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Firm-Heterogeneous Biased Technological Change: A nonparametric approach under endogeneity

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Abstract

We propose a fully nonparametric framework to test to what extent technological change is factor-biased and heterogeneous. We show in a Monte Carlo simulation that our framework resolves the endogeneity issue between productivity and input choice and provides accurate estimates of firm-specific biases. For all Belgian manufacturing industries analyzed, we reject the predominant assumption of Hicks-neutral technological change over the period 1996-2015. We find that technological change is skill-biased, capital saving and domestic materials using. Moreover, we find significant heterogeneity in the pattern of technological change between and within industries. Relying on a rich dataset of firm characteristics, we provide robust indications that firm-level technological change can be attributed to specific firm strategies and technological characteristics.

Keywords: Productivity and competitiveness, Technological change, firm heterogeneity, nonparametric, endogeneity.

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1 Introduction

Optimization of the interrelation between technological change and the use of input factors is a core aspect of management decision-making. If technological change is the consequence of management decisions aimed at increasing profitability, it is likely its pattern will differ between firms in function of their characteristics. Hence, when analyzing technological change at the firm level, two dimensions must be taken into account: the direction of technological change and the firm specificity thereof.¹

In this paper, we propose a novel nonparametric approach to test for firm heterogeneity in factor-biased technological change in noisy settings with endogeneity. We show the empirical applicability of our advocated framework using a Monte Carlo (MC) analysis and using data of Belgian manufacturing firms for the period 1996-2015. We find that the pattern of technological change is very heterogeneous between industries, but generally skill-biased, capital saving and domestic materials using.

The first contribution of this paper is to propose a fully nonparametric framework to study factor-biased technological change that controls for endogeneity without requiring a priori parametrization of the production technology. Current nonparametric approaches allow for biased technological change to be considered in a natural way (see e.g. Färe et al. (1997), Walheer (2016), Hampf and Krüger (2017)), but are not robust to endogeneity issues resulting from input choice dependency on unobserved productivity (Cordero et al., 2015; Santín and Sicilia, 2017). Simar et al. (2016) propose a nonseparable nonparametric model to identify this unobserved heterogeneity as the part of a particular input that is independent from an instrumental variable. This paper proposes to rely on a firm-year specific technology indicator that can freely interact with all inputs to control for unobserved heterogeneity, merely requiring a certain smoothness of productivity. A Monte Carlo analysis

¹ Firm heterogeneity in productivity is well-established in the theoretical and empirical production and trade literature (e.g. Bernard et al. (2012); Melitz and Redding (2014)), implying that profit opportunities may differ between firms, even within the same industry.

shows that this method adequately tackles the endogeneity problem of production function estimations.

The second contribution of our paper is the identification of firm heterogeneity in factor-biased technological change. Whereas firm heterogeneity and factor bias in technological change are well-identified separately, the identification of both simultaneously proves to be more difficult. Non-structural parametric productivity estimators identify factor biases in technological change by a time trend or a general index of technological changes and its interaction effects with inputs (Adams, 1999; Baltagi and Griffin, 1988; Kumbhakar et al., 1999; Sun et al., 2015). The staggering amount of heterogeneity across firms, however, makes it difficult to interpret a time trend as a meaningful average economy- or sector-wide measure of technological change (Doraszelski and Jaumandreu, 2018, p.1028). Structural parametric efficiency estimators, on the other hand, rely on the structuring of the evolution of productivity, the timing of input decisions and the production structure to identify firm heterogeneity in technological change (Olley and Pakes (1996); Levinsohn and Petrin (2003); Wooldridge (2009); Akerberg et al. (2015); Gandhi et al. (2018)). While these approaches have recently been restructured to allow (partly) for factor-biased technological change at the firm level (Raval, 2019; Doraszelski and Jaumandreu, 2018; Zhang, 2019),² the parametric structure causes a model selection problem: empirical results are dependent on the parametrization of technological change and its interaction with inputs (Kumbhakar et al., 1999). Our nonparametric, reduced-form approach allows us to obtain firm-time specific output elasticities and factor biases. As such, we are able to track technological change to its roots, the firm, and assess the heterogeneity in technological change between firms.

Our third contribution is to show to what extent technological change is factor-biased and heterogeneous for a set of Belgian manufacturing firms. As is evident from the previous

² Note that the methods of both Doraszelski and Jaumandreu (2018) and Zhang (2019) require input prices, which are not commonly available.

section, current evidence on firm-level factor biases is scarce. We apply our estimator to a unique firm-level dataset of 2,893 Belgian firms in 14 selected manufacturing industries spanning 20 years, from 1996 till 2015. The uniqueness stems from our ability to match firm-level balance sheet and income statement data with firm-level expenditures on research and development, as well as the import and export activities of firms over an extensive time period. For all industries analyzed, our estimates reject the predominant assumption of Hicks-neutral technological change. The pattern of technological change is very heterogeneous between industries, but generally low-skilled labor and capital saving while high-skilled labor and domestic materials using. Overall, our results provide strong evidence for the existence of skill-biased technological change.

Our results not only reveal significant heterogeneity in the pattern of technological change between industries, but also between firms within industries. Several strands in the existing literature suggest that this firm specificity is not random. If biased technological change is the consequence of purposeful activities to increase profitability, as argued amongst others in Acemoglu (2002) and Acemoglu et al. (2015), then the pattern of technological change is likely to differ between firms in function of their characteristics, as in the seminal paper of Atkinson and Stiglitz (1969). Following Yeaple (2005), a number of models consider firm heterogeneity in technology as the endogenous outcome of firm choices (in particular regarding their internationalization strategy).³ For instance, it is argued that skill and technology complementarity implies skill-biased technological change as a consequence of trade liberalization (Bas, 2012), foreign acquisitions (Koch and Smolka, 2019) or foreign sourcing (Kasahara et al., 2016). Therefore, we explore the link between our obtained factor biases and firm characteristics. Our results indicate that large and exporting firms might redirect their technology more from low-skilled to high-skilled labor compared to small firms. Also, initial output elasticities affect the evolution of firm-level technology in

³This stands in contrast with the models assuming firm heterogeneity in technology to be constant, and therefore exogenous, over time (see Melitz (2003) in the case of total factor productivity and Crozet and Trionfetti (2013) for factor-augmenting productivity).

the subsequent period.

The remainder of this paper is structured as follows. In the following section, we present our nonparametric framework to estimate the production function and identify the (non-) neutrality of technological change. In section 3, we describe the unique dataset of Belgian manufacturing firm. Section 4 contains the estimation results and discusses the heterogeneity of factor-biased technological change and Section 5 concludes.

2 Methodology

2.1 Recovering factor-biased technological change

Our firm-level analysis of firm heterogeneity in factor-biased technological change is based on production functions and corresponding output elasticities. Identification of (the components of) production functions is complicated by a potential transmission bias originating from the dependency of production factor choice on unobserved productivity variation (Marschak and Andrews, 1944).⁴ A number of methods have been developed to tackle the endogeneity bias (see Akerberg et al. (2015); Gandhi et al. (2018) for a discussion of the available methods). A distinguishing feature of our identification strategy is that we resolve the endogeneity issue by including a smooth firm-year specific technology indicator rather than (semi-)parametrically structuring the production technology and production behavior.

Our identification strategy starts – as is common practice – from specifying produced log output y_{ft} , with firms $f \in \{1, 2, \dots, F\}$ and periods $t \in \{1, 2, \dots, T\}$.⁵ We consider log

⁴Other, more data-driven issues relate to the multi-product nature of firms (Bernard et al., 2009) and unobserved establishment-level prices (De Loecker, 2011). Only relying on cost minimization at the firm level, our framework could be adapted to allow for firm-specific price setting at the output market as well as the existence of multi-product firms. This is not pursued in this paper as we focus on the identification of factor-biased technological change under the presence of endogenous inputs.

⁵While we acknowledge possible biases arising in approximating log production (Sun et al., 2011), we prefer a log-specification as this allows for a straightforward interpretation of the estimated gradients as partial

output as non-decreasing with m -dimensional log inputs \mathbf{x}_{ft} (see Eq. 1). Productivity ω_{ft} captures the firm heterogeneity in managerial skills and strategy, information technology, environmental effects, etc., which imply a higher output over input ratio (see Syverson (2011) for productivity drivers within or beyond the firms' control). Productivity can relate to input choice in an unobserved firm-period specific manner. In addition to influences of inputs and productivity via the function h , we introduce error term u_{ft} , which includes measurement error or an ex-post productivity shock realized only after firm f 's decisions in period t are made. We assume that u_{ft} is normally distributed, with its mean invariant of \mathbf{x}_{ft} and ω_{ft} .

$$y_{ft} = h_{ft}(\mathbf{x}_{ft}, \omega_{ft}) + u_{ft}. \quad (1)$$

The endogeneity problem in (1) arises from the possibility that ω_{ft} influences input choices \mathbf{x}_{ft} , while being unobserved by the empirical analyst. Thus, if ω_{ft} is not correctly controlled for, input coefficients can be biased. To illustrate the input choice dependency on unobserved productivity – implying an endogeneity issue – consider the textbook example of cost minimizing firms using a simple 2-input Cobb-Douglas production function with Constant Returns to Scale and Hicks-neutral productivity. Assuming input x_1 to be the sole perfect variable input in the short run, the optimal choice of this input will depend on productivity: $x_1 = \left(\frac{p_2}{p_1} \frac{\alpha}{1-\alpha}\right)^{1-\alpha} \frac{Y}{\omega}$, with p_1, p_2 the input prices, α the output elasticity of input 1 and Y an arbitrary output level. In this example of cost minimizing firms, use of x_1 and productivity are negatively related. Omitting productivity in the production function estimation would imply correlation between the residual and input use and thus an endogeneity issue.

We resolve this bias approximating ω_{ft} with firm-specific fixed effects FE and a time trend t which can interact in a nonparametric fashion (see section 2.2.) both with each other and the inputs \mathbf{x}_{ft} (see (2)). This approximation merely requires a certain smoothness

output elasticities. Moreover, a log-transformation can increase the precision of our local-linear estimates if the relationship between inputs and output is more likely to be log-linear than linear.

of productivity over time.⁶ More specifically, it requires the existence of the cross partial derivatives of the production function h with respect to the time trend t and the inputs (i.e., $\exists \frac{\partial^2 h}{\partial x^i \partial t}$ for $i = 1, \dots, m$). As such, our model does not preclude the existence of a stochastic component to Hicks-neutral ex-post productivity (captured by u_{ft}). It does not control, however, for stochastic (i.e., non-smooth) components of ω_{ft} that correlate with inputs. We avoid an incidental parameter problem for our estimation of factor-biased technological change as we include FE as a one-dimensional discrete variable with F levels and not by means of $F - 1$ dummies as would be the case in parametric regression framework (see Racine and Li (2004)). This attractive feature of nonparametric estimation allows us to model ω_{ft} by the inclusion of t and FE , which can smoothly interact with each other and with \mathbf{x} .⁷

$$y_{ft} = h_{ft}(\mathbf{x}_{ft}, \underbrace{t, FE}_{\omega_{ft}}) + u_{ft}. \quad (2)$$

It is standard practice to specify h in a log-additive manner (which facilitates parametric structuring of the production behavior). This implies that the variation of the productivity term over time, called technological change, is not correlated with the marginal products of each input. Technological change, then, is *Hicks-neutral*, as the output elasticity of an input j , ϵ_j , the shadow price version of the cost share of input j , is assumed constant over time at given inputs levels (Blackorby et al., 1976):

$$B_j = \Delta_t \left(\frac{\partial h}{\partial x_j} \right) \Big|_{\bar{\mathbf{x}}} \times 100 = 0, \quad \forall j \in \{1, \dots, m\}. \quad (3)$$

To relax the assumption of Hicks neutrality, we allow for technological change to be cor-

⁶ While adding time as a discrete variable would not worsen the curse of dimensionality (Racine and Li, 2004), it renders obtaining consistent estimates of the individual effects difficult. In effect, combining both an F-dimensional firm fixed effect with a T-dimensional discrete time variable means we would try to estimate FT effects from FT data points. Assuming a relatively smooth productivity reduces the parameter space and results in a feasible estimation strategy.

⁷ See Henderson and Simar (2005) for a similar methodology used in the stochastic frontier context.

related with the marginal products of each input. Stated differently, we allow the output elasticity of some factor $j \in \{1, \dots, m\}$ to change over time and thus allow for technological change that is non-Hicks neutral, or *factor-biased*. If the output elasticity of a factor increases over time ($B_j > 0$), technological change is *j-input using*. It indicates a B_j percentage point increase in output elasticity, the shadow price version of the cost share, of input j between t and $t - 1$, at constant input levels. Vice versa, a decreasing output elasticity over time ($B_j < 0$) is the result of *j-input saving* technological change.⁸

2.2 Nonparametric estimation

To estimate the functional relations in (2) – the basis for our identification of factor-biased technological change – we use a flexible nonparametric approach that does not impose ‘*a priori*’ a functional relationship on h .⁹ In particular, we advocate the use of a kernel-based ‘*local linear least square regression*’ (LLS),^{10,11} the localized first-order Taylor expansion of the production model. The model is solved by the following minimization problem:

$$\min_{\{\alpha_0, \alpha_1\}} \sum_{l=1}^{FT} [y_l - \alpha_0 - (\tilde{\mathbf{x}}_l^c - \tilde{\mathbf{x}}^c) \alpha_1]^2 \mathcal{K}_\gamma(\tilde{\mathbf{x}}_l, \tilde{\mathbf{x}}). \quad (4)$$

with FT firm observations (e.g., an unbalanced panel), \mathcal{K}_γ representing the Racine and Li (2004) generalized kernel function that weighs – using bandwidth γ – both continuous

⁸ Throughout the paper, we assume time-invariant elasticities of substitution. See Diamond et al. (1978) for a discussion.

⁹ As such, our approach follows micro-economic theory, which almost never dictates a specific functional form relating economic variables, rather it stipulates properties of the relationship (Yatchew, 1998). Functional form misspecification can lead to biased estimates, which in turn can imply erroneous inference.

¹⁰ Nonparametric approaches do not impose ‘*a priori*’ a functional relationship between output and the explanatory variables but localize the production model estimation. See Li and Racine (2007) and Henderson and Parmeter (2015) for an extensive overview of the used kernel regression approach. We opt for the local-linear regression as it has better boundary properties than the local-constant regression and nests OLS as a special case (Hall et al., 2007).

¹¹ Kernel-weighting is often used in the DEA literature to introduce influences of environmental variables (Daraio and Simar, 2005). See Cordero et al. (2017); Hennebel et al. (2017); Bjørndal et al. (2018) for recent applications.

(i.e. \mathbf{x} and t) and discrete data (i.e., FE) which are captured by $\tilde{\mathbf{x}} = [\mathbf{x}, t, FE]$.¹² $\boldsymbol{\alpha}_1$ represents the firm-year specific coefficient parameters that are estimated, while bandwidths are obtained from a least-squares cross-validation approach.

Increasingly allowing for flexibility in regression methods may result in an estimated function that does not satisfy certain prior information, such as monotonicity. This is a well-known fact heavily discussed both for parametric (following on the seminal Diewert and Wales (1987)-paper) and nonparametric (surveyed in Parmeter et al. (2014)) estimators. We rely on constrained weighted bootstrapping as presented in Parmeter et al. (2014) to ensure that our estimates are consistent with the warranted property of monotonicity. We refer to the overviews of Li and Racine (2007) and Henderson and Parmeter (2015) and references therein for a detailed discussion of the theoretical properties of generalized kernel approaches. A more extensive explanation of the used nonparametric techniques can be found in the [on-line Appendix](#).

As such, our nonparametric regression framework allows us to recover a global production function from combined local fits to a set of observations with similar input levels. As the model is localized by kernel weighting, partial derivatives $\frac{\partial h(\cdot)}{\partial x_l}$ are also local and specific for each level of \tilde{x}_l . Stated differently, the advocated nonparametric estimator enables us to recover firm heterogeneity in B_j for all $j \in \{1, \dots, m\}$.

2.3 Monte Carlo

Nonparametric estimators with both categorical and continuous regressors have proven to be robust to functional form (mis)specification (see for instance Racine and Li (2004)) and achieve the standard nonparametric rate of convergence. We test the ability of our

¹²Relying on a common bandwidth for the continuous variables across firms within a NACE 2-digit industry imposes the assumption of a similar degree of smoothness of the regression relationship for this group of firms. See Li et al. (2016) for estimation biases arising when this assumption does not hold. We thank an anonymous referee for pointing out this vulnerability.

proposed estimator to cope with the endogeneity problem and factor-biased technological change (FBTC) using a Monte Carlo exercise. All scenarios start from a Cobb-Douglas production function with input coefficients that may vary over time and across firms:

$$y_{ft} = \sum_{i=1}^2 \gamma_{ft}^i x_{ft}^{*i} + \omega_{ft} + u_{ft}, \quad (5)$$

for $t \in \{1, 2, \dots, T\}$ periods over $f \in \{1, 2, \dots, F\}$'s firms with $T \in \{10, 20, 30\}$ and $F = 50$. As such, we obtain a balanced short panel with $FT \in \{500, 1000, 1500\}$ observations. γ_{ft}^i represents firm-year specific coefficients of the log input x^i , with $i = 1, 2$. These log inputs are generated according to a bivariate vector autoregression (VAR) model (Sickles, 2005):

$$x_{ft} = R x_{f,t-1} + \eta_{ft}, \quad \text{where } \eta_{ft} \sim \mathcal{N}(0, I_2), \quad R = \begin{pmatrix} 0.4 & 0.05 \\ 0.05 & 0.4 \end{pmatrix}, \quad (6)$$

where I_z defines an identity matrix of size z . We initialize the input variable choosing the variables $x_{f1} \sim \mathcal{N}\left(0, (I_2 - R^2)^{-1}\right)$ and generate the samples using (6) for $t \geq 2$, shifted around three different means ($\mu_1 = (5, 5)'$, $\mu_2 = (7.5, 7.5)'$, $\mu_3 = (10, 10)'$) to obtain three balanced groups of firms from small to large.

Following Gandhi et al. (2018), we assume the error term to be an independent and identically distributed random variable $u_{ft} \sim iid(0, 0.07)$.

We specify a parametric counterpart to our nonparametric estimator as flexible translog production function with firm-time specific technological change and factor biases. Estimated using OLS, this so-called OLS-TT3 model came out favorably in the analysis of Kumbhakar et al. (1999):

$$\begin{aligned}
y_{ft} &= \alpha_0 + \sum_{i=1}^2 \alpha_i x_{ft}^i \\
&+ FE + \alpha_t t + \frac{1}{2} \sum_{i=1}^2 \sum_{l=1}^2 \alpha_{il} x_{ft}^i x_{ft}^l \\
&+ \frac{\alpha_{tt}}{2} t^2 + \sum_{i=1}^2 \alpha_{it} x_{ft}^i t + \frac{1}{2} t \left(\sum_{i=1}^2 \sum_{l=1}^2 \alpha_{ilt} x_{ft}^i x_{ft}^l \right) + u_{ft}.
\end{aligned} \tag{7}$$

Our MC exercise models productivity ω_{ft} , the output elasticities γ_{ft} and endogenous inputs \mathbf{x}_{ft}^* under four different scenarios, as laid out in Table 1:

Table 1: Outline of the Monte Carlo Specification

	ω_{ft}	γ_{ft}^2	\mathbf{x}_{ft}^*
Scenario 1	$FE + 0.1t$	$0.25 + 0.025t$	$\mathbf{x}_{ft} + [FE + 0.1t] \boldsymbol{\rho}$
Scenario 2	$0.1FEt$	$0.25 + 0.025FEt$	$\mathbf{x}_{ft} + [0.1FEt] \boldsymbol{\rho}$
Scenario 3	$0.1FE + 0.8\omega_{ft-1} + \eta_{ft}$	$0.25 + 0.025FEt$	$\mathbf{x}_{ft} + [0.1FE + 0.8\omega_{ft-1} + \eta_{ft}] \boldsymbol{\rho}$
Scenario 4	$0.1FE + 0.8\omega_{ft-1} + \eta_{ft}$	$0.25 + 0.25(0.1FE + 0.8\omega_{ft-1} + \eta_{ft})$	$\mathbf{x}_{ft} + [0.1FE + 0.8\omega_{ft-1} + \eta_{ft}] \boldsymbol{\rho}$

1. *FBTC as a time trend*: we model productivity as a time trend ($\omega_{ft}^{S1} = FE + 0.1t$), with firm fixed effects drawn from a uniform distribution ($FE \sim \text{runif}(0, 3)$). As such, we allow for productivity to have differing growth rates over time. We model factor-biased technological change such that the output elasticity of the first input is not factor-biased ($\gamma_{ft}^1 = 0.5$) while the output elasticity of the second input (γ_{ft}^2) follows the time trend part of productivity, as specified in the third column of Table 1. Endogeneity is introduced by setting $\boldsymbol{\rho}$ such that the correlation between the inputs and productivity equals 0 and 0.5 respectively.
2. *FBTC as a firm-specific time trend*: we model productivity as the interaction between a time trend and firm fixed effects ($\omega_{ft} = 0.1FEt$). Factor biases and endogeneity are modeled as the first scenario, with factor biases being firm-specific now.

3. *FBTC as a firm-specific time trend and Markov process productivity*: we use the specification of the second scenario, but replace the Hicks-neutral productivity component with a firm-specific first-order Markov process, such that $\omega_{ft} = 0.1FE + 0.8\omega_{ft-1} + \eta_{ft}$, with $\eta_{ft} \sim iid(0, 0.04)$. This specification of the productivity process is similar to Gandhi et al. (2018) with the addition of fixed effects.
4. *FBTC as a Markov process*: we use the same first-order Markov process as the third scenario, but model the factor bias and endogeneity in function of this Markov productivity. As such, the inputs correlate with random productivity shocks. In this case, we expect both the parametric and nonparametric model to break down due to the non-smoothness of productivity.

We perform 1000 Monte Carlo replications on the four different scenarios for three different sample sizes. We report the average normalized mean squared errors of the output elasticities ($NMSE_\gamma$) and factor biases ($NMSE_B$) over the Monte Carlo replications in Table 2, as well as the Spearman correlation between the true and estimated biases ($corr(B, \hat{B})$). The NMSE averages the errors for both inputs ($i \in 1, 2$) over every MC simulation ($m \in MC$) and every firm-time specific observation ($l \in FT$):

$$NMSE = \frac{1}{2MC} \sum_{m=1}^{MC} \sum_{i=1}^2 \left(\frac{\sum_{l=1}^{FT} (u_l^{i,m} - \hat{u}_l^{i,m})^2}{\sum_{l=1}^{FT} (u_l^{i,m})^2} \right). \quad (8)$$

If the NMSE equals one, we have an error of a 100%, i.e. the error on the estimate is on average as large as the variable itself.

Under scenario one, we observe very low NMSE for the parametric model compared to the nonparametric model, with a NMSE of the output elasticities up to 100 times smaller for the smallest sample (F=50, T=10). This is expected, as a correctly specified parametric model always performs better than a nonparametric regression. Nevertheless, both

Table 2: Monte Carlo Results

	F=50,T=10		F=50,T=20		F=50,T=30	
	OLS-TT3	NONP	OLS-TT3	NONP	OLS-TT3	NONP
Scenario 1: FBTC as time trend						
$NMSE_\gamma$	0.0001	0.0144	0.0000	0.0060	0.0000	0.0038
$NMSE_B$	0.0006	0.4689	0.0001	0.0892	0.0000	0.0356
$corr(B, \hat{B})$	-	-	-	-	-	-
Scenario 2: FBTC as firm-specific time trend						
$NMSE_\gamma$	0.1966	0.0198	0.3829	0.0085	0.4878	0.0058
$NMSE_B$	4.7231	0.3116	4.9051	0.0662	4.6832	0.0282
$corr(B, \hat{B})$	0.0048	0.7431	0.0060	0.9586	0.0062	0.9826
Scenario 3: FBTC as firm-specific time trend and Markov process productivity						
$NMSE_\gamma$	0.1219	0.0201	0.2407	0.0096	0.3360	0.0068
$NMSE_B$	2.3794	0.2953	2.2408	0.0725	2.1639	0.0315
$corr(B, \hat{B})$	0.0169	0.7459	0.0035	0.9580	0.0069	0.9822
Scenario 4: FBTC as Markov process						
$NMSE_\gamma$	0.0215	0.0239	0.0282	0.0237	0.0314	0.0234
$NMSE_B$	2.1809	2.9295	1.7872	6.8176	1.6498	7.7612
$corr(B, \hat{B})$	0.4889	0.1382	0.5339	0.1881	0.5391	0.1858

models do appear to control for the endogeneity problem, certainly as the time dimension increases. Errors strongly decrease when individual firms are tracked over a longer time period, showcasing the consistency of both estimators.

As soon as we introduce firm-specific factor-biased technological change, however, the errors of the parametric OLS-TT3 model increase while the nonparametric model showcases similar performance to scenario 1. This performance also holds when we model the Hicks-neutral component of productivity as a Markov process in scenario three. The nonparametric model is able to capture factor-biased technological change and tackle the endogeneity problem, while the parametric model showcases too large errors to be eligible for empirical analysis. The correlations between the true and estimated biases are practically zero for the parametric model, while they are high and consistently increasing with the time horizon for the nonparametric model.

In the fourth scenario, we allow random shocks to be correlated with inputs. In this case, the assumption that anticipated productivity evolves smoothly over time is too restrictive for both the parametric and nonparametric model to be able to capture these non-smooth random shocks. Therefore, the errors significantly increase, resulting in large errors on the estimated biases.

The evaluation of the estimators using NMSE gives larger weight to larger errors, meaning that outliers have a high impact. It is not unlikely that a highly nonlinear method has some bad draws in a large Monte Carlo exercise. Nevertheless, as is obvious from Figure 1, the nonparametric method is rather stable across replications. Overall, the NMSE of the bias is dense and close to zero, with bad draws not significantly influencing its result. The superior performance of this highly nonlinear estimator is therefore even more convincing.

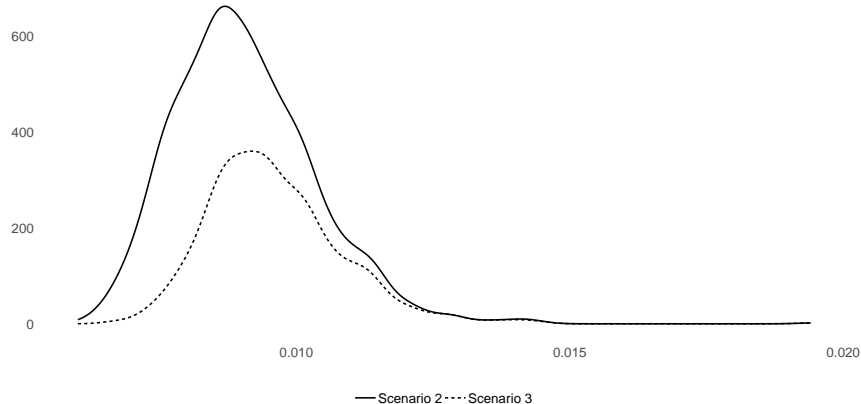


Figure 1: $NMSE_B$ -density of the nonparametric estimator for scenario two and three over 1000 Monte Replications.

When an empirical analyst wants to estimate the production function of multiple industries, choosing the correct parametric model has proven to be a difficult task, and is likely to be a hit-and-miss. The specified nonparametric model performs satisfyingly in comparison to correctly specified parametric models, but is robust to model (mis)specification. It is therefore our preferred estimator.

3 Data

Our empirical analysis of firm heterogeneity in factor-biased technological change starts from the BELFIRST database provided by Bureau Van Dijk. It is a database of annual accounts and (social) balance sheets. Further, the database allows us to obtain firm characteristics such as a firms' primary industry, location, and date of incorporation. Because a specific issue or version of the database only contains information for the last ten years, we compiled different November issues of the database (see Merlevede et al. (2015) for more details). 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 1995-2015.

We link the resulting database to the firm-level international trade data of the National Bank of Belgium. The combination of balance sheet and export data of Belgian firms has been previously used by i.a. Amiti et al. (2014); Muûls and Pisu (2009). Moreover, we were able to augment our database with data on firm-level R&D activities (expenditures and personnel) of Belgian companies from the Belgian Science Policy Office.

Our final database contains 14 selected manufacturing industries listed in Table 3.¹³ It consists of 2,893 firms spanning over 20 years, from 1996 till 2015, resulting in a total of 32,032 observations. The size of the sectors differs, ranging from 91 firms with 941 observations in the Computer, elec. and opt. (26) industry to 479 firms with 5561 observations for the Food industry (10). The distribution of firms by size reveals a skew towards larger firms compared with official distributional statistics.^{14,15} This is due to our focus on firms that are ‘large enough’ to avoid extreme changes in input use. Moreover, smaller firms¹⁶ are allowed to report their annual accounts using an abbreviated model in which gross revenue and intermediate input use do not have to be stated separately, excluding those firms from our analysis. Besides heterogeneity in size, we observe that approximately 24% of the firms in our database are active in research and development, defined as firms reporting personnel active in research and development for more than half the years a firm resides in our database. Equivalently, we define exporting and importing dummies, revealing that approximately 80% of the firms report exporting and/or importing activities over more

¹³We clean the data both on levels and on growth rates to prevent effects of extreme outliers and extreme noise on the analysis. Specifically, we limit the sample to observations with a labor use of minimum 5, strictly positive levels for both low-skilled and high-skilled labor, a number of months in a book year between 6 and 24 and limit deflated turnover, deflated materials and deflated capital to values 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). As the coverage of firms in 1995 is lower than in the other years we focus on the period 1996-2015.

¹⁴We group firms by size, defining Small (Labor in FTE from 10 till 50), Medium (Labor in FTE from 50 till 250) and Large (Labor in FTE larger than 250).

¹⁵See the on-line Appendix for a comparison of our dataset with the Structural Business Statistics (SBS) database.

¹⁶According to Belgian law, smaller firms are those firms that either have on average less than 100 employees during the year or that do not exceed two of the following three criteria: annual average of 50 employees, annual turnover of 7300000 EUR or a balance-sheet total of 3650000 EUR.

than half the period in our database, demonstrating the openness of the Belgian economy.

Table 3: Summary statistics of the manufacturing sectors included in the analysis

Industry	Nr. Obs.	Nr. firms	% Micro	% Small	% Medium	% Large	% R&D	% Exp.	% Imp.
10 - Food	5561	479	7.72	49.69	34.03	8.56	21.09	76.83	86.01
13 - Textiles	2352	244	2.05	40.98	51.23	5.74	21.72	86.89	93.44
16 - Wood	1042	108	3.70	61.11	29.63	5.56	11.11	71.30	87.04
17 - Paper	1211	95	0.00	37.89	44.21	17.89	18.95	89.47	92.63
18 - Printing	1607	163	0.61	50.31	47.24	1.84	2.45	80.98	70.55
20 - Chemicals	2838	231	3.46	38.96	41.99	15.58	38.53	91.77	97.84
22 - Rubber-Plastic	2325	193	4.15	42.49	46.11	7.25	37.31	87.56	91.19
23 - Non-metallic mineral.	2788	241	6.64	52.70	31.54	9.13	13.28	60.17	75.93
24 - Basic metals	1721	137	4.38	35.77	49.64	10.22	27.01	88.32	91.24
25 - Fabricated metal prod.	4535	436	3.67	55.28	36.93	4.13	17.43	63.99	76.61
26 - Computer, elec. and opt.	1006	98	6.12	35.71	45.92	12.24	57.14	86.73	93.88
27 - Electrical equipment	941	91	6.59	40.66	37.36	15.38	39.56	82.42	89.01
28 - Mach. and Equipm.	2766	258	4.26	52.71	36.05	6.98	33.33	80.62	88.76
31 - Furniture	1339	119	3.36	40.34	53.78	2.52	20.17	83.19	87.39
10t31 - All sectors	32032	2893	4.42	47.25	40.30	8.02	24.06	78.36	85.97

Our production function estimation in the next section relies on output (Y), approximated by deflated revenue, and five inputs: low- and high-skilled labor, capital and domestic and foreign materials. Low-skilled labor (L) is approximated by the full-time equivalent (FTE) number of workers and ‘other’, while we approximate high-skilled labor (H) by the FTE number of employees and management.¹⁷ Capital (C) denotes tangible fixed assets. Materials are split up using firm-specific import shares from the NBB into domestic materials (M_d) and imported (foreign) materials (M_f). The monetary variables turnover, materials and capital are deflated using industry-wide deflators from EU-KLEMS.¹⁸

Average statistics for the production function variables in Table 4 again reveal the bias towards larger firms. Nevertheless, the large standard deviation on all variables signals the

¹⁷Obviously this classification is imperfect, but it is the most reliable at hand. The classification is more suited to show factor biases for low-skilled labor than for the high-skilled employees as we cannot disentangle medium-skilled from high-skilled labor. Results on high-skill using technological change needs, therefore, to be interpreted with care.

¹⁸Firm-specific prices are not available for the given dataset.

presence of quite some heterogeneity. We cover firms with less than one low- or high-skilled FTE employee up to firms hiring approximately 3700 low-skilled or 2000 high-skilled FTE employees. Yearly average growth of sales in the manufacturing industry reaches 0.27%. This growth is supported by a relatively strong growth in high skilled-labor and domestic material intermediate input use. Foreign intermediate input use declined, but this average hides the strong growth of inputs arriving from China and Eastern Europe.¹⁹ The growth in domestic intermediate inputs is not matched by other inputs, especially low-skilled labor. On average, the labor- domestic material and capital- domestic material ratio has been decreasing over time.

Table 4: Summary statistics of the production function variables

	Mean	St. Dev.	Min.	IQR	Max.	Av. growth (%)
Y^*	376.33	773.52	7.49	263.64	24306.52	0.27
L	77.25	125.07	0.21	64.37	3672.83	-0.06
H	37.55	79.71	0.29	28.73	2033.97	0.42
C^*	59.22	155.57	0.09	44.41	4187.48	0.22
M_d^*	141.52	334.37	0	97.1	10333.2	0.29
M_f^*	87.55	238.23	0	61.46	9618.49	-0.12
M_{China}^*	2.23	22.83	0	0.05	1104.04	1.21
$M_{Eastern Europe}^*$	3.45	37.96	0	0.27	5424.22	1.17

Variables indicated by a * are divided by 100000 for expositional purpose.

Eastern Europe consists of the so-called EU13 countries: Bulgaria, Croatia, Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia and Slovenia.

4 Results

Having established that our estimator performs well in the Monte Carlo simulations, we apply the estimator to Belgian firm-level data over the period 1996-2015. The output elasticities obtained from the nonparametric procedure seem sensible and time-varying, as

¹⁹Eastern Europe consists of the so-called EU13 countries: Bulgaria, Croatia, Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia and Slovenia.

we can deduce from Figure 2. On average, the output elasticities of low-skilled labor seem to be decreasing over time, while those of high-skilled labor and domestic materials display increasing output elasticities. On top of that, we observe heterogeneity in both elasticity levels and growth rates between size groups of firms. Average low-skilled labor elasticity, for instance, decreases from 0.17 with 0.024 for small firms. Medium firms' initial elasticity, meanwhile, decreases from 0.15 with 0.016 and large firms' elasticity starts at only 0.14 to decrease with 0.036. A similar picture can be observed for high-skilled labor and domestic material elasticities. Capital elasticities, on the other hand, differ barely both in levels and growth rates between size groups of firms.

In this section, we reveal the differential movement of output elasticities over time to be evidence of non-neutral technological change. We show that technological change, on top of being factor-biased, is heterogeneous between firms. This firm heterogeneity can be linked to specific firm strategies and technological characteristics such as size, export and import activities and initial technology.

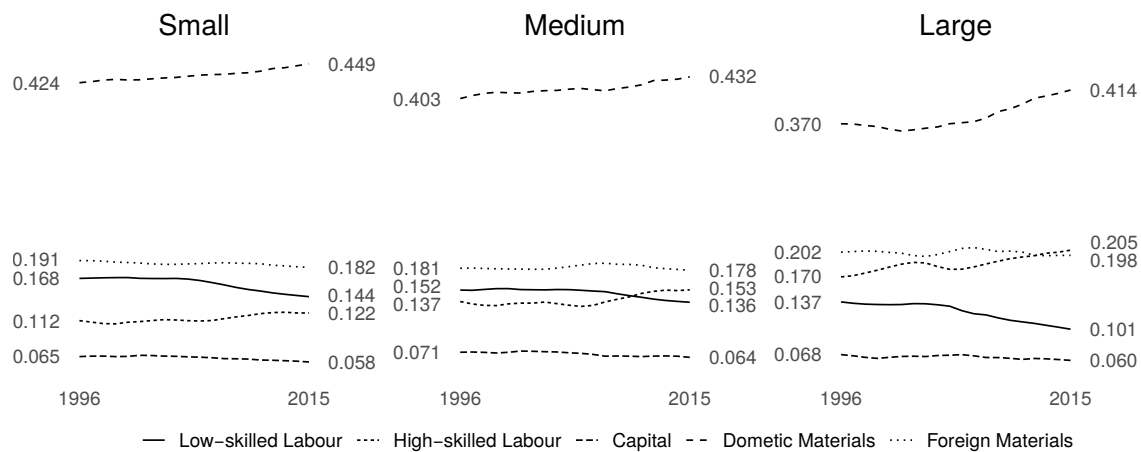


Figure 2: Average output elasticities obtained from the nonparametric procedure for small, medium and large firms between 1996-2015.

4.1 Factor-biased technological change

In order to investigate the factor bias of technological change, we evaluate the evolution of output elasticities over time at fixed input levels (see Section 2.1). Table 5 reports the average percentage point change in output elasticities between 1996 and 2015, holding inputs fixed at their 1996 levels.²⁰ As such, we can interpret a unit increase in the output elasticity as a 1 percentage point increase in the cost share of this input at constant input use. Confidence bounds are obtained from a clustered wild bootstrap with 99 replications.

We find at least one significant factor bias in each sector, in line with a rejection of Hicks neutrality. Overall, the pattern of technological change is low-skilled labor and capital saving while high-skilled labor and domestic materials using. 10 of the 14 sectors exhibit falling output elasticities of low-skilled labor over time at fixed input levels, of which 8 are statistically significant. 13 (10 significant) sectors exhibit increasing high-skilled labor elasticities and 11 (9 significant) sectors exhibit increasing domestic material elasticities. Capital elasticities are decreasing in 9 sectors, of which 7 significantly so. The direction of the bias for foreign materials is more mixed, with 9 (6 significant) sectors showcasing increasing efficiency, but also 5 (3 significant) with decreasing efficiency, resulting in an average negative bias. Overall, our results provide clear evidence of the existence of skill-biased technological change.

Next to its non-neutral character, the *heterogeneity* in technological change is striking. Already at the sectoral level we notice substantial specificities and differences between the sectoral and the overall pattern of manufacturing. This is reflected in the variance decomposition of the factor biases for each input between and within each manufacturing sector, shown in the bottom two rows of Table 5. The substantial variance in output

²⁰Fixing the inputs levels at their 1996 levels, we limit the sample of firms to those present in 1996. We evaluate the global production function at those values over the time period. This strategy tracks both incumbents and firms that exit over the time period, preventing influence from sample fluctuations. Incumbents and firms that exit make up of the largest part of our dataset. We provide robustness results with inputs fixed at their 2015 levels in the [on-line Appendix](#).

elasticity change, not only between sectors but within sectors as well, points to patterns of technological change that are essentially *firm-specific*.

4.2 Firm heterogeneity in technological change

If biased technological change is the consequence of purposeful activities to increase profitability, as argued amongst others in Acemoglu (2002) and Acemoglu et al. (2015), then the pattern of technological change is likely to differ between firms in function of their characteristics

We investigate the regularities of the firm specificities of technological change by correlating our factor biases with several (categorical) firm characteristics present in our dataset. Table 6 shows that the pattern of technological change differs between firms depending on their size. While small firms showcase a significant negative correlation with high-skilled labor and foreign material biased technological change, large firms correlate positively with a high-skilled labor and a foreign material bias. They also correlate negatively with the evolution of low-skilled labor bias. Exporters to the EU13 and importers from China are positively correlated with a foreign material bias, while importers from the EU13 are positively correlated with a domestic material bias.

While the correlation table gives an indication of the pattern of technological change for firms with different characteristics, a multivariate analysis is required to have a more precise view of the size and significance of the effects. Table 7 presents the results of an OLS regression of the change in output elasticities at constant 1996 input levels on firm characteristics thought to be closely linked with factor-biased technological change. These include firm size, R&D status, exporting and importing status as well as the output elasticities in the initial year (a proxy for firm-level technological characteristics), while controlling for industry fixed effects. This way, we obtain an estimate of the partial effects of the characteristics.

In comparison with micro and small firms, technological change of medium and large

Table 5: Factor-biased technological change 1996–2015 at 1996 input levels

Industry	B_l	B_h	B_c	B_{md}	B_{mf}
10 - Food	0.33 (0.19)	1.11*** (0.20)	-0.51*** (0.12)	1.42*** (0.24)	0.31 (0.21)
13 - Textiles	0.33*** (0.16)	0.99** (0.13)	-0.02 (0.11)	-0.27 (0.20)	-0.73*** (0.11)
16 - Wood	-0.13*** (0.05)	0.26*** (0.08)	0.04 (0.03)	0.09 (0.08)	-0.01 (0.07)
17 - Paper	-2.02*** (0.44)	-0.94*** (0.32)	0.44 (0.37)	4.98*** (0.44)	1.11*** (0.64)
18 - Printing	-2.00*** (0.44)	4.63*** (0.35)	-1.61*** (0.30)	1.91*** (0.49)	2.60** (0.20)
20 - Chemicals	-2.95*** (0.20)	2.36*** (0.48)	-0.56* (0.19)	8.98*** (0.46)	-9.14*** (0.26)
22 - Rubber-Plastic	-0.63*** (0.08)	0.30*** (0.10)	0.12 (0.11)	0.09 (0.12)	0.67* (0.07)
23 - Non-metallic mineral.	-8.36*** (0.26)	2.52*** (0.33)	-1.41*** (0.18)	6.61*** (0.54)	1.21*** (0.27)
24 - Basic metals	-2.01*** (0.55)	1.56*** (0.42)	-2.76*** (0.33)	2.10** (0.41)	-1.14*** (0.30)
25 - Fabricated metal prod.	-4.24 (0.27)	2.47*** (0.27)	0.38*** (0.23)	4.38*** (0.41)	0.69 (0.25)
26 - Computer, elec. and opt.	0.40 (0.22)	2.00 (0.25)	-3.48 (0.22)	6.84*** (0.24)	-4.76 (0.12)
27 - Electrical equipment	-8.60*** (0.87)	2.42*** (0.67)	0.80*** (0.27)	4.51*** (0.62)	0.41 (0.57)
28 - Mach. and Equipm.	0.05 (0.08)	0.88 (0.11)	-0.45* (0.06)	-0.21 (0.11)	0.19** (0.05)
31 - Furniture	-0.25 (0.40)	0.02 (0.32)	-2.58*** (0.31)	-1.17*** (0.37)	2.25*** (0.30)
10t31 - All Sectors	-2.07*** (0.07)	1.58*** (0.09)	-0.70*** (0.06)	2.83 (0.10)	-0.52* (0.08)
Sum of Squares Within	73416	69961	30547	115067	37589
Sum of Squares Between	10477	1822	1535	12124	11708

*, **, *** indicate significance at the 10%, 5% or 1% levels respectively. Standard errors in parenthesis. Confidence intervals obtained from a clustered wild bootstrap with 99 replications.

Table 6: Correlation factor bias and firm characteristics within industries

Input	R&D	Small	Medium	Large	X	X _{EU13}	X _{NEU}	I _{EU13}	I _{China}	I _{NEU}
<i>l</i>	-0.01	-0.03	0.04	-0.05*	-0.04	-0.03	-0.02	-0.07**	-0.01	-0.04
<i>h</i>	0.03	-0.06**	0.00	0.10***	0.04	-0.01	0.02	-0.02	0.03	0.02
<i>c</i>	-0.01	-0.01	0.02	-0.01	0.01	-0.04	-0.01	-0.04	-0.02	0.04
<i>m_d</i>	0.01	-0.02	0.01	0.03	-0.02	0.02	0.02	0.05*	0.00	0.03
<i>m_f</i>	0.04	-0.08***	0.05*	0.05*	0.05	0.05*	0.04	0.03	0.06**	0.00

*, **, *** indicate significance at the 10%, 5% or 1% levels respectively.

X and *I* identifies exporting and importing firms respectively. The *EU13* countries are Bulgaria, Croatia, Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia and Slovenia. *NEU* stands for countries outside the European Union.

firms is characterized by a significantly larger high-skilled labor bias and a more negative low-skilled labor bias (though not significantly). Moreover, these differences in the skill-bias are increasing with firm size. For exporting firms, technological change is significantly more low-skilled labor saving relative to non-exporting firms, without significant differences according to the export destination (-new- EU member states (EU13) or non-EU countries). These results are in line with theoretical extensions of the Melitz (2003)-model linking skill-biased technological change to more productive, and therefore larger and exporting, firms (see for instance Bas (2012) and Bustos (2011)). Technological change of exporting firms to the new EU member states (EU13) shows a (significantly) lower high-skilled labor and capital bias but a higher bias in foreign material inputs. Also for importing firms, the size of the factor biases seems to be geographically related. Importers from more distant countries (Non-EU and China) are characterized by a more domestic materials saving and foreign materials using technical change compared to firms that import from Western European countries or do not import at all. They do not, however, provide evidence of a different evolution for the labor bias. Importers from new European member states (EU13), on the other hand, do showcase a significant more negative low- and high-skilled labor bias compared to the reference group, combined with a relatively significant higher domestic-materials bias. Finally, initial technology seems to have a significant impact on the orientation of technological change as well. Almost all initial output elasticities (i.e.

Table 7: Regression of factor biases on firm characteristics

Determinants	l	h	c	m_d	m_f
R&D	-0.422 (0.450)	0.385 (0.448)	0.278 (0.294)	0.317 (0.591)	-0.253 (0.362)
Medium	-0.018 (0.399)	1.293*** (0.397)	0.319 (0.261)	0.107 (0.524)	0.065 (0.329)
Large	-1.073 (0.668)	4.358*** (0.664)	0.089 (0.437)	-0.358 (0.877)	0.341 (0.539)
X	-2.072*** (0.646)	0.896 (0.642)	-0.276 (0.422)	-0.466 (0.847)	0.790 (0.562)
X_{EU13}	0.082 (0.474)	-1.093** (0.472)	-0.773** (0.310)	0.130 (0.623)	0.638* (0.382)
X_{NEU}	-0.234 (0.571)	0.605 (0.568)	0.068 (0.373)	0.466 (0.750)	0.005 (0.465)
I_{EU13}	-1.258*** (0.459)	-0.896* (0.457)	-0.382 (0.300)	1.086* (0.603)	0.296 (0.367)
I_{China}	0.234 (0.522)	0.782 (0.519)	-0.028 (0.341)	-1.217* (0.685)	0.861** (0.417)
I_{NEU}	0.544 (0.500)	0.485 (0.498)	0.574* (0.327)	-1.217* (0.657)	0.396 (0.408)
ϵ_l^{1996}	-43.443*** (1.994)	8.598*** (1.983)	1.369 (1.303)	-3.342 (2.617)	-11.756*** (1.681)
ϵ_h^{1996}	-0.080 (2.194)	-43.005*** (2.182)	-1.867 (1.434)	0.274 (2.880)	-1.291 (1.836)
ϵ_c^{1996}	5.408* (2.961)	2.650 (2.945)	-43.485*** (1.936)	-12.584*** (3.886)	-5.070** (2.581)
ϵ_{md}^{1996}	-5.115*** (1.582)	-1.299 (1.573)	-3.106*** (1.034)	-36.451*** (2.076)	-5.866*** (1.325)
ϵ_{mf}^{1996}	-15.133*** (2.072)	-4.195** (2.061)	-2.027 (1.354)	-4.604* (2.719)	-26.240*** (1.700)
R^2	0.444	0.344	0.350	0.377	0.391
Obs.	1309	1309	1309	1309	1243

*, **, *** indicate significance at the 10%, 5% or 1% levels respectively. Standard errors in parenthesis.

X and I identifies exporting and importing firms respectively. The $EU13$ countries are Bulgaria, Croatia, Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia and Slovenia. NEU stands for countries outside the European Union.

of 1996) have a significant effect on the change in output elasticity by input factor, the impact of initial factor output elasticity on its change over the period being systematically significantly negative.

Robustness results with inputs fixed at their 2015 levels can be found in the [on-line Appendix](#). Overall, the size and direction of the biases are robust to the levels at which inputs are fixed. Again we find indications of technological change that is low-skilled labor and capital saving while high-skilled labor and domestic materials using. The between as well as the within sector variation of the factor biases remains substantial. The most notable difference is the stronger evidence for larger skill-biased technological change and the emergence of a significant lower domestic materials bias for medium and large firms compared to micro and small firms.

5 Conclusion

This paper proposes a nonparametric framework to test the extent to which technological change is biased, in contrast with the assumption - implicit in many studies - of Hicks-neutral technological change. Our advocated approach is fully nonparametric and deals with the endogeneity issue resulting from input choice dependency on unobserved productivity. A Monte Carlo assessment of the estimator confirms the appropriateness of this estimator for the study of firm heterogeneity in factor-biased technological change.

In our empirical application, we consider a wide range of factor biases. In addition to capital, low- and high-skilled labor, we research both domestic and imported materials. We acknowledge firm heterogeneity in technology due to differences in international activities (exports and outsourcing), R&D intensity or other firm characteristics such as firm size and initial technological characteristics. In order to do so, we opt for a fully nonparametric framework which imposes no restrictions on the specification of production technology

besides commonly accepted micro-economic assumptions. We then assess which firm characteristics are correlated with the estimated factor biases of technological change. The analysis is based on annual accounts data of Belgian firms that were matched with firm-level data on international trade and R&D activities, covering 14 manufacturing industries over the period 1996-2015.

The assumption of Hicks neutrality is rejected for all industries considered. Factor-biased technological change is low-skilled labor and capital saving while high-skilled labor and domestic materials using. Indications of a foreign materials bias are more industry-specific, with statistically significant opposite signs across industries. The latter result points out the potential pitfall of assessing factor biases at the aggregate level.

Besides between-industry heterogeneity, technical change is found to be heterogeneous between firms. The assessment linking technical change and firm characteristics provides robust indications that technical change is not purely random, but can be attributed to specific firm strategies. Large firms display a pattern of more low-skilled labor saving technological change while small firms had a smaller increase of high-skilled labor efficiency. Exporting firms are characterized by a significant low-skilled labor saving bias independent of the exporting destination. The complete pattern of technological change for both exporting and importing firms, however, is geographically dependent. Importers from more distant countries (beyond the EU) are characterized by a significant domestic-materials saving and foreign materials using bias. Firms with a high initial cost share for a certain factor saved on this factor in the subsequent period.

Our results clearly corroborate the conclusion of previous tests that the assumption of factor-neutral technological change is not warranted. Moreover, the robust evidence of a materials bias calls into question the appropriateness of productivity measures based on value added (which implicitly assume time-invariant marginal productivity of materials) and also points out the importance to distinguish between domestically purchased materials

and imported materials. Given that we are constrained to use an imperfect, however still informative, indicator of skilled labor, future research may try to extend the analysis of factor-biased technological change to datasets that include a better proxy, provided that the cost of a less detailed firm characterization can be avoided. This may allow to test whether firm heterogeneity in factor bias applies in more than just one case.

From a methodological viewpoint, our framework can be considered as a starting ground to estimate in a nonparametric fashion firm-specific biases under endogeneity. Further research is warranted on how to include multi-output structure into this framework. A promising starting point is the literature on multi-output Stochastic Frontier Analysis. Further, our framework is customized for the estimation of production function parameters under endogeneity. For this purpose, we model the productivity component in a highly flexible way. A disadvantage of this high flexibility is that it can imply non-identification of the productivity component itself. Further research is needed on how additional structure can be imposed on the productivity component to allow simultaneously in a nonparametric regression framework for identification of production function parameters and unobserved heterogeneity in productivity.

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