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IZA DP No. 12795

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ABSTRACT

Productivity, Wages and Profits: Does Firms' Position in the Value Chain Matter?*

This paper is the first to estimate the impact of a direct measure of firm-level upstreamness on productivity, wage costs and profits (i.e. productivity-wage gaps). To do so, we merged detailed Belgian linked panel data, covering all years from 2002 to 2010, to a unique data set developed by Dhyne et al. (2015), which contains accurate information on the position of (almost) each commercial firm in the value chain at each year. We rely on the methodological framework that has been pioneered by Hellerstein et al. (1999) to estimate dynamic panel data models at the firm level. Our estimates show that if upstreamness increases by one step (that is, by approximately, one standard deviation), productivity rises on average by 5%. They also indicate that productivity gains associated to upstreamness are shared almost equally between wages and profits. However, upstreamness is found to be more beneficial for workers' wages in less competitive environments, where the price-elasticity of demand for firms' products is typically smaller. Overall, these findings are compatible with the assertion that firms should move up the value chain to be more productive and profitable, but also that being higher in the value chain is likely to facilitate firms' control over strategic downstream activities.

JEL Classification: F61, J24, D30, D40, J50

Keywords: global value chains, upstreamness, productivity, rent-sharing, linked employer-employee panel data, product market competition

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1. Introduction

Over the last thirty years, production processes have become more and more fragmented and divided into ever smaller parts, considered as separate activities (OECD, 2013). In order to minimize costs, the production decision process now involves the sourcing of inputs from multiple suppliers often located in foreign places (Antràs *et al.*, 2012; Manello *et al.*, 2016). So truly global value chains (GVC) have emerged, in contrast to integrated production processes supported by the traditional view of international trade. Baldwin (2011) considers this radical change as a "globalization's second unbundling" that started in the late 1980's. He explains this phenomenon by sharply declining coordination costs induced by the information and communication technology (ICT) revolution. These strongly reduced costs enable not to bundle all major stages of the production process in the same location. In other words, unbundling the factories becomes easier and inevitable in case of economies of scale and comparative advantages (Baldwin, 2011). Small open economies like Belgium are particularly concerned by this fragmentation. If we consider for instance the share of imported inputs in total intermediates, i.e. a standard measure of offshoring (Feenstra and Hanson, 1996, 1999), Belgium appears to be 7th among 35 investigated OECD countries. More precisely, this share is equal to 34% in Belgium, while the weighted OECD average stands at 16% (OECD, 2010). Interestingly, Dhyne *et al.* (2015) also show that 82% (99%) of commercial enterprises in Belgium between 2002 and 2012 have been producing (consuming) goods and services that were either directly or indirectly exported (imported).

Given this context, a large literature has been focusing on the repercussions of international trade on economic growth (for a review see e.g. Singh (2010)). At the micro-level, many studies investigated the relationship between exporting and productivity using firm-level data (Berthou *et al.*, 2015). There is strong evidence that these variables are positively correlated. Whether this correlation can be ascribed to self-selection or causality is still examined. Yet, the dominant explanation appears to be self-selection. Using a sample of German manufacturing firms, Arnold and Hussinger (2005), for instance, show that above-average productivity firms self-select into export markets. In contrast, they do not support the learning effects associated to exporting, i.e. exporting does not make firms more productive. Along the same lines, using a sample of firms in the United Kingdom for the period 1989-2002, Greenaway and Kneller (2004) support both the self-selection mechanism and a causal effect from export market entry to productivity, though the latter is relatively small and short-lived.

Causality from exports to productivity could notably be explained through greater specialization and economies of scale/scope (OECD, 2013).

More recently, a small number of papers have been able to investigate how the productivity of firms is affected by their participation to a GVC. Baldwin and Yan (2014), for instance, examined this issue by using a sample of Canadian manufacturing firms over the period 2002-2006. They defined a firm as participating in a GVC if it both: i) imported intermediate inputs, and ii) exported intermediate or finished products. Controlling for self-selection using propensity-score matching and a difference-in-difference framework, the authors found that firms being part of a GVC had a 5% higher productivity growth compared to their opposite numbers not involved in GVCs.[1] Their results also indicate that firms that exited from a GVC experienced *ceteris paribus* a drop in their productivity growth, both in the short- and long-run. Finally, Baldwin and Yan (2014) investigated how the magnitude and timing of the benefits of a GVC participation differ across: i) industrial sectors, ii) routes adopted for participating to a GVC (i.e. starting importing and exporting simultaneously, exporters starting importing, or importers starting exporting), and iii) trading partners (i.e. low- *vs.* high-wage countries). The mechanisms through which productivity spills over across firms in vertical relationships have been investigated by Serpa and Krishnan (2018). To do so, they relied on a sample of 22,383 US supply chain dyads between 1983 and 2013. Their model of upstream spillovers (i.e. from major customers to suppliers) compares two channels through which the productivity of a firm (supplier) can be influenced by its vertical partner (customer): i) "endogenous channels", where the firm directly benefits by interacting with a more productive partner through knowledge transfers, and ii) "contextual channels", referring to the characteristics of the partner which are independent of its productivity, such as geographic location or financial liquidity for instance. Their results indicate that the most important source of spillovers is the effect of the customer's own productivity on the supplier's productivity (i.e. the endogenous channel). They also put forward several contextual characteristics and facets of supply chain structures (in terms of maturity of the relationship, degree of supply chain concentration and homogeneity between partners) that reinforce this effect.

Besides potential productivity effects associated to whether a firm participates to a GVC or not, another important issue – still quite under-researched – is whether the position of a firm

[1] This productivity gain is even found to reach 9% after 4 years of participation in a GVC.

in a GVC matters for the creation of value.[2] The study of Rungi and Del Prete (2017) is the first one to address this question with firm-level data. More precisely, the authors estimated the relationship between firms' value added and their position on a productive sequence, ranging from upstream "pre-production" activities (such as R&D) to downstream "post-production" ones (such as marketing and retail), passing through middle "production" activities (such as manufacturing). The position of a firm in a GVC is established by merging its core industrial activity (at the NAICS 4-digit level) along the productive sequence with downstreamness measures (i.e. the distance in the GVC between the first level of value added creation and the level of value added as created by the firm) sourced from Antràs and Chor (2013). Controlling for country, industry and firm-level characteristics, their OLS findings based on a cross-section of about 2 million firms located in the European Union for the year 2015 suggest the existence of a "smile curve". Accordingly, the creation of value would be highest for tasks lying at the top and at the bottom of the supply chain. In contrast, intermediate activities would bring less value and would therefore be more likely to be offshored, notably to emerging economies. A related study is that of Ju and Yu (2015). The authors investigated how the position of a firm in a GVC, measured through an upstreamness index (i.e. the average distance from firm's production to final use) affects its productivity and profitability. Applying the methodology developed by Antras *et al.* (2012) to Chinese data, they computed: i) an industrial upstreamness index for 120 different sectors, and (ii) a firm-level upstreamness index – but only for exporting firms – in an indirect way, i.e. using firm's average upstreamness in exports as a proxy to its production index. Their OLS estimates, controlling for firm characteristics such as sectoral affiliation, location (i.e. province), ownership and export status, suggest that upstreamness fosters productivity and profits. Ju and Yu (2015) also show that companies belonging to upstream industries are more capital-intensive. Accordingly, the cut-off productivity to operate in more upstream industries would be higher, which in turn could explain why companies in more upstream industries are found to be more productive and profitable.

Our paper contributes to this important but still very small literature in four different ways. First, we put the relationship between firms' upstreamness and productivity to an updated test. To do so, we rely on detailed Belgian linked employer-employee panel data that have been merged with a unique data set derived from the NBB B2B transactions data set, developed by Dhyne *et al.* (2015), which provides an accurate direct measure of upstreamness for each firm

[2] The scarcity of evidence on this issue can be explained by the fact that accurate measures of the position of a firm in a GVC, such as upstreamness, have only been designed recently (see Fally (2011) and Antràs *et al*. (2012)) and that data to compute these measures are quite difficult to obtain.

(i.e. the steps – weighted distance – before the production of a firm meets either domestic or foreign final demand) in each year from 2002 to 2010. Put differently, our study is the first (as far as we know) to examine the impact of firms' position in the value chain on productivity using a *direct*, firm-level measure of upstreamness. Besides this unique feature, our data offer other distinctive advantages. Our panel covers a large part of the private sector, provides precise information on the average productivity of each firm (i.e. on the average value added per worker) and allows us to control for key worker characteristics (e.g. education, age, occupation, working time) in addition to the usual firm characteristics that are considered in the few existing studies (e.g. capital stock, size, industry). It also enables us to address important methodological issues, neither controlled for in Ju and Yu (2015) nor in Rungi and Del Prete (2017), such as state dependence of productivity, firm-level invariant unobserved heterogeneity, and endogeneity of upstreamness (using the dynamic system generalised method of moments (SYS-GMM) and *à la* Levinsohn and Petrin (2003) estimators). Moreover, our paper adds to the existing literature by investigating whether and how the potential gains or losses associated to upstreamness are shared between workers and firms. This is done by estimating the impact of upstreamness on productivity, wage costs and productivity-wage gaps[3] at the firm level. We also test for possible nonlinearities, that is for the fact that the upstreamness-productivity-wage nexus might for instance be U-shaped. Finally, we examine the role of a potentially important moderator, namely product market competition. Economic theory suggests that workers' ability to bargain higher wages is stronger when the price-elasticity of demand for products or services in the sector is lower, i.e. in the case of monopolistic or oligopolistic competition (Boeri and van Ours, 2014; Bryson, 2014). We test the accurateness of this prediction in the context of GVCs. More precisely, we examine whether the consequences of upstreamness for wages and productivity-wage gaps depend on the degree of competition that firms face on their product market. More rent-sharing is anticipated among establishments operating is less competitive environments.

The remainder of this paper is organised as follows. Our methodology and data set are described in sections 2 and 3. Next, we estimate the impact of upstreamness on productivity and wage costs at the firm level, test for potential nonlinearities and investigate the moderating role of product market competition. The last section concludes.

[3] By definition, the gap between productivity and wage costs corresponds to the gross operating surplus.

2. Methodology

2.1. Benchmark specification

Our empirical strategy relies on the estimation of a value added function and a wage cost equation at the firm level. The former yields parameter estimates for the impact of upstreamness on firms' average productivity, while the latter estimates the influence of upstreamness on the average wage bill paid by firms. Given that both equations are estimated on the same samples with identical control variables, the parameters for productivity and wage costs can be compared and conclusions can be drawn on how upstreamness affects firms' productivity-wage gaps. Put differently, parameters enable us to highlight whether upstreamness is beneficial or harmful for firms' productivity, and whether and how the gains or losses associated to upstreamness are shared with workers (in terms of higher or lower wages). This technique was pioneered by Hellerstein *et al.* (1999) and refined by van Ours and Stoeldraijer (2011) among others. It is now standard in the literature on the productivity and wage effects of worker and firm heterogeneity (see e.g. Cardoso *et al.*, 2011; Devicienti *et al.*, 2018; Garnero *et al.*, 2014, 2018; Giuliano *et al.*, 2017; Göbel and Zwick, 2012; Ilmakunnas and Maliranta, 2005; Mahlberg *et al.*, 2013; Nielen and Schiersch, 2014).

The estimated firm-level productivity and wage cost equations are the following:

$$\ln va_{jt} = \beta_0 + (\beta_1 \ln va_{jt-1} +)\ \beta_2\ up_{jt} + \mathbf{x_{jt}}\ \boldsymbol{\beta_3} + \mathbf{z_{jt}}\ \boldsymbol{\beta_4} + (\delta_j +)\ \partial_t + \nu_{jt} \qquad (1)$$

$$\ln w_{jt} = \gamma_0 + (\gamma_1 \ln w_{jt-1} +)\ \gamma_2\ up_{jt} + \mathbf{x_{jt}}\ \boldsymbol{\gamma_3} + \mathbf{z_{jt}}\ \boldsymbol{\gamma_4} + (\delta_j +)\ \partial_t + \omega_{jt} \qquad (2)$$

The dependent variable in equation (1) is firm j's value added per capita, obtained by dividing the total value added (at factors costs) of firm j in period t by the total number of workers employed in firm j during the same period. The dependent variable in equation (2) is firm j's average wage bill (including payroll taxes and variable pay components, such as wage premia for overtime, weekend or night work, performance bonuses and other premia). It is obtained by dividing the firm j's total wage costs in period t by the total number of workers employed in firm j during the same period. Hence, the dependent variables in the estimated equations are firm averages (in logarithms) of value added and wage costs (net of social security tax cuts) on a per capita basis.

The main variable of interest, up_{jt}, is the firm's level of upstreamness. It measures the steps (weighted distance) before the production of a firm j at period t meets either domestic or foreign final demand (see Dhyne *et al.* (2015) for more details). Equations (1) and (2) also include the vector $\mathbf{x_{jt}}$. It contains a set of variables controlling for observable worker characteristics. More precisely, it includes the share of the workforce within a firm that: i) is younger than 30 and older than 49 years, respectively, ii) has a Bachelor, a Master and a post-Master degree, respectively, iii) is blue-collar, and iv) works part-time. The vector $\mathbf{z_{jt}}$, also included in equations (1) and (2), controls for firm characteristics. It includes respectively firm's sectoral affiliation (8 dummies), size (number of workers) and capital stock per worker, which has been estimated through the "perpetual inventory method".[4] δ_j is a dummy variable for each firm which captures unobserved time-invariant workplace characteristics, ∂_t is a set of year dummies (8 dummies), and ν_{jt} (ω_{jt}) is the error term.

2.2. Estimation techniques

We first estimated equations (1) and (2) by pooled ordinary least squares (OLS). The OLS estimator is based on the cross-section variability between firms and the longitudinal variability within firms over time. However, this estimator suffers from a potential heterogeneity bias because firm productivity and wages can be related to firm-specific, time-invariant characteristics (e.g. the quality of management, an advantageous location, the ownership of a patent, or other firm idiosyncrasies) that are not reported in our data set.

The conventional way to remove unobserved firm characteristics that remained unchanged during the observation period is by estimating a fixed effects (FE) model. This boils down to estimate a within differentiated model, i.e. a model where the mean of each variable has been subtracted from the initial values. This approach cannot be applied for the firms in our sample: the variable of interest, i.e. the level of upstreamness, does not show sufficient variation over time to be a useful explanatory variable of firm-level wages or productivity after mean differencing (see e.g. Wooldridge (2010)). Moreover, neither pooled OLS nor the FE estimator address the potential simultaneity between a firm's level of upstreamness and its productivity/wage cost.[5] However, reverse causality is likely to be an issue due to: i) the

[4] The "perpetual inventory method" (or PIM) incorporates the idea that the capital stock results from investment flows and corrects for capital depreciation and efficiency losses. Following standard practice, we assume a 5 percent annual rate of depreciation. See e.g. OECD (2009) for more details.

[5] Expected biases associated with OLS and the relatively poor performance and shortcomings of the FE estimator in the context of firm-level productivity regressions are reviewed in Van Beveren (2012).

correlation between upstreamness and the export behaviour of firms (the number of steps before firms' production meets final demand is typically bigger among exporting firms (OECD, 2012)), and ii) ample evidence supporting reverse causality between the export behaviour of firms and their productivity/wages (Arnold and Hussinger, 2005; Berthou and Vicard, 2013; Eaton *et al.*, 2007; Freund and Pierola, 2010).[6] We have performed a direct endogeneity test on the upstreamness variable in our sample and indeed reject the null hypothesis that our main variable of interest can actually be treated as exogenous.[7] To control for this endogeneity issue, in addition to state dependence of firm productivity/wages[8] and the presence of firm fixed effects, we re-estimated equations (1) and (2) using the dynamic system Generalized Method of Moments (GMM-SYS) proposed by Arellano and Bover (1995) and Blundell and Bond (1998). This approach is standard in the literature regarding firm-level determinants of productivity and wages (Buhai *et al.*, 2017; Göbel and Zwick, 2012; van Ours and Stoeldraijer, 2011). It boils down to simultaneously estimating a system of two equations (one in level and one in first differences) and to rely on internal instruments to control for endogeneity. More precisely, firm's level of upstreamness is instrumented by its lagged levels in the differenced equation and by its lagged differences in the level equation.[9] The implicit assumption is that differences (levels) in (of) productivity and wages in one period, although possibly correlated with contemporaneous differences (levels) in (of) firm's level of upstreamness, are uncorrelated with lagged levels (differences) of the latter. Moreover, differences (levels) in (of) the firm's upstreamness variable are assumed to be reasonably correlated to their past levels (differences).

One advantage of *system* GMM is that time-invariant explanatory variables can be included among the regressors, while the latter typically disappear in difference GMM. Asymptotically, the inclusion of these variables does not affect the estimates of the other

[6] As highlighted in the introduction, the traditional explanation for this phenomenon, in line with international trade models with heterogeneous firms (Bernard *et al.*, 2003; Melitz, 2003; Melitz and Ottaviano, 2003), is related to a self-selection mechanism whereby more productive firms (also paying higher wages) are more likely to export.

[7] We have performed such a test by using a 2SLS estimator on an equation in levels in which our variable of interest is instrumented by first differences. Both equations (i.e. value added and wage costs) pass standard underidentification and weak identification tests. This means that the endogeneity test for the upstreamness variable is valid. This test suggests that for both equations we have to reject the null hypothesis that upstreamness can actually be treated as exogenous.

[8] The assumption of persistent productivity both at the industry and firm level finds some support in the literature (see e.g. Bartelsman and Doms (2000)). Researchers "documented, virtually without exception, enormous and persistent measured productivity differences across producers, even within narrowly defined industries" (Syverson, 2011: 326). Large parts of these productivity differences are still hard to explain. The persistence of wage costs is also highlighted in the literature (see e.g. Heckel *et al.* (2008) and Fuss and Wintr (2009)). Wage stickiness is notably the outcome of labour market institutions, adjustment costs and efficiency wages' motives.

[9] Bond and Söderbom (2005) provide a review of the literature regarding the identification of production functions. The authors notably highlight that adjustment costs of labour and capital can justify the use of lagged values (of the endogenous variable) as instruments.

regressors because instruments in the level equation (i.e. lagged differences of upstreamness) are expected to be orthogonal to all time-invariant variables (Roodman, 2009). To examine the validity of our estimates, we applied the Hansen's (1982) and Arellano-Bond's (1991) tests. The first is a test for overidentification which allows to test the validity of the instruments. The second is a test for autocorrelation, where the null hypothesis assumes no second-order autocorrelation in the first differenced errors. The non-rejection of the two tests is required in order to assume that our estimates are reliable.

The adoption of a *dynamic* GMM specification aims to account for the persistency in firm-level wage costs and productivity. It is also likely to improve the identification of the parameters of interest (even though the coefficients on the lagged dependent variables are not a central issue of the analysis). Indeed, as illustrated by Bond (2002), the use of a dynamic model is necessary to obtain consistent results when estimating a production function with serially correlated productivity shocks and explanatory variables that are correlated to these shocks. While serial correlation may arise if e.g. "the effects from demand shocks are only partially captured by the industry-specific control variables" (Hempell, 2005), the responsiveness of input factors to productivity shocks may be explained by the above-mentioned endogeneity issue. Interestingly, the inclusion of the lagged dependent variable in the OLS, FE and GMM-SYS specifications also provides an ad hoc test for the appropriateness of the latter. As outlined by Roodman (2009), this test consists in checking whether the regression coefficients on the lagged dependent variables obtained with GMM-SYS fall between the OLS and FE estimates.

Finally, as an alternative to the GMM-SYS method to address the endogeneity of upstreamness in the *productivity* equation (i.e. equation (1)), Olley and Pakes (1996) have developed a consistent semi-parametric estimator. This estimator, particularly well-suited for panels with small t and big N, controls for endogeneity by using the employer's investment decision to proxy for unobserved productivity shocks. The intuition is that firms respond to time-varying productivity shocks observed by managers (and not by econometricians) through the adjustment of their investments. Put differently, profit-maximizing firms react to positive/negative productivity shocks by increasing/decreasing their output, which requires more/less investments (or intermediate inputs, see below). The OP estimation algorithm relies on the assumptions that there is only one unobserved state variable at the firm level (i.e. its productivity) and that investments increase strictly with productivity (conditional on the values of all state variables). This monotonicity condition implies that any observation with zero investment has to be dropped from the data, which generally leads to a sharp decrease in sample size. To avoid this drawback, Levinsohn and Petrin (2003) use intermediate inputs (i.e. inputs such as energy, raw materials, semi-finished goods, and services that are typically subtracted from gross output to obtain value added) rather than investments as a proxy for productivity shocks. Given that firms typically report positive values for intermediate inputs in each year, most observations can be kept with the LP approach. An additional argument for using intermediate inputs rather than investments is that the former may adjust more smoothly to the productivity term than the latter, especially if adjustment costs are an important issue. For instance, "if adjustment costs lead to kink points in the investment demand function, plants may not respond fully to productivity shocks, and some correlation between the regressors and the error term can remain" (Petrin *et al.*, 2004: 114). Intermediate inputs would thus provide a better proxy for unobserved productivity shocks. When relying on the *à la* LP estimation algorithm, standard errors are computed using a bootstrap approach taking the panel structure of the data into account (Petrin *et al.*, 2004).[10]

3. Data set

Our empirical analysis is based on a combination of three large data sets. The first is the new and unique dataset derived from the NBB B2B transactions data set (hereafter NBB B2B) developed by Dhyne *et al.* (2015), covering the whole Belgian private sector over the period 2002-2012. It provides direct, yearly information on the upstreamness of (almost)[11] each commercial firm in Belgium, i.e. on the number of steps (weighted distance) before the production of each firm meets either domestic or foreign final demand.

Our second source of data is the Structure of Earnings Survey (SES), carried out by Statistics Belgium. It is representative of firms operating in Belgium, between 1999 and 2010, that employ at least ten workers and with economic activities within sections B to N of the NACE Rev. 2 nomenclature. The survey contains a wealth of information, provided by the HR departments of firms, both on the characteristics of the latter (e.g. sector of activity, number of

[10] Our estimation technique is actually *à la* Levinhson and Petrin. Indeed, we do not start by estimating a production function to measure total factor productivity, but instead directly use labour productivity, i.e. the value added per worker at the firm level, as dependent variable.

[11] For instance, a few i) micro enterprises, which are almost sole traders and who do not have to fill VAT declarations, and ii) firms that have no enterprise-to-enterprise transactions inside Belgium (i.e. they only import, export or sell to final demand) are not included in Dhyne *et al.*'s (2015) dataset.

workers) and on the individuals working there (e.g. age, education, gross earnings, paid hours, occupation).[12]

The SES provides no financial information. It has therefore been merged with a firm-level survey, the Structure of Business Survey (SBS). The SBS, also conducted by Statistics Belgium, provides information on financial variables such as firm-level material inputs, investments, added value, and gross operating surplus per worker. The coverage of the SBS differs from that of the SES in that it does not cover the whole financial sector (NACE K), but only other financial intermediation and activities auxiliary to financial intermediation. The merger of our three data sets, i.e. the SES, SBS and NBB B2B data, has been carried out by Statistics Belgium, in collaboration with the National Bank of Belgium, using firms' VAT codes.[13]

Our preferred estimator (GMM-SYS) requires firm information on (at least) two consecutive years. Given that sampling percentages of firms in our data set increase with the size of the latter (see footnote 11), medium-sized and large firms are thus over-represented in our econometric investigations. Note that workers and firms for which data are missing or inaccurate have been excluded.[14] We also drop firms with fewer than 10 observations, because the use of average values of worker characteristics at the firm level requires a suitable number of observations.[15] Our final sample covering the period 2002-2010 consists of an unbalanced panel of 12,340 firm-year-observations from 3,625 firms. It is representative of medium-sized

[12] The SES is a stratified sample. The stratification criteria refer respectively to the region (NUTS-groups), the principal economic activity (NACE-groups) and the size of the firm. The sample size in each stratum depends on the size of the firm. Sampling percentages of firms are respectively equal to 10, 50 and 100% when the number of workers is between 10 and 50, between 50 and 99, and above 100. Within a firm, sampling percentages of employees also depend on size. Sampling percentages of employees reach respectively 100, 50, 25, 14.3 and 10% when the number of workers is between 10 and 20, between 20 and 50, between 50 and 99, between 100 and 199, and between 200 and 299. Firms employing 300 workers or more have to report information for an absolute number of employees. This number ranges between 30 (for firms with between 300 and 349 workers) and 200 (for firms with 12,000 workers or more). To guarantee that firms report information on a representative sample of their workers, they are asked to follow a specific procedure. First, they have to rank their employees in alphabetical order. Next, Statistics Belgium give them a random letter (e.g. the letter O) from which they have to start when reporting information on their employees (following the alphabetical order of workers' names in their list). If they reach the letter Z and still have to provide information on some of their employees, they have to continue from the letter A in their list. Moreover, firms that employ different categories of workers, namely managers, blue- and/or white-collar workers, have to set up a separate alphabetical list for each of these categories and to report information on a number of workers in these different groups that is proportional to their share in total firm employment. For example, a firm with 300 employees (namely, 60 managers, 180 white-collar workers and 60 blue-collar workers) will have to report information on 30 workers (namely, 6 managers, 18 white-collar workers and 6 blue-collar workers). Finally, let us notice that no threshold at the upper limit of wages is found in the SES. To put it differently, wages are not censored. For an extended discussion see Demunter (2000).

[13] We had access to a fully anonymized version of the merged data which prevents from directly identifying an individual firm.

[14] For instance, we eliminate a (very small) number of firms for which the recorded value added was negative.

[15] This restriction is also unlikely to affect our results as it leads to a very small drop in sample size. The average number of observations per firm in each year stands at around 35 in our final sample.

and large firms in the Belgian private sector, with the exception of large parts of the financial sector (NACE K) and the electricity, gas and water supply industry (NACE D+E).

[Insert Table 1]

Table 1 depicts the means and standard deviations of selected variables. It indicates that firms' mean annual value added per worker stands at 91,358 EUR, while their mean annual wage cost per worker reaches 47,801 EUR. Regarding the upstreamness variable, we find that the mean number of steps before the production of a firm meets either domestic or foreign final demand is equal to 2.31. We also observe that around 61% of workers within firms are prime-age (i.e. between 30 and 49 years old), 26% have a tertiary education degree (15% possess a Bachelor's, 10% a Master's and 1% a post-Master's degree, respectively), 53% are blue collars, and 16% are part-timers (i.e. have less than 30 hours per week of paid work). Furthermore, we see that firms in our sample employ on average 217 workers and that their capital stock per worker amounts to approximately 231,000 EUR. Firms are essentially concentrated in NACE sectors C (manufacturing - 51%), G (wholesale and retail trade, repair of motor vehicles and motorcycles - 16%), and L-M-N (real estate activities; professional, scientific and technical activities; administrative and support service activities - 13%).

4. Results

4.1. Benchmark estimates

We first estimated equations (1) and (2) by pooled OLS, without any covariate. Results, presented in the first two columns of Table 2, point towards the existence of a positive and significant relationship between upstreamness and firm productivity (coefficient = 0.140), on the one hand, and upstreamness and wage costs (coefficient = 0.083), on the other.

[Insert Table 2]

After controlling for time fixed effects, worker and firm characteristics (see columns (3) and (4)), regression coefficients associated to the upstreamness variable decrease somewhat (to 0.091 and 0.033, respectively), but they remain positive and significant. Appendix Table A1 shows detailed OLS estimates. We find that almost all covariates are significant with the expected sign, both in the productivity and wage regressions. For instance, we observe that a higher share of younger workers is associated to lower productivity and wages. As regards older workers, they are found to increase wage costs without affecting productivity significantly. This outcome appears to be in line with earlier findings suggesting the over-payment of older workers (Cataldi *et al.*, 2011, 2012; Vandenberghe, 2013). We also find that education has a positive and somewhat stronger effect on productivity than on wage costs. This finding is compatible with the "wage compression effect" highlighted by Kampelmann *et al.* (2018). Not surprisingly, we also find a strong negative effect of the share of part-time workers on productivity and wages per capita. In line with the literature on inter-industry wage differentials (du Caju *et al.*, 2011), we further observe that productivity and wages are highest in sectors D and E (i.e. electricity, gas, steam and air conditioning supply; water supply, sewerage, waste management and remediation activities) and lowest in sector I (accommodation and food service activities). Results also show that firm size and capital stock have a positive and significant impact on productivity and wages, which is notably consistent with findings of Lallemand *et al.* (2006, 2007).

Next, to control for the potential state dependence of productivity and wages, we included the lagged dependent variable as an additional covariate, both in equations (1) and (2). Results, reported in columns (5) and (6) of Table 2, confirm that productivity and wages depend significantly on their past values. Interestingly, they also show that upstreamness still has a positive and significant effect on productivity and wages in this dynamic specification. Corresponding regression coefficients now reach 0.011 and 0.005, respectively.

However, as argued in Section 2, OLS estimates should be considered with caution due to potential biases associated with firm-level fixed effects and endogeneity. To account for these issues, equations (1) and (2) have been re-estimated with the dynamic GMM-SYS estimator proposed by Arellano and Bover (1995) and Blundell and Bond (1998). Variables in the differenced equation have thus been instrumented by their lagged levels and variables in the level equation have been instrumented by their lagged differences. Time dummies have been considered as exogenous and we use first and second lags of other explanatory variables as instruments. Results are presented in columns (1) and (2) of Table 3.[16] To examine their reliability, we applied the Hansen (1982) test of overidentifying restrictions and the Arellano-Bond's (1991) test for second-order autocorrelation in the first-differenced errors. As shown in

[16] Note that the GMM coefficients on the lagged dependent variables fall systematically between the OLS and FE estimates (available on request). As outlined by Roodman (2009), this result supports the appropriateness of our dynamic GMM-SYS specification.

Table 3, they respectively do not reject the null hypothesis of valid instruments and of no autocorrelation. As expected, we also find that current productivity and labour costs are to a significant and important extent related to their past values. The coefficients associated to upstreamness remain highly significant and are now equal to 0.053 and 0.046 respectively in the productivity and wage costs regressions. These coefficients are statistically different from each other, as shown by a standard *t*-test (*t* = 25,72). Accordingly, findings suggest that when upstreamness increases by one unit (i.e. when a firm's position in the value chain moves one step away from final demand), firm's productivity and wages increase on average by 5.3 and 4.6%, respectively.[17] Yet, it should be highlighted that like for the literature on exporting and productivity, the relationship between upstreamness and productivity could also be explained by self-selection mechanism. Indeed, good firms may also be more likely to be selected as suppliers by other firms, moving them in the more upstream production segments. Hence, one should be cautious when pointing to a causal link between upstreamness and productivity.[18]

[Insert Table 3]

What about productivity-wage gaps? Given that mean sample values of productivity and wage costs reach respectively 91,358 and 47,801 EUR, GMM-SYS estimates suggest that moving up the value chain by one step increases firms' annual productivity per worker on average by 4,842 EUR (i.e. 0.053 * 91,358 EUR) and firms' annual wage cost per worker by 2,199 EUR (0.046 * 47,801 EUR). Put differently, we find that: (i) profitability (i.e. the productivity-wage gap) depends positively on firm's upstreamness (i.e. profitability increases by around 5% when upstreamness increases by one step), and (ii) productivity gains associated to upstreamness are shared almost equally between wages and profits.

As a robustness test, we also estimated the impact of upstreamness on firm's productivity with an *à la* LP estimator, i.e. using an external rather than internal instruments to address endogeneity. Results are reported in Appendix Table A2. They confirm that moving up the value chain exerts a significantly positive impact on productivity. More precisely, they suggest that firms' average productivity rises on average by approximately 6% following a one-step increase in the level of upstreamness.

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[17] These estimates are computed at the mean sample value of firms' upstreamness, which is equal to 2,31 steps. Moving one step away from this mean corresponds to a one standard deviation change in the upstreamness variable (see Table 1).

[18] This potential issue is discussed further.

4.2. Nonlinear relationships?

In order to test for potential nonlinear relationships between upstreamness, productivity and wage costs, we estimated the following variants of equations (1) and (2):

$$\ln va_{jt} = \beta'_0 + (\beta'_1 \ln va_{jt-1} +) \beta_{2.1}\, upD1_{jt} + \beta_{2.2}\, upD2_{jt} + \mathbf{x_{jt}}\, \boldsymbol{\beta'_3} + \mathbf{z_{jt}}\, \boldsymbol{\beta'_4} + (\delta_j +) \partial_t + \nu'_{jt} \qquad (1')$$

$$\ln w_{jt} = \gamma'_0 + (\gamma'_1 \ln w_{jt-1} +) \gamma_{2.1}\, upD1_{jt} + \gamma_{2.2}\, upD2_{jt} + \mathbf{x_{jt}}\, \boldsymbol{\gamma'_3} + \mathbf{z_{jt}}\, \boldsymbol{\gamma'_4} + (\delta_j +) \partial_t + \varpi'_{jt} \qquad (2')$$

where $upD1_{jt}$ ($upD2_{jt}$) is a dummy variable that is equal to one if firm j's level of upstreamness at time t ranges between 2.5 and 4.5 (is greater than 4.5) steps. The reference category is thus composed of firms whose level of upstreamness is below 2.5 steps, a level close to the sample mean of 2.31 steps.

GMM-SYS estimates of equations (1') and (2') are reported in columns (3) and (4) of Table 3. Our findings support the existence of a monotonically (and fairly linear) upward-sloping profile between upstreamness and productivity. Indeed, the productivity of firms with a level of upstreamness ranging from 2.5 to 4.5 (above 4.5) is found to be on average 10.2% (20.9%) higher than that of the reference category. As regards wage costs, the relationship is found to be less steep but still significant and monotonically increasing. In comparison to the reference category, wage costs appear to be on average 8% (9.7%) higher among firms with an upstreamness index between 2.5 and 4.5 (above 4.5). Overall, this implies that the relationship between upstreamness and firms' profitability (i.e. the productivity-wage gap) is significantly positive and convex. Alternative specifications, including different thresholds for $upD1_{jt}$ and $upD2_{jt}$ but also polynomials of the upstreamness variable[19], have been tested. Overall, they confirm that productivity, wage costs and profitability rise steadily as firms' move up the value chain.

4.3. Does product market competition matter?

To investigate whether the upstreamness-productivity-wage nexus depends on the degree of product market competition, we relied on an Herfindahl-Hirshman Index (HHI) at the NACE 3

[19] The inclusion of the upstreamness variable as a polynomial of order 2 or 3 in equations (1) and (2) led to multicollinearity issues. Therefore, we have chosen to report regression results using dummy variables identifying firms with varying upstreamness levels.

digits level. This indicator, computed by Statistics Belgium (2016), measures the sum of squared market shares of all firms within a given industry. The HHI ranges from 1/N to 1, where N is the number of firms in the industry. Product market competition is expected to be stronger when the HHI is smaller. In the case of a monopoly, the HHI is equal to 1.

Equations (1) and (2) have been estimated separately for firms belonging to industries whose HHI is below *vs.* above the mean sample value[20], i.e. for firms operating in more *vs.* less competitive environments.[21] GMM-SYS estimates are reported in columns (1) to (4) of Table 4. They show that moving one step away from the final consumer increases productivity almost equally (by 5.5 and 5.6%) in both investigated environments.[22] Results are somewhat different for wage costs. We find that upstreamness has a significantly bigger impact on wages among firms operating in less competitive environments (5.6 *vs.* 3.8%).[23] Productivity gains associated to upstreamness are thus found to generate more rent-sharing when competition is weaker. This outcome is in line with economic theory. The latter indeed predicts that the wage premium associated to upstreamness should be higher when the price-elasticity of demand for products or services in the sector is lower, i.e. in the case of monopolistic or oligopolistic competition. The argument goes that employers in less competitive environments can more easily pass wage increases on to consumers, without fearing of being undercut by other producers, or meet additional costs from above-normal profits (Boeri and van Ours, 2014). Trade unions are also expected to be more demanding when labour demand is less elastic and rents to be shared bigger (Bryson, 2014).

5. Conclusion

This paper is the first to estimate the impact of a *direct* measure of firm-level upstreamness (i.e. the steps – weighted distance – before the production of a firm meets either domestic or foreign final demand) on productivity, wage costs and profits (i.e. productivity-wage gaps). To do so, we take advantage of access to detailed Belgian linked employer-employee panel data that have

[20] Descriptive statistics for firms operating respectively in more and less competitive environments are reported in Appendix Table A3.

[21] We also estimated the interaction effect between upstreamness and the HHI at the NACE 3-digit level. To do so, we created a dummy variable, set equal to one, for firms operating in less competitive environments. This dummy has been included in equations (1) and (2) as an additional control variable and in interaction with our main variable of interest ('upstreamness'). Unfortunately, GMM-SYS results could not be interpreted as they do not pass standard diagnoses tests for over-identification and/or second-order autocorrelation in first differenced errors. Therefore, we have chosen to estimate separate regressions for firms operating respectively in more and less competitive environments.

[22] Yet, the *t*-statistic for equality of regression coefficient is significant and equal to -2.14.

[23] As shown by a standard *t*-test, these coefficients are statistically different from each other (t = 25.3).

been merged with a unique data set developed by Dhyne *et al.* (2015), the so-called NBB B2B transactions data set, which contains accurate information on the position of virtually all commercial firms in the value chain at each year. We rely on the methodological framework pioneered by Hellerstein *et al.* (1999) and estimate dynamic panel data models at the firm level.

Findings, based on the generalized method of moments (GMM) and *à la* Levinsohn and Petrin (2003) estimators, show that if upstreamness increases by one step (that is, by approximately, one standard deviation), productivity rises on average by 5%. This relationship appears to be monotonous and fairly linear. Indeed, the productivity of firms with an upstreamness index ranging from 2.5 to 4.5 (above 4.5) is found to be on average 10% (21%) higher than that of the reference category (i.e. firms with an upstreamness index below 2.5 steps). Upstreamness is also found to foster wage costs, albeit to a significantly lesser extent. In comparison to the reference category, wage costs appear to be on average 8% (10%) higher among firms with an upstreamness index between 2.5 and 4.5 (above 4.5). Taken together, these estimates suggest that profits (i.e. productivity-wage gaps) are enhanced when firms move up the value chain. More precisely, they indicate that productivity gains associated to upstreamness are shared almost equally between wages and profits. However, product market competition is found to be an important moderator. Indeed, results show that workers benefit substantially more from being employed in upstream firms when product market competition is weaker.

How can these results be interpreted? Overall, our findings are in line with the hypothesis that upstream activities (such as innovation, R&D, design, etc.) create a lot of value added, while pure manufacturing/assembly stages located closer to the final consumers would add less value (OECD, 2012). Some downstream activities (marketing, branding, logistics, etc.) are also typically thought to create a lot of value (OECD, 2013). At face value, our findings do not support this assumption.[24] However, 'leading' firms,[25] whose activities are *mostly upstream* due to intensive innovation/R&D/design/etc., generally keep a strong control on high value-added downstream activities (e.g. marketing). Accordingly, our estimates are compatible with the assertion that firms should move up the value chain to be more productive and profitable, but also that being higher in the value chain is likely to facilitate firms' control over strategic

[24] In contrast to Rungi and Del Prete (2017), our estimates provide no direct evidence for a productivity premium in firms whose main activity is close to final demand. Yet, it should be recalled that our study differs from theirs in several key dimensions, including the measurement of firms' position in the value chain (direct longitudinal indicator at firm level *vs.* indirect cross-sectional indicator at sectoral level), the estimation method (GMM and *à la* LP estimators *vs.* OLS/Probit/Logit), the data coverage (Belgium *vs.* EU countries) and the number of covariates. For more details, see discussion in Section 1.

[25] Within the Belgian production network, one could notably think at international companies such as ABInBev, Bekaert, Engie, GSK, Ontex, Pfizer, Proximus, Solvay or UCB.

downstream activities bringing extra value.[26] Our estimates can also be understood through the application of Melitz (2003) model to the value chain framework. Indeed, as upstream firms are significantly more capital-intensive than downstream ones,[27] the cut-off productivity for firms to operate in upstream industries will be higher. Moreover, given that the survival rate of firms is typically higher among more productive ones, mean productivity and profitability will be higher in more upstream industries. Finally, our findings showing that productivity gains associated to upstreamness are quite equally split between capital and labour seem quite sound in light of the Belgian industrial relations system, which is notably characterised by strong collective bargaining centralisation/coordination and high trade union coverage/density (OECD, 2018). As regards interaction effects with product market competition, they are consistent with theoretical arguments suggesting that rent-sharing should be fostered when the price-elasticity of demand for firms' products and/or services is lower (Bryson, 2014).

Our findings reinforce and extend those reported for China by Ju and Yu (2015). Indeed, their estimates suggest the existence of a positive relationship between upstreamness and corporate performance (measured both through productivity and profitability). Yet, their study differs from ours in several ways. Firstly, unlike us, Ju and Yu (2015) have no information about the outputs of all products a firm produces. Therefore, their upstreamness indicator is computed at the industry level (i.e. for 120 different sectors) in 2002 following the methodology developed by Antras *et al.* (2012).[28] They also calculate a firm-level upstreamness index but only for exporting firms and in an indirect way, i.e. using firm's average upstreamness in exports as an approximation to its production index. In this study, we take advantage of access to Dhyne *et al.* (2015) unique data set which provides a direct and accurate measure of upstreamness for (almost) each commercial firm (operating both in manufacturing and services) in each year from 2002 to 2010. Secondly, Ju and Yu (2015) estimate the relationship between upstreamness and industry/firm performance by OLS, controlling for firm characteristics such as industry, province, ownership and export status. In contrast, we rely on dynamic panel data estimation techniques which account for state dependence of dependent variables, firm fixed effects and endogeneity of firms' upstreamness. Moreover, our data do not only enable us to

[26] Buciuni *et al.* (2014) highlight, on the basis of a case study relative to the furniture industry, that control over operations is key for product innovation and competitiveness of firms participating to a GVC. Along the same lines, Dedrick *et al.* (2010) show that Apple has captured a great deal of value from the innovation embodied in the iPod.

[27] In our data set, the mean capital stock per worker among firms whose upstreamness is higher (lower) than the average sample value – i.e. 2,31 steps from final demand – is equal to 231,208 EUR (138,143 EUR).

[28] They also compute an industrial upstreamness index (for 135 different sectors) for the year 2007. Yet, given that their upstreamness indicators relative to 2002 and 2007 are highly correlated, they essentially rely in their regression analysis on the 2002 industrial upstreamness index.

control for firm characteristics (such as industry, size and capital stock) but also for key variables reflecting the composition of the workforce within those firms (such as education, age, occupation, working time). Thirdly, Ju and Yu (2015) do not focus on wage costs. Put differently, in contrast to us, they pay little attention to distributional issues, i.e. the way productivity gains associated to upstreamness are shared between capital and labour. Be that as it may, both studies suggest that upstreamness fosters productivity and profitability.

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Table 1. Firm-level descriptive statistics of selected variables, 2002-2010

Variables:	Mean	Std. Dev.
Annual value added per worker (€ [1])	91,358	597,08
Annual value added per worker (ln)	11.09	0.62
Annual wage cost per worker (€ [1])	47,801	23,74
Annual wage cost per worker (ln)	10.68	0.44
Upstreamness (in steps)	2.31	0.94
Age (%):		
Less than 30 years	21.6	15.09
Between 30 and 49 years	60.91	14.7
50 years and more	17.49	13.31
Education (%):		
Non-tertiary education	73,64	23,98
Bachelors	15.47	17.35
Masters	10.32	15.75
Post-Masters	0.57	3.08
Blue-collar workers [2] (%)	53.25	34.64
Part-time workers (%)	16.41	17.75
Sector (%):		
Mining and quarrying (B)	0.15	
Manufacturing (C)	51.43	
Electricity, gas, steam and air conditioning supply; Water supply, sewerage, waste management and remediation activities (D+E)	0.62	
Construction (F)	8.74	
Wholesale and retail trade, repair of motor vehicles and motorcycles (G)	15.98	
Accommodation and food service activities (I)	1.97	
Transport and storage; Information and communication (H+J)	6.49	
Financial and insurance activities (K)	1.69	
Real estate activities; Professional, scientific and technical activities; Administrative and support service activities (L+M+N)	12.93	
Size (number of workers)	217.04	413.13
Capital stock per worker (€ [1])	231,208	1,874,025
Number of observations	12,340	
Number of firms	3,625	

[1] At 2004 constant prices. [2] The distinction between blue- and white-collar workers is based on the International Standard Classification of Occupations (ISCO-08). Workers belonging to groups 1 to 5 are considered to be white-collar workers (1: Legislators, senior officials and managers; 2: Professionals; 3: Technicians and associate professionals; 4: Clerks; 5: Service workers and shop and market sales workers) and those from groups 7 to 9 are considered to be blue-collar workers (7: Craft and related trades workers; 8: Plant and machine operators and assemblers; 9: Elementary occupations).

Table 2: Upstreamness, productivity and wage costs
Firm-level OLS estimates, 2002-2010

	OLS		OLS		OLS	
Dependent variable:	Productivity	Wage cost	Productivity	Wage cost	Productivity	Wage cost
	(1)	(2)	(3)	(4)	(5)	(6)
Value added per worker (one year lagged, in ln)					0.871*** (0.019)	
Wage cost per worker (one year lagged, in ln)						0.841*** (0.038)
Upstreamness [1]	0.140*** (0.004)	0.083** (0.003)	0.091 *** (0.005)	0.033*** (0.003)	0.011*** (0.003)	0.005** (0.002)
Worker characteristics [2]	No	No	Yes	Yes	Yes	Yes
Firm characteristics [3]	No	No	Yes	Yes	Yes	Yes
Year dummies (8)	No	No	Yes	Yes	Yes	Yes
Adjusted R^2	0.041	0.025	0.394	0.477	0.847	0.849
Sig. Model (p-value)	0.000	0.000	0.000	0.000	0.000	0.000
Number of observations	12,340	12,337	12,340	12,337	12,340	12,337
Number of firms	3,625	3,624	3,625	3,624	3,625	3,624

Notes: ***/**/* significant at the 1, 5 and 10% level, respectively. Robust standard errors are shown in brackets. The dependent variable is either the value added per worker in ln ('productivity') or the wage cost per worker in ln ('wage cost') at the firm level. [1] Steps (distance) before the production of a firm meets either domestic or foreign final demand. [2] Share of the workforce that: i) is younger than 30 and older than 49 years, respectively, and ii) is highly educated (3 categories). The share of blue-collar workers and the share of part-time workers are also included. [3] Sectoral affiliation (8 dummies), number of workers and stock of capital per worker (estimated through the "perpetual inventory method").

Table 3: Upstreamness, productivity and wage costs
Firm-level GMM-SYS estimates, 2002-2010

	GMM-SYS			
Dependent variable:	Productivity	Wage cost	Productivity	Wage cost
	(1)	(2)	(3)	(4)
Value added per worker (one year lagged, in ln)	0.793***		0.793***	
	(0.036)		(0.033)	
Wage costs per worker (one year lagged, in ln)		0.745***		0.747***
		(0.053)		(0.051)
Upstreamness [1]	0.053**	0.046***		
	(0.025)	(0.017)		
Upstreamness between 2.5 and 4.5 [2]			0.102**	0.080***
			(0.042)	(0.028)
Upstreamness above 4.5 [2]			0.209**	0.097**
			(0.092)	(0.045)
Worker characteristics [3]	Yes	Yes	Yes	Yes
Firm characteristics [4]	Yes	Yes	Yes	Yes
Year dummies (8)	Yes	Yes	Yes	Yes
Sig. Model (p-value)	0.000	0.000	0.000	0.000
Hansen statistic	288.31	329.72	312.34	342.54
p-value	0.71	0.13	0.75	0.31
Arellano-Bond statistic (AR2) [5]	1.57	1.11	1.58	1.10
p-value	0.12	0.27	0.11	0.27
Number of observations	12,340	12,337	12,340	12,337
Number of firms	3,625	3,624	3,625	3,624

Notes: ***/**/* significant at the 1, 5 and 10% level, respectively. Robust standard errors are shown in brackets. The dependent variable is either the value added per worker in ln ('productivity') or the wage cost per worker in ln ('wage cost') at the firm level. Second and third lags of all explanatory variables are used as instruments in the GMM-SYS specification, excluding time dummies. [1] Steps (distance) before the production of a firm meets either domestic or foreign final demand. [2] The control group is composed of firms whose upstreamness is below 2.5. [3] Share of the workforce that: i) is younger than 30 and older than 49 years, respectively, and ii) is highly educated (3 categories). The share of blue-collar workers and the share of part-time workers are also included. [4] Sectoral affiliation (8 dummies), number of workers and stock of capital per worker (estimated through the "perpetual inventory method"). [5] AR2 displays the test for second-order autocorrelation in the first-differenced errors.

Table 4. Upstreamness, productivity and wage costs: the role of product market competition
Firm-level GMM-SYS estimates, 2002-2010

	GMM-SYS			
Dependent variable:	Productivity		Wage cost	
	(1)	(2)	(3)	(4)
	Lower HHI [5] (Stronger competition)	Higher HHI [6] (Weaker competition)	Lower HHI [5] (Stronger competition)	Higher HHI [6] Weaker competition)
Value added per worker (one year lagged, in ln)	0.830*** (0.031)	0.739*** (0.035)		
Wage cost per worker (one year lagged, in ln)			0.785*** (0.061)	0.766*** (0.060)
Upstreamness [1]	0.055** (0.028)	0.056** (0.022)	0.038** (0.019)	0.056*** (0.017)
Worker characteristics [2]	Yes	Yes	Yes	Yes
Firm characteristics [3]	Yes	Yes	Yes	Yes
Year Dummies (8)	Yes	Yes	Yes	Yes
Sig. Model (p-value)	0.000	0.000	0.000	0.000
Hansen statistic	251.23	456.02	325.42	313.00
p-value	0.66	0.21	0.16	0.29
Arellano-Bond statistic (AR2) [4]	1.30	-0.06	1.12	-0.08
p-value	0.20	0.96	0.26	0.94
Number of observations	5,163	7,177	5,163	7,177
Number of firms	2,036	2,429	2,036	2,429

Notes: ***/**/* significant at the 1, 5 and 10% level, respectively. Robust standard errors are shown in brackets. The dependent variable is either the value added per worker in ln ('productivity') or the wage cost per worker in ln ('wage cost') at the firm level. Respectively third and fourth lags (equation 1), first and third lags (eq. 2) and second and third lags (eq. 3 and 4) of explanatory variables are used as instruments in the GMM-SYS specification, excluding time dummies. [1] Steps (distance) before the production of a firm meets either domestic or foreign final demand. [2] Share of the workforce that: i) is younger than 30 and older than 49 years, respectively, and ii) is highly educated (3 categories). The share of blue-collar workers and the share of part-time workers are also included. [3] Sectoral affiliation (8 dummies), number of workers and stock of capital per worker (estimated through the "perpetual inventory method"). [4] AR2 displays the test for second-order autocorrelation in the first-differenced errors. [5] Sample of firms belonging to NACE 3 digit industries whose Herfindahl-Hirshman Index (HHI) is below the mean sample value. [6] Sample of firms belonging to NACE 3 digit industries whose Herfindahl-Hirshman Index (HHI) is above the mean sample value.

Table A1. Upstreamness, productivity and wage costs
Detailed static OLS estimates, 2002-2010

	OLS	
Dependent variable:	Productivity	Wage cost
	(1)	(2)
Upstreamness [1]	0.091 ***	0.033***
	(0.005)	(0.003)
% of workers younger than 30	-0.486***	-0.480***
	(0.038)	(0.027)
% of workers older than 49	0.066	0.096***
	(0.045)	(0.027)
Highly educated – short (Bachelor)	0.528***	0.467***
	(0.037)	(0.025)
Highly educated – long (Master)	1.020***	0.940***
	(0.042)	(0.029)
Highly educated – third level (post-Master)	2.075***	1.538***
	(0.230)	(0.157)
Blue Collars	-0.047**	0.009
	(0.020)	(0.015)
Part-timers	-0.951***	-0.823***
	(0.031)	(0.027)
Nace C	0.235**	0.038
	(0.112)	(0.046)
Nace D+E	0.764***	0.216***
	(0.281)	(0.060)
Nace F	-0.071**	0.029
	(0.028)	(0.021)
Nace G	-0.018	-0.001
	(0.025)	(0.016)
Nace I	-0.376***	-0.333***
	(0.095)	(0.083)
Nace H+J	-0.023	0.021
	(0.049)	(0.025)
Nace K	0.251	0.021
	(0.162)	(0.138)
Nace L+M+N	-0.164***	-0.072***
	(0.035)	(0.021)
Size	0.0001***	0.0001***
	(0.00002)	(0.0001)
Capital stock per worker	$6.63e^{-08}$***	$6.83e^{-09}$***
	($1.14e^{-08}$)	($1.42e^{-09}$)
Year dummies (8)	YES	YES
Adjusted R^2	0.394	0.477
Sig. Model (p-value)	0.000	0.000
Number of observations	12,340	12,337
Number of firms	3,625	3,624

Notes: ***/**/* significant at the 1, 5 and 10% level, respectively. Robust standard errors are shown in brackets. [1] Steps (distance) before the production of a firm meets either domestic or foreign final demand.

Table A2. Upstreamness and productivity
Firm-level *à la* LP estimates, 2002-2010

	LP
Dependent variable:	Productivity
Upstreamness [1]	0.061*** (0.011)
Worker characteristics [2]	Yes
Firm characteristics [3]	Yes
Year dummies (8)	Yes
Sig. Model (p-value)	0.000
Number of observations	12,272
Number of firms	3,625

Notes: ***/**/* significant at the 1, 5 and 10% level, respectively. Firm-level *à la* LP estimates stand for results obtained with an estimation technique *à la* Levinsohn and Petrin (2003), in which we do not start by estimating a production function to measure total factor productivity, but instead directly use labour productivity, i.e. the value added per worker at the firm level, as dependent variable. [1] Steps (distance) before the production of a firm meets either domestic or foreign final demand. [2] Share of the workforce that: i) is younger than 30 and older than 49 years, respectively, and ii) highly educated (3 categories). The share of blue-collar workers and the share of part-time workers are also included. [3] Sectoral affiliation (8 dummies), number of workers and stock of capital per worker (estimated through the "perpetual inventory method").

Table A3. Descriptive statistics by degree of product market competition, 2002-2010

	Lower HHI [3] (Stronger competition)		Higher HHI [4] (Weaker competition)	
Variables:	Mean	Std. Dev.	Mean	Std. Dev.
Annual value added per worker (ln)	11.00	0.59	11.15	0.64
Annual wage costs per worker (ln)	10.61	0.41	10.73	0.45
Upstreamness (in steps)	2.20	0.99	2.38	0.89
Age (%):				
Less than 30 years	21.99	15.12	21.32	15.07
Between 30 and 49 years	60.25	14.72	61.37	14.68
50 years and more	17.76	13.11	17.31	13.45
Education (%):				
Non-tertiary education	79.33	22.79	69.70	28.70
Bachelors	12.22	14.63	17.72	18.68
Masters	8.07	13.60	11.88	16.91
Post-Masters	0.38	2.43	0.70	3.45
Blue-collar workers [2] (%)	57.06	34.23	50.61	34.68
Part-time workers (%)	18.26	18.24	15.13	17.28
Sector (%):				
Mining and quarrying (B)	0.87		0.00	
Manufacturing (C)	38.01		78.63	
Electricity, gas, steam and air conditioning supply; Water supply, sewerage, waste management and remediation activities (D+E)	0.00		2.63	
Construction (F)	10.85		0.00	
Wholesale and retail trade, repair of motor vehicles and motorcycles (G)	22.13		1.59	
Accommodation and food service activities (I)	2.54		0.17	
Transport and storage; Information and communication (H+J)	7.19		1.99	
Financial and insurance activities (K)	2.79		2.62	
Real estate activities; Professional, scientific and technical activities; Administrative and support service activities (L+M+N)	15.62		12.37	
Size (number of workers)	195.77	329.97	231.77	461.47
Capital stock per worker (€ [1])	188,988	1,392,249	261563	2,154,438
Number of observations	5,163		7,177	
Numbers of firms	2,036		2,429	

[1] At 2004 constant prices. [2] The distinction between blue- and white-collar workers is based on the International Standard Classification of Occupations (ISCO-08). Workers belonging to groups 1 to 5 are considered to be white-collar workers (1: Legislators, senior officials and managers; 2: Professionals; 3: Technicians and associate professionals; 4: Clerks; 5: Service workers and shop and market sales workers) and those from groups 7 to 9 are considered to be blue-collar workers (7: Craft and related trades workers; 8: Plant and machine operators and assemblers; 9: Elementary occupations). [3] Sample of firms belonging to NACE 3 digit industries whose Herfindahl-Hirshman Index (HHI) is below the mean sample value. [4] Sample of firms belonging to NACE 3 digit industries whose Herfindahl-Hirshman Index (HHI) is above the mean sample value.