999), TFP growth of cost-minimizing firms in a setting of competitive input markets (without price information) can be decomposed in technical change $\frac{\partial lnY}{\partial t}$ and a scale component:

$$\widehat{TFP}_t = \frac{\partial lnY}{\partial t} + (RTS-1)\sum_j \epsilon_j \frac{\dot{X}_j}{X_j}, \epsilon_j = \frac{\partial lnY}{\partial lnX_j}, \tag{2}$$

where ϵ_j is the shadow price approximation of the cost share S_j of input X_j and factor bias $B_j = \frac{\partial S_j}{\partial t} = \frac{\partial \epsilon_j}{\partial t} = \frac{\partial^2 lnY}{\partial lnX_j \partial t}$, with $j = 1, ..., m$.

They consider a translog production function with both alternatives for technological change[4]: technological change as a time trend t[5] and technological change reflected by a general index A(t) (proposed by Baltagi and Griffin, 1988)[6]. In the first alternative, TFP growth can be calculated after estimation as (and similar for the general index):

$$\widehat{TFP}_t^{TT1} = \left[\alpha_t + \alpha_{tt}t + \sum_j \alpha_{jt} lnX_j\right] + (RTS-1)\sum_j \epsilon_j \frac{\dot{X}_j}{X_j}, \tag{3}$$

The term in square brackets reflects technological change. TFP growth will only equal technological change for constant returns to scale (elasticity of scale (RTS) = 1). A potential factor bias of technological change is reflected by α_{jt} in the time trend model, which is

[4]Kumbhakar, Heshmati and Hjalmarsson (1999) consider a production function with variable as well as quasi-fixed inputs. For ease of exposition only variable inputs are considered

[5]I.e. the production function specification $lnY = \alpha_0 + \sum_j \alpha_j lnX_j + \alpha_t t + \frac{1}{2}\left(\sum_j \sum_k lnX_j lnX_k + \alpha_{tt}t^2\right) + \sum_j \alpha_{jt} lnX_j t$.

[6]I.e. $lnY = \alpha_0 + \sum_j \alpha_j lnX_j + A(t) + \frac{1}{2}\left(\sum_j \sum_k lnX_j lnX_k\right) + \sum_j \alpha_{jt} lnX_j A(t)$.

constant over time and across firms. In the general index model, the factor bias can change over time ($\alpha_{jt}[A(t) - A(t-1)]$). A potential scale bias is reflected by $\sum_j \alpha_{jt}$ in the time trend model and $[A(t) - A(t-1)] \sum_j \alpha_{jt}$ in the general index model. Kumbhakar, Heshmati and Hjalmarsson (1999) propose further extensions, allowing for a more firm-specific pattern of technological change and its factor bias. In their empirical work on plant-level data of the Swedish cement industry over the period 1955-1979, the model that appears to perform best is one in which the following term is added to the time trend specification, as proposed by Stevenson (1980): $\frac{1}{2}t\left(\sum_j \sum_k \phi_{jk} lnX_j lnX_k\right)$.

For this specification the factor bias for production factor j is given by $\alpha_{jt} + \sum_k \phi_{jk} lnX_k$ and the scale bias by $\sum_j \left(\alpha_{jt} + \sum_k \phi_{jk} lnX_k\right)$. Oh, Heshmati and Lööf (2012), applying the same alternative specifications as Kumbhakar, Heshmati and Hjalmarsson (1999) to data on Swedish firms over the period 1992-2000 lend further support for the latter specification.

Although most studies use, directly or indirectly, a translog specification, this functional form is known to have limitations (see for example, Berndt and Khaled, 1979; Berndt and Wood, 1982; Diewert and Wales, 1987; Barnett, 1985; Barnett et al., 1985; Henderson and Kumbhakar, 2006) and some studies have considered alternative specifications. Following David and Van der Klundert (1965), Klump et al. (2007) assume a CES production function in which technological change is pure factor-augmenting, modelled as a factor-specific constant growth rate function. Some of the most recent studies use a CES production framework as well, but consider technical change as an unobserved component, as in Olley and Pakes (1996) or Levinsohn and Petrin (2003), though now factor-specific. The factor-augmenting components are recovered from the inverted input demand function. Dorazelski and Jaumandreu (2012) assume that technical change consists of a Hicks-neutral and a labour-augmenting (unobserved) component, both modelled as Markov processes of which the expected terms are (unknown) functions of R&D expenditures. Assuming profit maximization, the demand functions for labour and materials are derived, which can be solved for the Hicks-neutral and labour-augmenting productivity component. These solutions are solely functions of observable variables and can be substituted in the expected productivity component, which is further taken as the complete set of third order polynomials of the one-period lagged productivity component and R&D expenditures. From this, a system of two semi-parametric equations is formulated, the estimation of which allows to obtain an estimation of the labour-augmenting and Hicks-neutral productivity component.

Zhang (2014) also models productivity as an unobservable component of the production function, though he adopts the assumption of pure factor-augmenting technical change and uses a translog production framework. Again, the input demand functions of labour and materials allow to solve for the unobserved productivity components, from which, after substitution in the production function, the error term can be solved (i.e. the unobserved productivity component can be separated), the moment conditions can be specified to estimate the parameters of the production function consistently and the productivity components recovered.

The estimation of the factor bias of technical change is also related to the literature on the impact of technical change on relative factor demand, in particular the skill bias in labour demand, of which the earlier contributions are reviewed in Sanders and ter Weel (2000) and Chennells and Van Reenen (1999). Most empirical studies estimate the factor bias of technological change indirectly by estimating cost share equations that can be derived by applying Shephard's lemma to a translog cost function. The cost shares are regressed on proxy variables of technology, the coefficients of which are then considered to provide evidence of a factor bias. Empirical studies that apply this approach tend to indicate that investment in ICT and R&D activities shifts relative demand in favour of high-skilled workers (for example, Berman, Bound and Griliches, 1994; Machin and Van Reenen, 1998; Autor, Katz and Krueger, 1998; Adams, 1999; Abowd et al., 2007). The regression of cost or employment shares on a number of technology and other variables provides estimates of the impact of specific technological activities on the shift in relative demand of production factors. However, as (1) shows, changes in factor shares can be due to substitution between factors (e.g., due to changes in relative prices) as well as due to a bias in technological change. These regressions therefore conflate the impact of the factor bias with the impact of factor substitution.

Finally, Kumbhakar and Sun (2012) use a kernel-based semiparametric modelling of the factor bias in technical change, in addition to a parametric translog production framework. Either parametrically specified or semiparametrically, from the estimation of the input distance function, obtained by normalizing the input demand function with a production factor taken as numéraire, the three components of total factor productivity growth can be identified, similar to the expression in (3): the bias in technical change, the scale component and the allocative efficiency component[7].

The use of a flexible methodology such as the translog and semiparametric models to assess factor biases is however not without disadvantages. First, although flexible, the models impose a functional form that can lead to a misspecification bias. An important second drawback is that output elasticities, the basis of factor bias estimation, can be negative, which violates the warranted monotonicity property (i.e. strong or free disposability) that implies that more inputs cannot lead to less output and producing less output cannot lead to more input use. Stated differently, monotonicity excludes congestion by imposing that the marginal rates of substitution/transformation (between inputs and between inputs and outputs) are non-negative. In this paper, we advocate the use of a fully nonparametric methodology that is constrained to behave in line with micro-economic theory.

3 Methodology

To show how factor biases and TFP growth can be estimated fully nonparametrically, we first define the empirical model, then discuss the local linear regression approach and last, show how economic restrictions can be imposed.

[7]The last component does not appear in (3), which is derived under the assumption of cost minimization and hence allocative efficiency.

3.1 The production model

We start from a production model with log output lnY, m-dimensional log input lnX, time $t = t_0, ..., t_T$ (our proxy for technical variation) for a set of observations $S = \{1, ..., i, ..., n\}$. u defines the variation (assumed exogenous) in observed firm performance that we cannot capture by the model. In the dominant literature, the empirical model is specified imposing Hicks neutrality as in (4). Hicks neutrality implies that the effect of time and inputs lnX are additive. Formally, $\forall lnX_j : \partial^2 lnY/\partial lnX_j \partial t = 0$, with $j = 1, .., m$.

$$lnY_i = g(lnX_i) + A(t) + u_i, \text{ with i=1,...,n.} \tag{4}$$

A general model that relaxes Hicks neutrality by allowing for factor-biased technical change is given in (5). There is a factor bias in technical change if the output elasticity of an input j, the shadow price version of the cost share of input j, changes over time. Formally, following Binswanger (1974) a factor bias is defined as $B_j = \frac{\partial S_j}{\partial t} = \frac{\partial \epsilon_j}{\partial t} = \frac{\partial^2 g}{\partial lnX_j \partial t} \neq 0$, for some j in $1, ..., m$.

$$lnY_i = g(lnX_i, t) + u_i, \text{ with i=1,...,n.} \tag{5}$$

To allow for heterogeneity in technology across groups of firms, we add categorical variables to the production model that interact with the time trend t and log inputs lnX. For ease of notation, we group the continuous values in $X^c = [lnX, t]$ and define the explanatory variables by $\tilde{X} = [lnX, t, X^u] = [X^c, X^u]$, with X^u a vector of unordered discrete values. $\tilde{X}_i$ defines the value of $\tilde{X}$ for observation i, with $i = 1, ..., n$ and the production model is given by:

$$lnY_i = g(\tilde{X}_i) + u_i, \text{ with i=1,...,n.} \tag{6}$$

3.2 Local linear regression

In a nonparametric (generalized) kernel regression, the conditional expected output $E[lnY_i|\tilde{X} = \tilde{X}_i]$ is not parametrized, but estimated by means of a localized regression. Stated differently, the main idea is to consider $\hat{g}(\tilde{X}_i) = E[lnY_i|\tilde{X}$ close to $\tilde{X}_i]$ as an approximation of $E[lnY_i|\tilde{X} = \tilde{X}_i]$. Nonparametric approaches do not impose *'a priori'* a functional relationship between the output and explanatory variables but '*let the data speak*' by localizing the production model[8].

In a local linear regression, a linear model is imposed only locally for the set of observations that have similar levels of input. Kernel weight functions are used to give more weight to observations with similar characteristics and bandwidths impose the window of localization. For large bandwidths the relationship will tend towards a straight line (surface), implying that a model with a linear relationship between (log) inputs and (log) output is a special case of nonparametric local linear regression. The parametric least squares estimator can thus be seen as a special case of the local-linear estimator (Li and Racine, 2007, p. 83). The regression is localized when the bandwidth sizes are smaller, implying that the model allows for non-linearities and that the fitted relationship becomes more wiggly. Literature shows that the choice of the weighting function is far less important than the choice of the window of localization - which we discuss below.

In equations (7) and (8), we define kernel weights (l^c, l^u) with bandwidths (λ^c, λ^u). In particular, we specify a Gaussian kernel function l^c to weight the continuous variable X_k^c (see (7)). An Aitchison and Aitken (1976) kernel l^u is specified to weight discrete unordered variable X_l^u with c_l categories and $\lambda_l^u \in [0, (c_l - 1)/c_l]$ (see (8)).

$$l^c\left(\frac{X_{ik}^c - X_k^c}{\lambda_k^c}\right) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{X_{ik}^c - X_k^c}{\lambda_k^c}\right)^2} \tag{7}$$

[8]See Li and Racine (2007) for an extensive overview of the used kernel regression approach.

$$l^u(X^u_{il}, X^u_l, \lambda^u_l) = \begin{cases} 1 - \lambda^u_l \text{ if } X^u_{il} = X^u_l, \\ \lambda^u_l/(c_l - 1) \text{ otherwise} \end{cases} \tag{8}$$

We use product kernels to allow for multivariate regression. The product kernel of X^c is $W_{\lambda^c}(X^c_i, X^c) = \prod_{k=1}^{q}(\lambda^c_k)^{-1} l^c((X^c_{ik} - X^c_k)/\lambda^c_k)$. For X^u, the product kernel is defined as $L_{\lambda^u}(X^u_i, X^u) = \prod_{l=1}^{r} l^u(X^u_{il}, X^u_l, \lambda^u_l)$. To include both continuous and categorical variables together, we specify a Racine and Li (2004) generalized kernel function as $\mathcal{K}_\gamma(\tilde{X}_i, \tilde{X}) = W_{\lambda^c}(X^c_i, X^c)L_{\lambda^u}(X^u_i, X^u)$, with $\gamma = (\lambda^c, \lambda^u)$.

The local linear kernel regression is the localized first order Taylor expansion of the production model.[9] The model is solved by the following minimization problem:

$$\min_{\{\alpha_0,\alpha_1\}} \sum_{i=1}^{n}(lnY_i - \alpha_0 - (X^c_i - X^c)\alpha_1)^2 \mathcal{K}_\gamma(\tilde{X}_i, \tilde{x}). \tag{9}$$

As the model is localized by kernel weighting, partial derivatives $\frac{\partial g(\cdot)}{\partial X^c_q}$ are also local and specific for each level of $\tilde{X}$.

Choosing which observations have similar input levels by selecting an appropriate multivariate bandwidth γ is of crucial importance. We apply the least-squares cross-validation approach as defined in (10), a data-driven approach that minimizes the asymptotic integrated mean squared error (AIMSE).[10]

$$CV(\gamma) = \frac{1}{n}\sum_{i=1}^{n}(lnY_i - \hat{g}_{-i}(\tilde{X}_i))^2 w(\tilde{X}_i) \tag{10}$$

where $\hat{g}_{-i}$ is the leave-one-out local-linear kernel estimator of $E(lnY_i|\tilde{X}_i)$. $w(\cdot) \in [0, 1]$ is a weight function that serves to avoid difficulties caused by dividing by 0 or by the slower convergence rate arising when $\tilde{X}_i$ lies near the boundary of the support of $\tilde{X}$. Simulation results of Li and Racine (2004) confirm that cross-validated local-linear regressions indeed have much larger bandwidths as optimum if the true relationship is linear.

[9] We opt for the local-linear regression as it has better boundary properties than the local-constant regression (Hall et al., 2007) and nests least squares as a special case.

[10] We opt for this approach over the AIC cross-validation approach since the least-squares cross-validation approach is less computationally cumbersome and more frequently applied in the literature.

3.3 Nonparametric regression-based TFP estimation

Analogously to TFP estimation in Kumbhakar et al. (1999), we can include nonparametric estimates of technical change and output elasticities into (2) to obtain nonparametric regression-based TFP estimates:

$$\widehat{TFP}_t^{NP} = \frac{\partial g(\cdot)}{\partial t} + (RTS - 1)\sum_j \epsilon_j \frac{\dot{X}_j}{X_j}, \epsilon_j = \frac{\partial g(\cdot)}{\partial lnX_j}. \tag{11}$$

The nonparametric TFP growth estimate $\widehat{TFP}_t^{NP}$ has as main advantage that no parametric structure is imposed on the functional relationship between inputs and output.

3.4 Imposing economic restrictions

Economic theory rarely dictates a specific functional form. Instead, it denotes which variables are possibly related and stipulates properties of the relationship (Yatchew, 1998). Deviating from (log-)linearity such as in the parametric translog model or the used kernel regression framework comes with the cost that the flexible fit may violate properties that are stipulated by economic theory (i.e., monotonicity or convexity of the production possibility set).

For our purpose of assessing factor biases in technical change, we impose as little assumptions as needed. As discussed, a property that is warranted is monotonicity (also referred to as strong or free disposability), implying non-negative output elasticities of all inputs j, with $j = 1, ..., m$.

As imposing a wrong production structure can lead to biased inference, we allow for non-constant returns to scale and non-convexity of the production possibility set[11].

While different approaches exist to constrain a nonparametric regression (surveyed in Parmeter et al. (2014)), a constrained weighted bootstrapping procedure as proposed by

[11] Imposing convexity on the production possibility set would imply that we exclude among others the possibility that a production function goes from increasing returns to scale (e.g. caused by indivisibility of inputs) to decreasing returns to scale (e.g. caused by coordination costs).

Hall and Huang (2001) is the most general as it can also be applied to parametric least squares regressions as shown in Parmeter et al. (2014). We refer to Parmeter et al. (2014) for a technical overview of the procedure and only provide here a general discussion of the proposed methodology to constrain (local) linear estimators.

The starting point is that the estimate $g_j(\tilde{X})$ of a linear estimator, with $j = 0$ representing the fit and with $j = 1, ..., m$ representing the first order derivative with respect to lnX_j, representing log input or time, can be formulated as a weighted sum of output, with weights $A_{j,i}(\tilde{X})$:

$$\hat{g}_j(\mathbf{x}) = \sum_{i=1}^{n} A_{j,i}(\tilde{X}) lnY_i. \tag{12}$$

In the case of a local linear regression, the weight $A_{0,i}(\tilde{X})$ is defined in (13) and $A_{1,i}(\tilde{X})$ is the first order derivative of $A_{0,i}(\tilde{X})$ with respect to input lnX_1 ($A_{1,i}(\tilde{X}) = \frac{\partial A_{0,i}(\tilde{X})}{\partial lnX_1}$).

$$A_{0,i}(\tilde{X}) = \left(\sum_{i=1}^{n} K_\gamma(\tilde{X}_i, \tilde{X}) \begin{pmatrix} 1 & (X_i^c - X^c) \\ (X_i^c - X^c) & (X_i^c - X^c)(X_i^c - X^c)' \end{pmatrix} \right)^{-1} K_\gamma(\tilde{X}_i, \tilde{X}) \begin{pmatrix} 1 \\ (X_i^c - X^c) \end{pmatrix}. \tag{13}$$

To impose monotonicity, which implies constraining $g_j(\tilde{X})$, with $j = 1, ..., m$, to be non-negative, we first introduce unconstrained weights $p_u = n^{-1}$ by multiplying (12) with n^{-1} and n to obtain (14) and choose weights p that replace p_u such that the non-negativity constraint and the constraint that $\sum_{i=1}^{n} p_i = 1$ are satisfied. The optimal p that satisfies the constraints is estimated by minimizing the L_2 metric function $D(p) = (p_u - p)'(p_u - p)$, subject to the imposed constraints in a quadratic programming procedure. This gives $\hat{g}_j(\tilde{X}|p)$, defined in (15), which is the monotonized estimate of $g_j(\tilde{X})$[12]

$$\hat{g}_j(\tilde{X}) = n^{-1} \sum_{i=1}^{n} A_{j,i}(\tilde{X}) \times n \times lnY_i \tag{14}$$

$$\hat{g}_j(\tilde{X}|p) = \sum_{i=1}^{n} A_{j,i}(\tilde{X}) p_i \times n \times lnY_i \tag{15}$$

[12] We use the software R for the estimation of a constrained local linear regression. The unconstrained local linear regression is estimated with the package *np*.

4 Data

Our dataset is based on downloads for firms in 14 selected manufacturing industries (see Table 1) in Belgium from November issues of the BELFIRST database provided by Bureau Van Dijk. It is a database of annual accounts and (social) balance sheets. The database further allows to obtain further firm characteristics such as a firms primary industry, location, and date of incorporation.

Table 1: Manufacturing sectors included into the analysis

Nace	Description
10	Manufacture of food products
13	Manufacture of textiles
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
17	Manufacture of paper and paper products
18	Printing and reproduction of recorded media
20	Manufacture of chemicals and chemical products
22	Manufacture of rubber and plastic products
23	Manufacture of other non-metallic mineral products
24	Manufacture of basic metals
25	Manufacture of fabricated metal products, except machinery and equipment
26	Manufacture of computer, electronic and optical products
27	Manufacture of electrical equipment
28	Manufacture of machinery and equipment not elsewhere classified
31	Manufacture of furniture

Because a specific issue or version of the database only contains information for the last ten years, we consulted different November issues of the database (new DVDs are released on a monthly basis). We consulted the DVDs of 2012, 2009, 2007, 2005, and 2002. The use of multiple issues allows to generate a dataset with better information on entry and exit as firms that exit the market are dropped rapidly from the database. Furthermore it allows to increase the time span of the data to 1995-2011.

Table 2 assesses the representativeness of our data. The first column lists the average number of firms in the different industries (averaged over years) ranging from a minimum of 382 in industry 24 (Manufacture of basic metals) to 3706 in industry 25 (Manufacture of fabricated metal products, except machinery and equipment). The following columns compare our data with data from the Structural Business Statistics database from Eurostat that refer to the population of firms (although these data are retrieved from a survey with incomplete coverage in Belgium, see CompNet Task Force (2014)). The comparison is based on the period 2008-2011 due to the availability of data at Eurostat. Our dataset covers on average, over industries, about 43 percent of firms. If we exclude firms with zero employees from the total SBS number (which is not available at the two-digit level) we cover on average 75 percent of firms. In terms of the coverage of the number of employees and value added, our dataset represents a little more than 70 percent of the employment and value added across industries on average. If we restrict attention to firms that report all the data that are typically used in estimating TFP (a.o. materials) we are left with 17 percent of the firms listed in the Structural Business database.

Table 2: Representativeness of the dataset

	avg. # firms in dataset	# firms as share of SBS	# firms zero # empl excl.	# employees	# firms 'TFP' vars.	value added
10	3155	0.30	0.46 (10-12)	0.60	0.09	0.68
13	861	0.39	0.69 (13-14)	0.68	0.14	0.71
16	959	0.30	0.71	0.86	0.08	0.91
17	269	0.66	0.74 (17-18)	0.85	0.31	0.83
18	2128	0.22	0.74 (17-18)	0.90	0.06	0.90
20	601	0.57	0.95 (20-21)	0.65	0.34	0.73
22	607	0.49	0.76	0.69	0.22	0.77
23	1116	0.44	0.76	0.68	0.17	0.67
24	382	0.63	0.71 (24-25)	0.39	0.32	0.33
25	3706	0.34	0.71 (24-25)	0.82	0.09	0.84
26	529	0.43	0.99 (26-27)	0.53	0.18	0.55
27	482	0.46	0.99 (26-27)	0.85	0.19	0.92
28	1310	0.49	0.93	0.76	0.18	0.78
31	981	0.26	0.60 (31-32)	0.73	0.07	0.78
average	1220	0.43	0.76	0.71	0.17	0.74
year						
2008		0.42		0.70	0.17	0.72
2009		0.42		0.73	0.17	0.74
2010		0.44		0.71	0.17	0.75
2011		0.43		0.71	0.17	0.76

From the social balance sheet we are able to recover the share of four categories in total employment at the firm level: management, employees (white collar), worker (blue collar), and other. Table 3 shows the evolution of the average share over the time span of our dataset. Because not all firms fill out the social balance sheet, the first column lists the number of firms on which the averages are based. On average workers account for a little more than two thirds of employment in a firm and employees for about 31 percent. Managers and others together account for the remaining 1.5 percent. The evolution is noteworthy as well. The average share of employees increases from 28 percent in 1997 to 34.8 percent in 2010, whereas the average share of workers decreases from 70 to 63.8 percent over the same period. Figures available upon request show the pervasiveness of this evolution across the entire distribution. The increase in the share of employees and a decrease of the share of workers can be seen at the 10th percentile, the median as well as the 90th percentile. Table 3 reports the average shares in the different industries as well as the change in percentage points between 1997 and 2010. Industries 27 (electrical equipment) and 31 (furniture) record the biggest changes over the period. The electrical equipment industry shows a rise of the share of employees of 36.0 to 51.6 percent, whereas the share of workers decreases from 61.1 to 46.5 percent.

For the analysis in this paper, we define 'low-skilled labour' as the full-time equivalent (FTE) number of workers and 'other' and define 'high-skilled labour' as the FTE number of employees and management. Obviously, this classification is imperfect, but it is the most reliable at hand. The classification is more suited to show factor biases for low-skilled labour than for the high-skilled employees, because we cannot disentangle medium-skilled from high-skilled labour. Results on (the absence of) high-skill using technical change need therefore to be interpreted with care.

Table 3: Skill heterogeneity

	# firms	share of			
		management	employees	workers	other
1997	3,027	1.2	28.0	70.0	0.8
1998	3,272	1.1	28.2	70.0	0.7
1999	3,374	1.1	28.4	69.8	0.8
2000	3,376	0.9	28.7	69.5	0.8
2001	3,422	1.0	29.4	68.8	0.7
2002	3,261	0.8	30.0	68.4	0.8
2003	3,163	0.7	30.4	68.2	0.7
2004	3,055	0.7	30.6	68.1	0.7
2005	2,837	0.8	31.5	67.0	0.7
2006	2,820	0.7	32.7	65.2	1.3
2007	2,793	0.8	33.2	64.8	1.2
2008	2,759	0.7	34.2	64.3	0.8
2009	2,644	0.7	34.6	64.1	0.6
2010	2,605	0.8	34.8	63.8	0.6
2011	1,153	0.9	41.0	57.5	0.6
average 1997-2010		0.9	31.1	67.3	0.8
change 1997-2010		-0.4	6.8	-6.1	-0.2

As we want to allow for heterogeneity in technology within sectors, we include information on firm age and R&D into the analysis[13]. We define firms as '*young*' ('*old*') if the firm age is at most 10 years (at least 20 years) and '*mature*' if the firm age is between 10 and 20 years.

Data on the R&D activities (expenditures and personnel) of Belgian companies, covering the period 1996-2011, have been kindly provided by the Belgian Science Policy Office. The data are from the biennial OECD business R&D survey, collected at the national level of Member states, following the recommendations of the OECD Frascati Manual. The data are provided at the level of the establishment (plant) where the R&D activities are carried

[13]See e.g. Van Biesebroeck (2003) for a parametric productivity model which allows for heterogeneity in technology.

out. As the other data are at the firm level, plant-level R&D data of firms with more than one R&D establishment have to be aggregated. As it is unlikely that all establishment where R&D activities actually take place are included in the survey, we test for influences of including R&D into the analysis for a subsample of observations for which R&D data is available. We define a firm to be R&D-intensive if the average over all years of R&D intensity, measured by the number of FTE employees active in R&D divided by the full work force ($L_{FTE}^{R\&D}/\ L_{FTE}$), is among the highest 25% of the firms of the nace two-digit sector.

We deflated turnover, materials and capital, using industry-wide deflators of EU-KLEMS[14] and cleaned the data both on levels and on growth rates to prevent effects of extreme outliers and extreme noise on the analysis.[15] As the coverage of firms in 1995 and in 2011 is lower than in the other years, we focus on the period 1996-2010. Table 4 summarizes the data available in the sample period. It shows that our data cover both small and large firms and documents the loss of observations by including R&D into the analysis.

Table 4: Summary statistics

	Obs	Mean	StDev	Min.	Q1	Med.	Q3	Max.
Defl. turnover/10,000	36979	2479.30	6759.69	21.82	305.24	815.29	2034.55	230951.09
Low-skilled (in FTE)	36979	59.65	115.29	0.73	10.40	27.00	62.00	3672.83
High-skilled (in FTE)	36979	27.50	68.73	0.32	3.73	9.58	24.34	2033.97
Defl. Capital/10,000	36979	403.82	1283.76	0.44	41.31	120.79	328.20	37676.64
Defl. Materials/10,000	36979	1919.70	5776.54	5.22	188.81	558.88	1489.99	192137.11
Firm age	36979	24.97	18.08	0.00	12.00	20.00	34.00	121.00
$L_{FTE}^{R\&D}/\ L_{FTE}$	10693	0.05	0.10	0.00	0.00	0.02	0.05	1

[14]Firm-specific prices are not available for the given dataset.

[15]Specifically, we limit the sample to observations with a labour use of minimum 5, strictly positive levels for both low-skilled and high-skilled labour, a number of months in a book year between 6 and 24 months and deflated turnover, deflated materials and deflated capital larger than 1,000 euro. Further, we removed the lowest and highest percentile of the included variables and dropped observations with growth rates of included variables lower (higher) than 10 (-10).

5 Results

5.1 Optimal level of localization

As discussed in the methodology section, bandwidths that are very high (and thus imply no localization) indicate a linear relationship (in logs). Table 5 shows the estimated optimal bandwidths from the least squares cross-validation routine. In all the sectors, it is optimal to localize in the direction of workers, employees and capital. Table 5 thus shows that allowing for non-linearity and interactions is warranted (as the mean squared error is lower) in all the sectors. For materials, the optimal bandwidth is very large in sector 16 (wood and products of wood and cork) and 23 (other non-metallic mineral products), implying that the relationship between log materials and log turnover is estimated to be linear.

The time trend (our proxy for technical change) is estimated to be linear in sector 10 (food products), 13 (textiles) and 20 (chemicals and chemical products). Technical change - discussed in section 5.2 - is thus estimated to be constant and Hicks-neutral in these sectors.

Table 5: Bandwidth size

sector	Log low-skilled	Log high-skilled	Log capital	Log materials	Year
10	0.535	0.682	0.390	3.620	341080.227
13	0.350	1.539	0.402	0.914	368683.967
16	0.650	0.863	0.223	48529.523	3.430
17	0.462	0.375	0.614	0.592	1.379
18	0.570	0.298	0.356	0.811	13.701
20	0.530	0.403	0.331	0.338	48.143
22	1.226	0.405	0.308	2.065	4.527
23	0.346	0.526	0.414	484078.458	4.121
24	0.480	0.595	0.583	0.844	13.600
25	0.552	0.469	0.484	2.065	5.721
26	0.907	0.133	1.593	0.479	2.598
27	0.855	0.844	0.468	0.638	1.002
28	0.166	0.585	0.997	1.970	3.842
31	0.667	0.967	0.243	1.267	2.801

5.2 Factor-biased technical change

Table 6 shows that in addition to sector 10,13 and 20, we cannot reject Hicks neutrality in sector 24 (basic metals) in the period 1996-2010. We omit sector 26 (computer, electronic and optical products) from the interpretation, as the changes are too high to make economic sense. Hence, eight sectors remain for which we reject Hicks neutrality for the full sample: sector 17 (paper and paper products), 18 (printing and reproduction of recorded media), 22 (rubber and plastic products), 23 (other non-metallic mineral products), 25 (fabricated metal products, except machinery and equipment), 27 (electrical equipment), 28 (machinery and equipment n.e.c.) and 31 (furniture).

For all eight sectors except sector 18, there are substantial factor biases, with output elasticity change larger than 0.05, i.e. an output change, resulting from a percentage change in an input, with more than 5 percentage points.

Table 6 indicates that in all of these eight sectors, the marginal productivity of low-skilled labour (i.e., workers) is diminishing over time. For five sectors (17, 18, 22, 23 and 28), this decline in output elasticity is significant at the 5% level.

We only find a statistically significant bias in favour of high-skilled labour in sector 23. The factor bias estimations provide little support for technical change that is both input-saving in low-skilled labour and input-using in high-skilled labour. This may be due to the fact that our proxy for skilled labour is too broad as it does not reflect differences between medium-skilled and high-skilled labour, but could also indicate the more ambiguous impact of technological change on high-skilled workers stressed in some task-based studies (for example Autor et al. (2003)) .

In contrast, we find evidence for materials-using technical change in three sectors (18, 25 and 31) and capital-using technical change in two sectors (17 and 23). Overall, the non-parametric factor biases show technical change is low-skilled labour-saving in a substantial part of the manufacturing sector, and depending on the sector either materials-using, capital-using or high-skilled labour-using.

To control for the effects of the 2008 crisis and post-2008 economic slowdown, we additionally estimate factor biases for the period 1996-2007. Overall, the results are in line with the 1996-2010 period. We find low-skilled labour-saving technical change to be significant in four sectors and little support for high-skilled using technical change (only in sector 23). In sector 18 and 25, we find a significant materials bias. There is mixed evidence of a capital bias, as the output elasticity is significantly increasing in sector 22 but significantly decreasing in sector 27 and 31.

The relative factor biases are in line with the 1996-2010 period as we find factor biases against low-skilled labour and in favour of either high-skilled, materials or capital.

Table 6: Factor-biased technical change: full sample

Nace	$\Delta\epsilon_{LS}$	$\Delta\epsilon_{HS}$	$\Delta\epsilon_{M}$	$\Delta\epsilon_{C}$
		1996-2010		
10	0	0	0	0
13	0*	0	0	0
16	-0.03	0.02	0.02	0.01
17	-0.12*	-0.06	0	0.15*
18	-0.02*	0.01	0.01*	0
20	0	0	0	0
22	-0.05*	0.04	0.05	-0.03
23	-0.08*	0.08*	-0.02	0.02*
24	0	0	0	0
25	-0.02	-0.01	0.05*	0
26	-0.07	-0.09	-0.81*	0.6
27	-0.04	-0.03	0.03	-0.04*
28	-0.15*	0	0.02	0
31	-0.05	-0.01	0.14*	-0.02
		1996-2007		
10	0	0	0	0
13	0*	0	0	0
16	0	0.02	0.05	0
17	-0.03	-0.02	-0.02	0
18	-0.01*	0.01	0.01*	0
20	0	0	0	0
22	-0.03*	0.04	0.03	-0.02
23	-0.06*	0.07*	-0.03	0.02*
24	0	0	0	0
25	-0.02	0	0.04*	0
26	-0.1	-0.08	-0.81*	0.9*
27	-0.05	-0.08	0.08	-0.04*
28	-0.1*	-0.01	0.01	-0.01
31	0.01	-0.02	0.05	-0.03*

From Table 6, we cannot conclude that the production structure of existing firms is changing over time. The factor biases we find can be the result of between firm market changes such as entry, exit and reallocation even without any changes in the production structure within firms. To obtain insight whether the documented factor biases also occur within firms, we test for factor biases for a balanced sub-sample of firms. For this, we focus on the sectors with more than 1,000 observations in the balanced panel.

Table 7: Factor-biased technical change: balanced sample

Nace	$\Delta\epsilon_{LS}$	$\Delta\epsilon_{HS}$	$\Delta\epsilon_{M}$	$\Delta\epsilon_{C}$
1996-2010				
10	0	0.01	-0.02	0
20	-0.09*	-0.12*	0.09*	0.01
22	0.01	-0.11	0.02	0.05*
23	-0.17*	-0.03	0	-0.07
24	-0.1	0.03	0.05	-0.07
25	-0.09*	-0.02	0.06	0
28	0.11	0.05	0.13	0
1996-2007				
10	0	0.01	-0.02	0
20	-0.1*	-0.12*	0.08*	0.02
22	0.02	-0.14*	-0.01	0.05*
23	-0.15*	-0.05	-0.03	-0.06
24	-0.01	-0.03	0.04	-0.06
25	-0.06*	-0.02	0.04	0
28	0.1	0.06	0.14	-0.01

Table 7 documents the changes in output elasticities for seven sectors. While for the full sample, there was no localization in the direction of time for sectors 10 and 20, there is localization for all the considered sectors when focusing on a balanced sample[16].

In sectors 20, 22, 23 and 25, we find indications for factor biases for the subgroup of incumbents. Overall, balanced sample results confirm the decreasing output elasticity of low-skilled labour. Sectors 20, 23 and 25 show factor biases against labour and in favour of capital and materials, especially pronounced for low-skilled labour. The balanced sample results do not support the finding of significantly increasing output elasticity of high-skilled labour in sector 23, indicating between-firm market changes drive the skill-using technical change in this sector.

Though most attention in the factor bias literature goes to skill biases or capital biases, we find that the materials bias is substantial in several sectors and also occurs within the group

[16] Bandwidth sizes available upon request.

of incumbents. We are not the first to document a materials bias (see e.g. Betts (1997) and Stevenson (1980)), but, to our knowledge, the first to show that technical change that is materials-using and low-skilled labour-saving is widespread in manufacturing. We expect that this is related to offshoring and inclusion in global value chain networks. Mion et al. (2010) and Hertveldt and Michel (2013) already relate demand of low-skilled and skill-upgrading to offshoring in Belgium. We contribute by showing nonparametrically that factor-biased technical change in favour of materials and against low-skilled labour may explain the decreased income share of low-skilled workers.

5.3 Allowing for heterogeneity in technology

Tables 6 and 7 document the rejection of Hicks neutrality in a substantial number of the manufacturing sectors considered. However, it is unlikely that all firms operate under the same technology as the 'average' firm and we need to test the sensitivity of the factor biases for altering the specification of the technology. Usual suspects to explain within-industry changes in production technology are very large firms (usually exporters) and young, innovative companies. By using the flexible nonparametric methodology, we control for variation in production scale as the production model is only imposed locally and thus allow for varying dynamics of factor biases between large and small firms.[17] By including information on firm age and R&D intensity, we can test whether we also find factor biases if we control for heterogeneity in technology.

For this, we focus on sector 25 (fabricated metal products, except machinery and equipment) as it is one of the largest manufacturing sectors in Belgium and it is a sector that shows robust indications for factor-biased technical change in favour of materials and against labour - especially low-skilled labour - in Tables 6 and 7. Bandwidth sizes and the analysis for other sectors are available upon request. Results for sectors 23 and 28 are

[17] As the number of very large firms is limited in all sectors, we do not test for different factor biases between firm of different size in this paper.

in line with the studied sector 25.

As discussed in section 4, firms with average ($L^{R\&D}_{FTE}/\ L_{FTE}$) among the highest 25% in their sector are categorized firms with high R&D intensity. As we exclude observations that were not included in the survey, the sample for sector 25 is reduced from 6209 observations to 2691 and for the balanced sample from 1710 to 1005 observations. For firms with high R&D intensity, we confirm in Table 8 the decline in output elasticity of low-skilled labour. Estimates for the balanced sample that focus on R&D intensive firms show a very pronounced increase of marginal productivity of materials. Indications for a capital bias are not robust for including R&D. Table 9 shows factor biases in sector 25, controlling for firm age, but no indications for a skill bias. However, for all firm-age categories, we find a significant material and capital bias.

Overall, we can conclude that sector 25 shows a robust material bias. Additionally, we find strong indications for a capital bias, which is however less robust for altering the specification of the production technology. No indications are found for a skill-using bias. In the Appendix, we discuss translog estimates of factor-biased technical change, which provide similar results for sector 25. The material bias found in sector 25 is thus robust for altering the specification of technology and not specific to the used nonparametric methodology.[18]

[18]Additional analysis available upon request shows that results are robust for including investments in the analysis. However, as investments were calculated by use of firm-level depreciation rates which are known to be unstable, we do not provide the results in the paper.

	Full sample			Balanced sample			High R&D			High R&D - Balanced		
	1996-2010	1996-2007	2007-2010	1996-2010	1996-2007	2007-2010	1996-2010	1996-2007	2007-2010	1996-2010	1996-2007	2007-2010
$\Delta\epsilon_{LS}$	-0.02	-0.02	-0.01*	-0.09*	-0.06*	-0.03*	-0.04*	-0.03*	0	-0.03	-0.01	-0.02
	[-0.05,0]	[-0.03,0]	[-0.01,0]	[-0.16,-0.02]	[-0.12,-0.01]	[-0.05,-0.01]	[-0.06,-0.01]	[-0.05,-0.01]	[-0.01,0]	[-0.13,0.08]	[-0.07,0.06]	[-0.06,0.02]
$\Delta\epsilon_{HS}$	-0.01	0	0	-0.02	-0.02	0	0.01	0.01	0	-0.04	-0.03	-0.01
	[-0.03,0.02]	[-0.02,0.02]	[-0.01,0]	[-0.09,0.04]	[-0.07,0.03]	[-0.02,0.02]	[-0.01,0.03]	[-0.01,0.02]	[0,0.01]	[-0.13,0]	[-0.09,0.01]	[-0.06,0.01]
$\Delta\epsilon_{M}$	0.05*	0.04*	0.01*	0.06	0.04	0.02	0.01	0.01	0	0.15*	0.11*	0.04*
	[0.02,0.07]	[0.02,0.06]	[0,0.02]	[-0.04,0.16]	[-0.03,0.11]	[-0.01,0.05]	[-0.03,0.04]	[-0.02,0.03]	[-0.01,0.01]	[0.07,0.24]	[0.05,0.18]	[0.01,0.08]
$\Delta\epsilon_{C}$	0	0	0	0	0	0	0	0	0	0.02	0.02*	0
	[-0.01,0.01]	[-0.01,0.01]	[0,0]	[-0.02,0.03]	[-0.01,0.02]	[-0.01,0.01]	[-0.01,0.01]	[-0.01,0.01]	[0,0]	[-0.01,0.04]	[0,0.04]	[-0.01,0.01]

Table 8: R&D and FBTC (Nace Sector 25)

	Young firms			Mature firms			Old firms		
	1996-2010	1996-2007	2007-2010	1996-2010	1996-2007	2007-2010	1996-2010	1996-2007	2007-2010
$\Delta\epsilon_{LS}$	-0.01	-0.01	0	-0.09*	-0.06*	-0.03*	-0.02	-0.01	0
	[-0.03,0.01]	[-0.02,0.01]	[-0.01,0]	[-0.16,-0.02]	[-0.12,-0.01]	[-0.05,-0.01]	[-0.04,0.01]	[-0.03,0.01]	[-0.01,0]
$\Delta\epsilon_{HS}$	-0.01	-0.01	0	-0.02	-0.02	0	-0.01	-0.01	0
	[-0.02,0]	[-0.02,0]	[0,0]	[-0.09,0.04]	[-0.07,0.03]	[-0.02,0.02]	[-0.02,0]	[-0.02,0]	[0,0]
$\Delta\epsilon_{M}$	0.03*	0.02*	0.01*	0.06	0.04	0.02	0.03*	0.02*	0.01*
	[0.02,0.04]	[0.01,0.03]	[0,0.01]	[-0.04,0.16]	[-0.03,0.11]	[-0.01,0.05]	[0.02,0.04]	[0.01,0.03]	[0,0.01]
$\Delta\epsilon_{C}$	0.01*	0.01*	0*	0	0	0	0.01*	0.01*	0*
	[0,0.02]	[0,0.02]	[0,0]	[-0.02,0.03]	[-0.01,0.02]	[-0.01,0.01]	[0,0.02]	[0,0.01]	[0,0]

Table 9: Firm age and FBTC (Nace Sector 25)

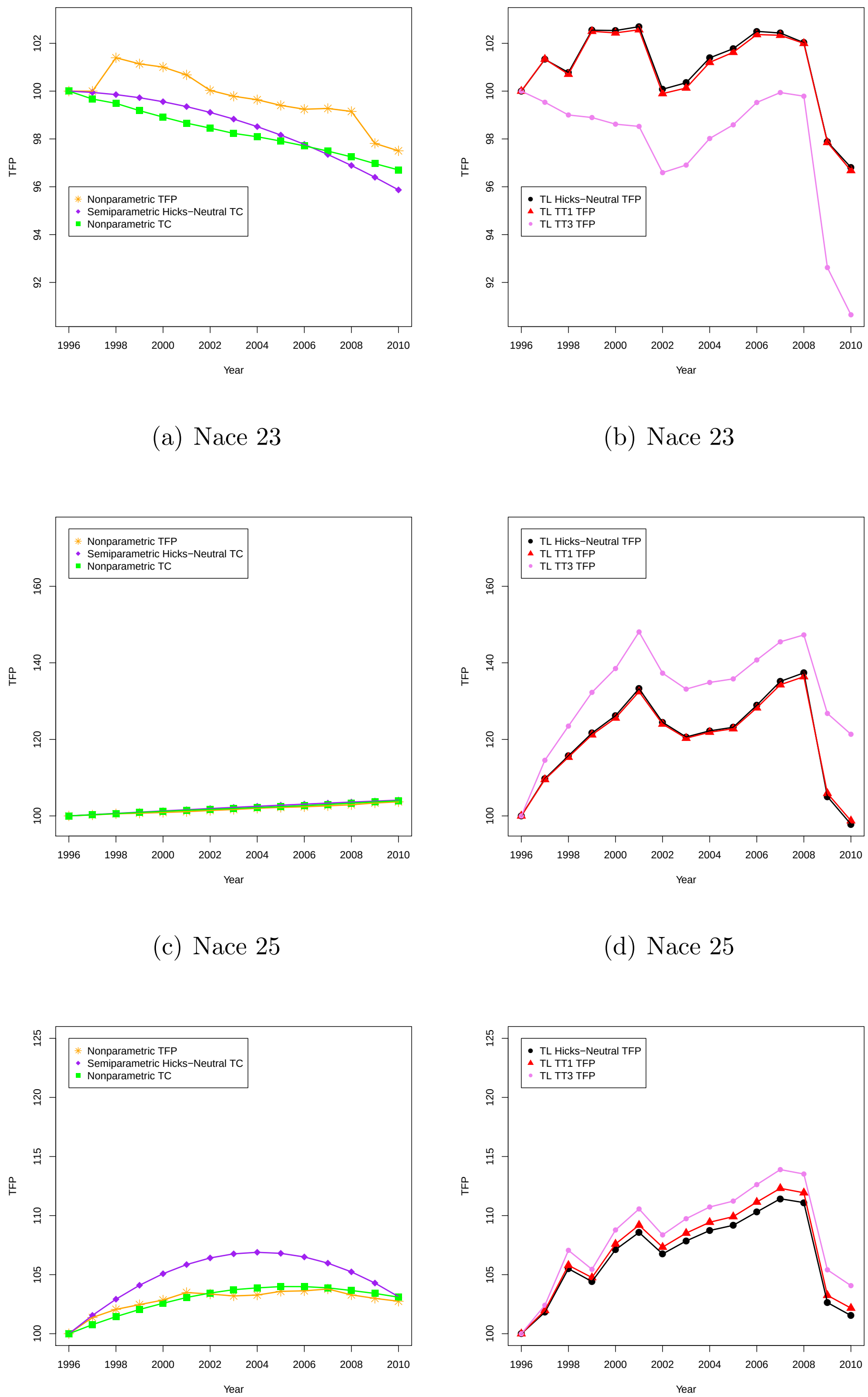
5.4 Implications for TFP analysis

As discussed in section 2.1, assuming erroneously Hicks neutrality may induce a bias in the estimation of TFP growth and thereby also bias the assessment of the determinants of TFP growth. In Figure 1 and in the Appendix (Figures 2 and 3) we compare estimations of TFP change at the sectoral level for different assumptions as regards the neutrality of technical change and the estimation method of TFP. First, we include the nonparametric TFP change estimates as defined in (11). Second, we include semiparametric Hicks-neutral technical change estimates by making use of a partially linear model of Gao et al. (forthcoming), with time and time-squared included parametrically and additive to a nonparametric smooth of the inputs. As output elasticities cannot be estimated in the routine used for the semiparametric model, we focus on technical change and additionally give nonparametric technical change estimates.[19] Third, we include a Hicks-neutral parametric translog model, the Kumbhakar et al. (1999) TT1 translog model, with TFP change defined in (3), and the Stevenson (1980) TT3 translog model. Recall that the latter two models allow for factor-biased technical change by interacting the time trend with input factors, but that the TT3 model allows for additional polynomials.

Figure 1 shows the time pattern of TFP between 1996 and 2010 for the Nace sectors 22, 25 and 28 (three sectors for which we find indications that technical change is low-skill saving and materials-using); in Figures 2 and 3 the evolution of TFP is shown for all Nace two-digit sectors of manufacturing in this period. Overall, the estimations suggest rather slow TFP growth (technical change) in the period considered. Yet, the choice of methodology is important. The estimates from the parametric translog models differ considerably from the nonparametric estimates. The nonparametric estimates are rather conservative and do not show the sharp TFP falls (e.g. in the crisis period). The Hicks-neutral and TT1 translog model show very similar patterns of TFP growth. In contrast, the TT3 translog

[19] Given that the returns to scale are estimated in the nonparametric model to be close to constant returns to scale (estimates available upon request), the difference between technical change and TFP change is modest.

model estimates can widely differ from the other models and are unstable. As regards the nonparametric estimations of TFP or technical change, the influence of imposing Hicks neutrality is modest. The effects of interactions between time and inputs are thus for a large part compensated by higher/lower output elasticities of the inputs and time trend, leading to a fit which is close to a production fit that allows for factor biases. However, in other sectors where a bias was found (in particular Nace sectors 17, 18 and 27), the difference in the technical change estimates with and without assuming Hicks neutrality, seems more substantial. In general, the assumptions made about the neutrality of technical progress, may affect the estimations results of TFP or technical change quite considerably. Therefore, it seems warranted to test for factor neutrality of technical change prior to the estimation of TFP growth, irrespective of which estimation procedure is considered.



(a) Nace 23 (b) Nace 23

(c) Nace 25 (d) Nace 25

(e) Nace 28 (f) Nace 28

Figure 1: TFP estimates at the Nace two-digit level

6 Concluding remarks

In most estimations of TFP growth at the firm level, Hicks neutrality is explicitly assumed. In this paper, we provide a test for factor biases in manufacturing sectors with distinct characteristics without imposing a parametric specification of the production function, constraining estimates to be in line with micro-economic theory, and discuss the implications of rejecting Hicks neutrality for TFP estimation. Additionally, we advocate a TFP change estimation framework that does not impose Hicks neutrality or a priori assumptions on the functional form of the production function.

For this purpose, we constructed a firm-level sample covering 1996-2010, based on the BELFIRST database of Bureau Van Dijk and firm-level R&D data from the Federal Public Planning Service Science Policy. A fully nonparametric framework is applied to test for changes in relative marginal productivity of inputs over time, estimate technical change and obtain firm-level estimates of TFP change without impose Hicks neutrality.

We tested for Hicks neutrality in 14 manufacturing sectors at the Nace two-digit level in Belgium and can reject Hicks neutrality for a substantial number of these sectors. We show that technical change that is low-skilled labour-saving and materials-using is widespread in the manufacturing sectors. The materials bias received little attention in the factor-biased technological change literature and is likely to be linked to offshoring and the inclusion of firms in global value chain networks. As offshoring and global value chains gain importance, we may expect the materials bias of technological change will persist in the future. Further, the materials bias has consequences for the appropriateness of value added measures (which implicitly assume a time-invariant marginal productivity of materials).

Factor-biased technical change at sector level does not necessarily imply changes of relative marginal productivity of inputs within incumbent firms and can be a mere result of entry or exit of firms with other production characteristics (for example, newer technologies). By limiting the sample to a balanced sample of incumbents, we show the changes in the relative marginal productivity of inputs also occur 'within-firm'.

It is unlikely that all firms operate under the same technology. To account for heterogeneity in technology, we show that the findings are not sensitive for including firm age and R&D, which are both linked to technological heterogeneity.

Further analysis is needed to understand the micro-dynamics of factor-biased technical change. We find no indications that factor biases are specific for either low- or high-technology firms or sectors. Export behaviour and the involvement and position of firms in global value chains of firms are likely micro-drivers of factor biases.

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Appendix

Translog estimations of factor bias and TFP growth

Most TFP measures result from calculation (index) or parametric estimation. To verify the robustness of the conclusions of the nonparametric approach and to assess the impact of the assumption of Hicks neutrality with a parametric approach, we also provide parametric estimates of the factor bias of technical change and TFP growth with potential non-neutral technical change. In this respect, we followed Kumbhakar et al. (1999) by estimating three alternative translog production function specifications. First, assuming Hicks-neutral technical change by including a time trend and its square in a translog function of factor inputs (i.e. capital, high-skilled labour, lower skilled labour and materials); second, allowing for factor-biased technical change, by extending the first translog specification with interaction terms between time and (the log of) factor inputs and, finally, in line with Stevenson (1980), extending the last specification with the third order interaction terms of time and the product of (the log of) factor inputs [20]. These two last specifications are indicated by Kumbhakar et al. (1999) as the TT1 and TT3model, respectively. The three translog functions were estimated by sector, for the same sample as used in the nonparametric approach, including firm-specific fixed effects. Following Kumbhakar et al. (1999), the factor bias of technical change is determined by the significance of $\frac{\partial^2 \ln Y}{\partial t \partial ln X_i}$ in TT1 and TT3. The growth of total factor productivity is calculated as indicated in expression (2).

[20] See also section 2.2

In the TT1 specification, the (estimated) factor i bias of technical change is equal to the estimated parameter $\hat{\alpha_{it}}$ and hence, sector specific but firm and year independent. Therefore, the sign and significance of the factor bias follows immediately from the parameter estimate and the ratio to its standard error. However, in the TT3 specification, the factor bias of technical change is specific to each firm-year combination. As an indication of its orientation and significance at the sectoral level, we considered a confidence interval of two times the standard error of its distribution around the mean, which, assuming that the annual distribution by sector of the bias of each factor is normal, allows to determine sign and significance of the bias with a 5% error.

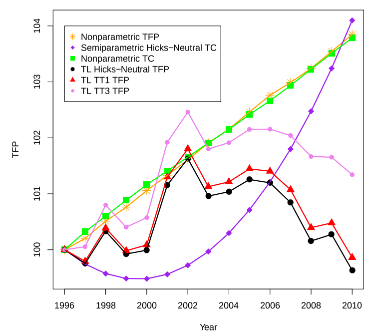
In the three models, TFP growth determined as in (2), is firm- and year-specific. By firm and year, we took the difference between the estimated TFP growth under the assumption of Hicks neutrality, with the estimated TFP growth in the TT1 and TT3 model, as well as the difference between the estimated TFP growth for the two factor bias specifications considered. Next, we verified whether, by sector and year, these differences are *on average* significantly different from 0.

For both specifications of the factor bias of technical change considered, we find pervasive indications of factor biases in technical change and hence, rejection of Hicks neutrality. However, the orientation of the factor bias appears to be sector-specific: whereas in one sector indications point at factor-saving technical change, in another we find indications of factor-using technical change. For the TT1 model this is in particular the matter for capital, high-skilled labour and materials. For low-skilled labour, in sectors where a bias is found, the bias pattern is more univocally negative. In addition, the orientation of the factor bias is sensitive to the estimated specification. While for the TT3 model, indications of factor biases in technical change are as pervasive as for the TT1 specification, the factor pattern of the bias only rarely corresponds to the bias derived from the TT1 model: factor biases have opposite signs (e.g. capital in sector 10 and 13), factor biases appear in the TT3 specification that are absent in the TT1 model and vice versa. Overall, the TT3 model points to a negative capital bias of technical change and the absence of a (high- as well as low-skilled) labour bias.

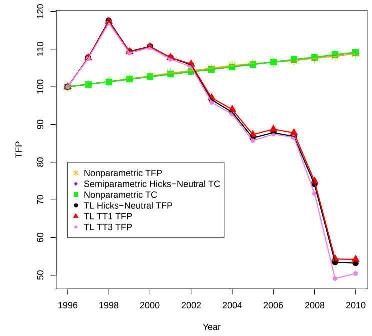
As regards TFP growth, we notice that, for many years and sectors, its estimation allowing for factor-biased technical change is (on average) significantly different from the estimation assuming Hicks neutrality, yet again characterised by substantial sector specificity. In some sectors, assuming Hicks neutrality implies an overestimation of TFP growth compared to that of the two models with factor-biased technical change (e.g. sector 13 or 17) but an underestimation of TFP growth in others (like sectors 18, 22 or 31). However, in many sectors the difference in TFP growth estimated in the three models, behaves more erratically, as both over- and underestimation of TFP growth assuming Hicks neutrality is found. In addition, the estimation of TFP growth is sensitive to the way the factor bias of technical change is modelled, as it differs significantly between the TT1 and TT3 specification in all the sectors considered, at least for one year. However, more often than not, the estimated returns to scale in the Stevenson specification are unrealistically high or low.

sector	capital bias	high-skilled labour bias	lower-skilled labour bias	materials bias
TT1 specification				
10	+			−
13	−	+		
16		+		
17	+	+	−	−
18		+		−
20	+	−	−	+
22	−			
23	−			+
24		−	−	+
25			−	+
26			+	−
27		−		+
28		+	−	+
31			−	
TT3 specification				
10	−			+
13	+	$+^*$		+
16			−	−
17			−	−
18	+		+	
20	−		−	+
22	−	$+^*$		+
23			+	−
24	−			+
25	−			+
26	−			−
27	−			−
28				+
31	−			+

Sector-level TFP change estimates



(a) Nace 10



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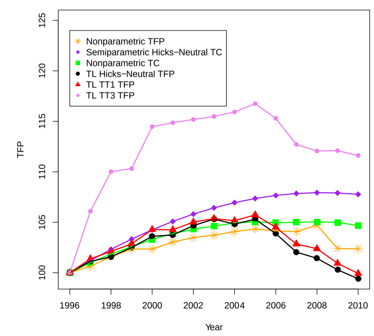
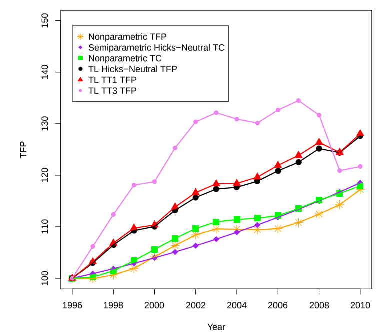


(c) Nace 16



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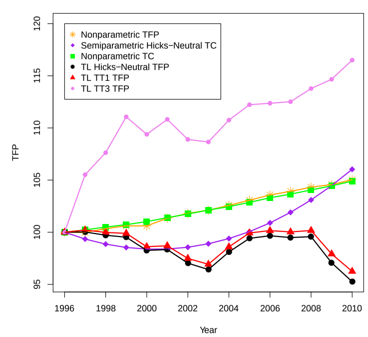

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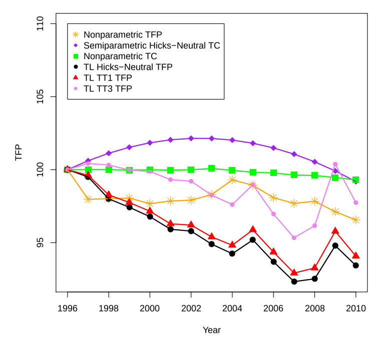
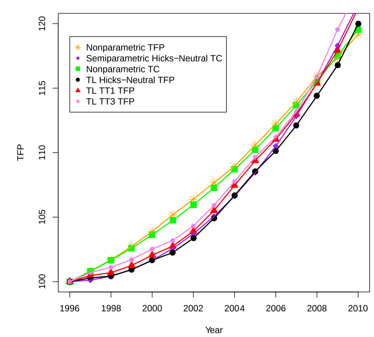
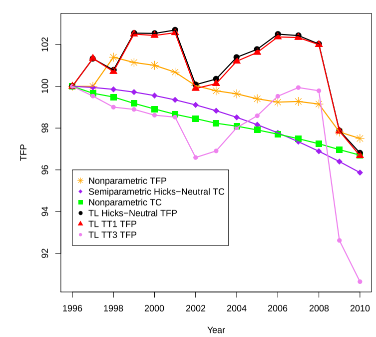


(f) Nace 20

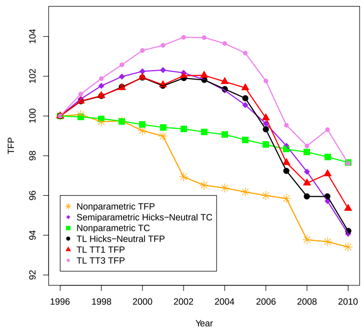


(g) Nace 22

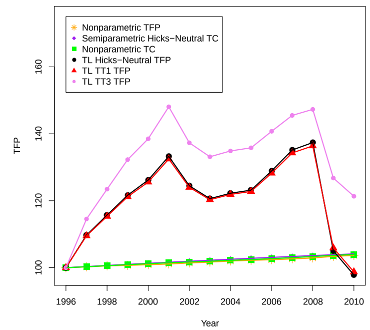


(h) Nace 23

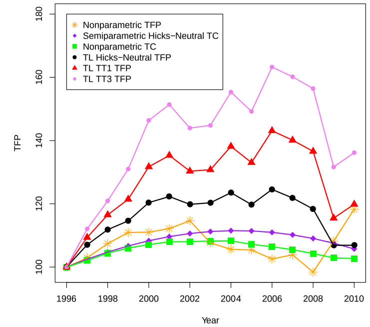
Figure 2: TFP estimates at the Nace two-digit level - Part I



(a) Nace 24



(b) Nace 25



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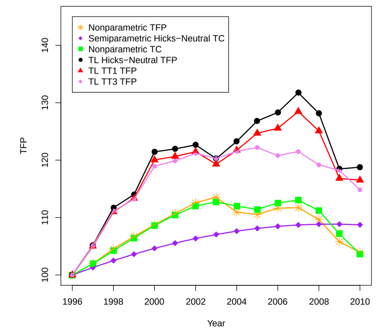
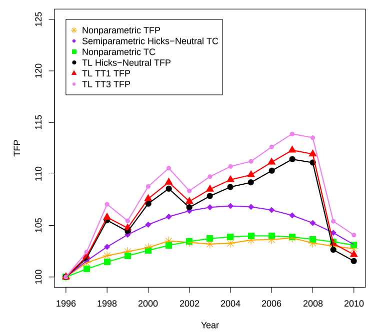
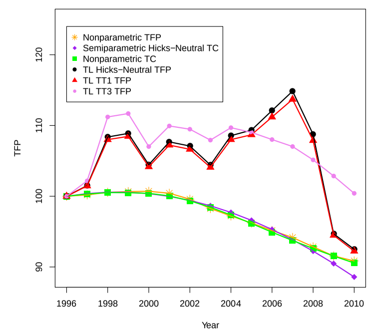


(d) Nace 27



(e) Nace 28



(f) Nace 31

Figure 3: TFP estimates at the Nace two-digit level - Part II

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Limited liability company
RLP Brussels – Company's number: 0203.201.340
Registered office: boulevard de Berlaimont 14 – BE-1000 Brussels
www.nbb.be

Editor

Jan Smets
Member of the Board of directors of the National Bank of Belgium

Layout: Analysis and Research Group
Cover: NBB AG – Prepress & Image

Published in October 2014