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Abstract

This paper examines the relation between productivity and specialization of firms in business functions. We distinguish between specialization in R&D, fabrication, and marketing based on the firm's employment composition over these functions using unique survey data of Dutch firms. Our results suggest that firms specialized in R&D and marketing are significantly more productive compared to firms specialized in fabrication. We find that measures of upstreamness based on input-output tables do not significantly relate to firm productivity and are uncorrelated to measures of functional specialization.

JEL codes: F14, L23, L25

Keywords: Specialization, Business functions, Upstreamness, Productivity, Firms

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1. Introduction

One of the defining characteristics of our modern economy is the fragmentation of production processes across national borders (Baldwin, 2016; Amador and Cabral, 2017). This fragmentation of production involves the cross-border flow of physical inputs as well as the provision of a range of professional business functions, such as the design, engineering, sourcing, marketing and sales of consumer products (Feenstra, 1998; Timmer et al. 2019). For various reasons, but in particular due to improvements in communication and management systems, firms have been specializing in activities (Feenstra, 1998; Dedrick et al. 2010; Bernard et al. 2017; Wood, 2017; Timmer et al. 2019). The best known example is the iPhone. On the back of the iPhone one reads it is designed by Apple in California, but assembled by Foxconn in Guangdong. This specialization in activities has been theoretically shown to relate to wages and productivity (Costinot et al. 2013, Fally and Hillberry 2017).

This paper proposes a straightforward yet novel approach to measure the specialization of firms and provides an empirical test of the relation between firm productivity and functional specialization.

We measure the functional specialization of firms using unique data from two survey rounds in 2012 and 2017, in which Dutch firms report on the composition of their employees by function. The surveys we use were administered by Statistics Netherlands and sent to private firms with at least 50 employees. Managers who complete such surveys indicate the allocation of their employees across business functions is a natural way for them to categorize their workers (Sturgeon and Gereffi, 2009). There is not yet a standardized classification of business functions, but typically the main distinction is between fabrication and headquarter (Markusen, 2002). We keep that distinction, and further split headquarter into R&D and marketing.

We adopt a Balassa-type indicator of specialization where the business function employment share of the firm is compared to the average employment share of that activity across all firms. In this approach, firms are specialized in a function if they have a relatively higher share of workers involved in that function. We combine these surveys with detailed data on firm employment, sales, production, input usage, imports and exports. It allows us to measure firm productivity and price mark-ups over marginal costs.

We find that firms specialized in R&D and marketing are significantly more productive compared to firms that specialize in fabrication. These findings are robust to controlling for other potential determinants of productivity. It suggests value added from research and design as well as marketing efforts like building brand names is higher compared to fabrication. Our analysis provides empirical support to the well-known “smile curve” of global value chains, where value added from fabrication activities is typically lowest relative to R&D at the conception and marketing at the end of the value chain (Mudambi, 2008). We do not observe a significant relation between functional specialization and mark-ups.

A common approach to characterize activities has been tracking the establishments in which the value is added, as e.g. in Ding et al. (2019). Value added from manufacturing establishments is then equated with fabrication activities and value added from establishments in services sectors with professional services. However, functions are not the same as sectors (Duranton and Puga, 2005). Establishments, be they classified in manufacturing or services, typically perform various functions and combine these in-house. Over time, this mix has been changing, sometimes denoted as the 'servicification of manufacturing' (Fontagné and Harrison, 2017; Thangavelu et al. 2018). This indicates that we cannot rely on a mere statistical classification of sectors to understand the functional specialization of firms. Instead, we prefer to measure specialization in functions on the basis of the activities workers perform.

There is a growing literature that provides empirical measures for the relative production line position of products. Such measures are commonly referred to as upstreamness and downstreamness measures (Fally, 2012; Antràs et al. 2012; Antràs and Chor, 2018). In this approach, the upstreamness or downstreamness - the average distance from final use - is decided on the basis of the products produced.

In some applications, discussed in section 2, upstreamness measures are interpreted to reflect specialization in activities. However, measures of upstreamness (or downstreamness) do not inform on the activities of firms. We argue these measures inform on *where* goods are positioned in the production chain, but not *what* firms producing these goods do.

Returning to the iPhone example: the upstreamness measure is the same for Apple and Foxconn, because they are involved in the same product. Yet it is immediately clear that what they do is very different.

In support of this view, the empirical analysis in this paper suggests that upstreamness measures do not significantly relate to firm productivity and price mark-ups over marginal costs. Furthermore, the analysis suggests that measures of upstreamness are unrelated to measures of functional specialization.

This paper relates to Timmer et al. (2019), who propose to measure the functional specialization of countries in international trade using information on the occupations of workers. In this approach, the occupation of a worker informs on the nature of the activity performed. Our approach is very similar, but at the firm level. We determine the specialization of a firm based on the composition of its workforce over functions.

The inference of activities from labor data is well-known in urban economics and economic geography. For example, Maurin and Thesmar (2004) study the business functions of French manufacturing firms using information on the occupations of workers. Duranton and Puga (2005) show how cities in the U.S. specialize in headquarter activities, while fabrication activities concentrate in less urbanized regions. Harrigan et al. (2016) argue that technology adoption is mediated by technically qualified managers and technicians ('techies'), and use the firm-level employment share of techies as a measure for the propensity to adopt new technology.

Our analysis also relates to recent work that examines structural change within firms. Ding et al. (2019) examine characteristics of manufacturing firms that have establishments providing professional services. They develop a model and examine US firms in which technical professionals complement physical production, and where reductions in the price of intermediate goods induce firms to reallocate towards the provision of services. Bernard et al. (2017) examine Danish firms that switch out of manufacturing. They define a firm that switches out when it no longer reports any establishment in a manufacturing industry but continues operations in services. Bernard et al. (2017) document that the occupational employment composition of switchers is concentrated in non-fabrication professional activities, such as managers, sales, and tech workers. Switchers are found to have a higher labor productivity compared to firms that did not switch out of manufacturing. In contrast to these studies, the analysis in this paper abstracts from changes within firms, as we use cross-sections from two survey waves.

This paper also relates to a rich body of literature that examines the relation between innovation and productivity. A broad consensus in this literature is that R&D investment and the adoption of new technologies relate positively to firm productivity (Aw et al., 2011; Syverson, 2011). Often, R&D investment is observable, and reflected in expenditures (Syverson, 2011). However, many firms undertake different types of innovation, such as process and product innovation without formally reporting R&D spending. Our conceptualization of R&D, based on the firm's employment share in R&D activities, is therefore complementary to the literature on the relation between R&D and productivity. It enlarges the concept of what constitutes R&D activities and also helps distinguish it from other innovative activities, such as building brand names.

This paper proceeds as follows. Section 2 outlines and describes the data and measurement of functional specialization. It also contrasts functional specialization to measures of upstreamness and downstreamness. Section 3 discusses the estimation of firm productivity and mark-ups. Section 4 provides descriptive statistics. Section 5 econometrically examines the relation between functional specialization, productivity, and mark-ups. Section 6 concludes.

2. Measuring the Functional Specialization of Firms

The data and the measurement of functional specialization is described in section 2.1. In section 2.2 we discuss a common set of upstreamness and downstreamness measures based on input-output tables that focus on the relative production line position of products and argue these are not informative regarding the activities that individual firms actually do, because they have a different purpose and interpretation.

2.1 The functional specialization of firms

Under the aegis of Eurostat, various statistical offices in Europe have implemented "International Sourcing & Global Value Chain Surveys" (Nielsen, 2018). The surveys were held in 2007, 2012

and 2017. Its focus is to map aspects of globalization, such as the relocation of business functions abroad and motives for and barriers against sourcing internationally, but it also collects other interesting information. The question on the employment composition by business function, which will be used in this paper, was asked in the survey waves 2012 and 2017.

We consider question 2.2: "Please give your best estimate of the employment in your enterprise at the end of 20[xx]".[1] For this question, the manager is asked to only include employment in her own enterprise, not employment at affiliates abroad. Persons undertaking more than one activity are included according to their main activity. Business functions are a relevant unit of analysis as (multinational) firms typically organize their activities around these (Sturgeon and Gereffi, 2009; Defever 2012).

Response rates are high. Sampling is based on the general business register, and hence representative of firms that meet the size threshold (CBS, 2018).[2] However, as common for surveys, the quality of information provided by the firm varies depending on whether the person completing the survey is knowledgeable on the subject. Data on exports and imports that we have for the firms included in the survey show they are actively involved in international trade, with most of them both importing and exporting goods.

Table 1 shows the potential allocation of workers in the survey questionnaire. The workers can be either allocated to a core or a support business function, and the latter is then split further. The core function refers to the primary activity of the enterprise. It includes production of goods or services intended for the market or third parties carried out by the enterprise. We will refer to these as fabrication activities. Support business functions facilitate the production of goods or services, and include a range of activities such as distribution, engineering, and sales services. These business functions are grouped into R&D and marketing, see the final column in Table 1. It is difficult to decide where to draw the boundaries between functions that go together and those that are different (Kemeny and Storper, 2015). We take a pragmatic solution and closely follow the set of functions distinguished by Bernard et al. (2017) and Timmer et al. (2019). The category 'other support functions' has been excluded as it does not easily map in one of the three business functions (R&D, fabrication, and marketing) distinguished in the empirical analysis.

[1] For the 2012 survey, it is the employment distribution at the end of 2011. For the 2017 survey it is the distribution at the end of 2016. Therefore, in the empirical analysis we will relate functional specialization to productivity and mark-ups in cross-sections for the years 2011 and 2016.

[2] The response rate is 81.6 (63) percent for the 2017 (2012) International sourcing survey. The 2017 survey sampled firms from the universe of Dutch firms with 50 or more employees. It includes firms in manufacturing and market-based services while excluding firms in agriculture, finance, government, education, health, and other social and personal services. The 2012 survey sampled firms with 100 or more employees. Sample weights are by industry and size class. Only very few firms in the 2012 survey are also sampled in the 2017 survey.

Table 1. Question on employment by business function in the survey.

	Number of persons employed	Business function aggregation
TOTAL (all functions)	[_ _ _ _ _]	
Core business function		
- production of goods for the market	[_ _ _ _ _]	Fabrication
- production of services for the market	[_ _ _ _ _]	Fabrication
Support business functions		
- Distribution and logistics	[_ _ _ _ _]	Marketing
- Marketing, sales services and after sales services, incl. help desks and call centers	[_ _ _ _ _]	Marketing
- ICT services	[_ _ _ _ _]	Marketing
- Administrative and management functions	[_ _ _ _ _]	Marketing
- Engineering and related technical services	[_ _ _ _ _]	R&D
- Research & Development	[_ _ _ _ _]	R&D
- Other support functions	[_ _ _ _ _]	Excluded

Notes: Question 2.2 in the International Sourcing Surveys 2012 and 2017. The final column shows our aggregation of business functions to R&D, fabrication, and marketing.

We use a straightforward yet novel approach to measure the functional specialization of a firm, adapting the Balassa (1965) indicator. That is, we compare the firm's employment share (emp_k) in activity a to the average employment share for that activity across all firms in the survey:

$$\mathrm{SI}_k^a = \frac{(emp_k^a / \sum_a emp_k^a)}{(\sum_k \mathrm{emp}_k^a / \sum_k \sum_a emp_k^a)} \tag{1}$$

The highest index across all possible activities is used to determine the Specialization Index (SI) of the firm. E.g. if the SI of firm k is equal to 1.4 for R&D activities, 1.1 for fabrication and 0.8 for marketing respectively, the firm is said to be specialized in R&D activities.

The specialization index can be easily implemented and is straightforward to interpret. It is akin to the functional specialization index introduced in Timmer et al. (2019). In particular, note

that the SI is related to concentration indices such as the Herfindahl index. However, the Herfindahl index and other concentration indices are based on the distribution of employment, whereas the specialization index is based on a comparison of shares.

2.2 Upstreamness and downstreamness

Scholars have proposed empirical measures for the production line position of products, counting the number of steps away from final consumption and weighting each stage by its output value (Fally, 2012; Antràs et al. 2012; Antràs and Chor, 2013). In this setup, a good that is used for final consumption is more downstream. Likewise, a good is more upstream if it is used to produce intermediate inputs (that are then used to produce intermediate inputs etcetera). In Appendix A we provide a formal exposition of upstreamness and downstreamness measures (see also Johnson, 2018).

The production line position of a firm can be based on direct observation of the firms' industry classification for which upstreamness or downstreamness is calculated. But firms may produce multiple products. Therefore, Chor et al. (2014) propose measures based on the product composition of the firms' exports. We follow Chor et al. (2014) and measure the upstreamness and downstreamness of firm k based on the export value of its products, W_{ks}. That is,

$$U_k = \sum_{s=1}^{S} \frac{W_{ks}}{W_k} U_s, \qquad D_k = \sum_{s=1}^{S} \frac{W_{ks}}{W_k} D_s, \tag{2}$$

where $W_k = \sum_{s=1}^{S} W_{ks}$, U_s upstreamness, and D_s the downstreamness of a product from industry s.

Intuitively, upstreamness or downstreamness appear to relate to functional specialization. Indeed, when Antràs and Chor (2013) develop measures of the production line position they write in the introduction that they consider sequential production processes where 'at a broad level, the process of manufacturing cannot commence until the efforts of R&D centers in the development or improvement of products have proven to be successful, while the sales and distribution of manufactured goods cannot be carried out until their production has taken place (page 2127).'

Sometimes, upstreamness and downstreamness measures are used in empirical applications for which they are not intended. For example, sometimes scholars aim to provide empirical content to the smile curve using estimates of upstreamness (or downstreamness), see e.g. Baldwin et al., 2015; Baldwin 2016; and Degain et al. 2017; Thangavelu et al. 2018; Deng et al. 2019. The well-known "smile curve" of global value chains originally proposed by Stan Shih of Acer in 1992 states that fabrication activities typically have the lowest remuneration relative to other activities in the chain (Mudambi, 2008; Park et al, 2013). In the applications, upstreamness is estimated and ordered on the horizontal axis.

Yet, input-output measures are informative about the relative production line position of products. They do not inform on what firms do. For example, cotton is a relatively upstream

product as it is typically an intermediate product, further used in the production process. Clothing is a more downstream product, because clothing is often for final use by consumers. Thus, the cotton production of a farmer is relatively upstream compared to the clothing production of a textile firm. But that does not inform on *what* the textile firm actually does. The textile firm might be involved in the design of a t-shirt, do the cut, make and trim assembly or nurture a brand name by focusing on marketing. These are very different activities and likely to differ in their potential for productivity growth and knowledge spillovers.

Appendix A describes measures of upstreamness using input-output tables. We use the 2016 release of the World Input-Output Tables (WIOTs), which provide tables for the period from 2000 to 2014 (Timmer et al. 2016). These tables give information on input purchases, the direct parent (downstream) industry and country, as well as direct source country and industry. The U_s and D_s statistics are calculated at the level of country-industry pairs. We focus here on the length and position of industries for products that are finalized in the Netherlands (for further analysis, see Appendix A). The WIOTs distinguish two services sectors that are of interest, namely 'Scientific research and development' and 'Advertising and market research'. At face value these two sectors might be considered to be upstream and downstream respectively, as e.g. in Rungi and Del Prete (2018). However, the findings suggest that the scientific research and development sector is one of the most downstream sectors (see the row in italics in Appendix Table 1). The upstreamness measure U_s for the sector advertising and market research suggests it is one of the most upstream sectors (also in italics in Appendix Table 1).

One reason why these findings do not conform with standard expectations is due to the definition of R&D in the System of National Accounts 2008 (SNA 2008, see UN et al. 2009). The SNA 2008 recognizes R&D as an investment, a produced asset, in the economy. Most spending on R&D is treated as investment in R&D assets. In input-output tables, investments are part of final demand. Hence, the R&D sector in the input-output tables is mainly delivering investments that are for final demand. From this point of view the scientific research and development sector is downstream.[3]

Estimates of upstreamness for manufacturing products are more intuitive. For example, manufactured basic metals are more upstream compared to motor vehicles (see Appendix Table

[3] More generally, input-output tables that are used to calculate up- and downstreamness have to create consistency between the prices that producers charge and the prices that are paid by consumers (2008 System of National Accounts, UN et al. 2009). The recommend price basis for producers is the basic price, the so-called factory gate price. This is the appropriate price basis when applying the Leontief inverse (Miller and Blair, 2009). Hence, input-output analyses trace back the steps that are involved in the product that is produced and valued at factory gate (or basic) prices. But any margins that are levied on the product before it is consumed may not be taken into account (Chen et al. 2018; Ahmad, 2018). In their famous decomposition of the value of the iPod, Dedrick et al. (2010) document that the factory gate price was about half the final (purchasers') price paid by consumers. The profits to Apple, basically the compensation for its research, design, and marketing activities are not included in the factory gate price. Therefore, upstreamness measures that use input-output tables at factory gate (basic) prices may not include income from R&D and marketing.

1). This is one reason why scholars usually only report upstreamness for manufacturing products (see e.g. Antràs et al. 2012). The next sections make comparisons between firm upstreamness (U_k) (and downstreamness (D_k)) calculated according to equation (2) and the functional specialization index (SI_k), see equation (1) for Dutch firms. Since scholars tend to focus on measures of upstreamness for manufacturing, we will focus on comparisons for manufacturing firms and show that functional specialization is not related to measures of upstreamness.

3. Productivity and mark-ups

In the empirical analysis below, we relate specialization to productivity and mark-ups. This section describes the estimation of Total Factor Productivity (TFP) using the econometric approach suggested by Wooldridge (2009), with a price mark-up correction from De Loecker and Warzynski (2012). We adopt this econometric approach, because estimating a production function using OLS to derive TFP results in biased coefficients due to endogeneity issues. Endogeneity issues arise, because of the correlation between factor inputs and unobservable productivity shocks (Syverson, 2011).

There are several solutions to endogeneity problems when estimating production functions. The most common solutions are the two control function approaches put forth by Olley and Pakes (1996, hereafter OP) and by Levinsohn and Petrin (2003, hereafter LP). A key assumption in these two approaches is that firm level investments (OP) or purchases of intermediate inputs (LP), conditional on the capital stock, can be related to unobserved firm-level productivity shocks. Under this strict monotonicity, one is able to invert the investment or intermediate input demand function. The form of the control function is nonparametric in capital, and investment (OP) or intermediate inputs (LP). The control function is estimated in two stages. The first stage estimates the labor coefficient in the production function. In the second stage, the estimates from the first stage are plugged in to estimate capital, and investment or intermediate inputs coefficients.

Ackerberg et al. (2015) points out that both OP and LP suffer from a functional dependence problem from estimating the first stage. Wooldridge (2009) suggests solving the problem by replacing the two step estimation procedure with a generalized method of moments (GMM) setup. Specifically, Wooldridge (2009) proposes an alternative moment that minimizes the first and second stage moments simultaneously. Apart from avoiding the functional dependence problem in the first stage, the joint estimation approach is also more efficient than previous control function approaches. We therefore use the method of Wooldridge (2009) to estimate TFP in our baseline analysis.

We run the Prodest program in Stata written by Mollisi and Rovigatti (2017) for the Wooldridge approach specifying a value-added based production function, wherein labor is treated

as a flexible input. We estimate a Cobb-Douglas production function by industry from 2009 to 2016:[4]

$$log\ v_{kst} = \beta_0 + \beta_1 log\ \text{Capital}_{kst} + \beta_2 log\ \text{Labor}_{kst} + \omega_{kst} + \vartheta_{kst}, \qquad (3)$$

where v is value added of firm k in industry s at time t, and ω is unobserved productivity. The sequence $\{\omega_{kst}: t = 1,\ldots, T\}$ is unobserved productivity, and $\{\vartheta_{kst}: t = 1, 2,\ldots, T\}$ is a sequence of shocks that are assumed to be conditional mean independent of current and past inputs (Wooldridge, 2009). Value added is in values rather than in quantities owing to the absence of information on prices and quantities of goods sold. This is a common limitation of firm level production data when estimating TFP. It is acceptable and even desirable when firm-level prices fully reflect product quality differences (Syverson 2011). However, it creates problems in estimating TFP whenever prices reflect differences in market power across firms. In that case, the estimated TFP may reflect differences in market power rather than differences in production efficiency across firms.

To separate mark-ups from TFP, we follow the approach by De Loecker and Warzynski (2012) to calculate firm- and time-specific mark-ups, μ_{kst} , further discussed below (see equation (5)). The mark-up corrected firm level TFP is derived as follows:

$$\text{TFP}_{kst}^{adj} = \log(\text{TFP}_{kst}) - \log(\mu_{kst}). \qquad (4)$$

TFP_{kst}^{adj} separates the price influence caused by market power differences. The key assumption to do so is that at least one factor input is fully flexible, which is labor in our setting. The mark-up is derived from minimizing the firm's cost with respect to the flexible input for a Cobb Douglas production function:

$$\mu_{kst} = \frac{P_{kst}}{MC_{kst}} = \text{Labor elasticity}_{kst}/\text{Labor share}_{kst} \qquad (5)$$

Where P is the output price and MC is marginal cost. The elasticity of labor is the estimate for β_2 in equation (3). The labor share is obtained by dividing labor cost by a corrected value added measure. This corrected value added measure arises because of the assumption that when making optimal input decisions, firms do not observe unanticipated shocks to production. Specifically, firms minimize costs according to a prediction of output, and the prediction is based on fitting equation (3) to a polynomial output function in terms of factor inputs:

$$v_{kst} = h(\log \text{Capital}_{kst}, \log \text{Labor}_{kst}) + \vartheta_{kst}, \qquad (6)$$

where the function h() includes the factor inputs and interactions with first- and second-order terms. Following De Loecker and Warzynski (2012), the predicted output is computed as: $\widehat{v_{kst}} = \frac{v_{kst}}{\exp(\widehat{\vartheta_{kst}})}$, where $\widehat{\vartheta_{kst}}$ is the first stage error term using the control function approaches of OP

[4] Coefficient estimates are industry specific, which aims to control for potential heterogeneity in production technologies across industries.

and LP and v_{kst} is observed value added. The labor coefficient β_2 is estimated for each industry *s*. Variation of firm level mark-ups within an industry are determined by the expenditure share of labor input in total expenditure.

The data to estimate firm TFP and mark-ups are obtained from the Structural Business Statistics (SBS) provided by Statistics Netherlands.[5] The SBS are from yearly enterprise surveys. Firms with less than 50 employees are sampled, but all enterprises with 50 or more employees are included. Since the firms in the surveys used to measure functional specialization are sampled from firms with at least 50 employees, we have a near perfect matching data from SBS. The variables we use are: gross output at basic prices, gross value added at basic prices, intermediate consumption costs, persons employed (FTEs), depreciation of fixed assets, and turnover.[6] The variables in value terms are deflated using industry price deflators.[7] The data includes other firm characteristics as well, such as age, size, and exports, which will be used in the empirical analysis.

The SBS data does not include information on capital stocks. Broersma et al. (2003) propose the 'booked depreciation method' to derive a long investment series based on depreciation reported by Dutch firms. This method is based on a standard accounting rule, namely linear depreciation. This rule indicates that an investment in year *t* will be depreciated uniformly over the lifetime of the asset. Therefore, the depreciation of the asset in year *t* is a function of the flow of investments in previous years. Broersma et al. (2003) use investment data for the period 1988-1994. However, investment data is not available for the years in our analysis. Therefore, we are unable to use investment data, which leaves using depreciation of capital as a proxy for capital input. Using capital depreciation as a proxy for capital input may be reasonable as capital stocks and depreciation costs are positively correlated. A similar approach has been adopted by other researchers, see e.g. Mohnen et al. (2018).

4. Descriptive analysis

For the descriptive statistics presented in Table 2 we pool observations for manufacturing firms in the 2012 and 2017 survey. The surveys provide information on the employment distribution across functions. Clearly, the majority of workers in manufacturing firms are involved in fabrication. The average employment share of fabrication is about 65 percent (not shown). Yet, we use relative employment shares, see equation (1), to determine the functional specialization of firms. The highest index across all possible activities is used to determine the functional specialization of the firm.

Table 2 suggests 172 firms or 27.5 percent are specialized in R&D (172/623 * 100%). About one third have a relatively higher share of workers in fabrication, whereas the remaining 248 firms (39.7%) are specialized in marketing. The upstreamness and downstreamness of firms

[5] We are grateful to Michael Polder for sharing his Stata codes for collecting and harmonizing data from the structural business statistics.
[6] Gross output and intermediate input costs are net of trading goods.
[7] Variables are deflated using 2-digit industry deflators.

are calculated according to (2). Upstreamness values range from a minimum of 1.63 to a maximum of 3.56.[8]

Table 2 also reports two estimates of firm productivity. Labor productivity is real value added divided by employment. Total factor productivity also accounts for capital inputs and is estimated econometrically using the approach suggested by Wooldridge (2009), with a price mark-up correction from De Loecker and Warzynski (2012), see section 3. Labor productivity and total factor productivity are positively correlated.

The average mark-up using the approach suggested by De Loecker and Warzynski (2012) is 0.90. The average mark-up is below one, which suggests firms price below marginal costs. Other studies also find mark-ups below one, see e.g. a study by CBS (2015) for Dutch firms. De Loecker and Warzynski (2012) point out that by relying on revenue but not quantity data, mark-up levels are affected. Relative mark-ups are less likely to be affected; these are considered in the econometric identification below.

Table 2. Descriptive statistics for manufacturing firms included in the surveys.

Variable	Obs.	Mean	Std. dev.	Min.	Max.
Specialization of firm in:					
R&D	623	0.28	0.45	0	1
Fabrication	623	0.33	0.47	0	1
Marketing	623	0.40	0.49	0	1
Upstreamness, U_k	623	2.55	0.62	1.63	3.56
Downstreamness, D_k	623	2.55	0.26	1.76	3.33
				Max-Min	
Labor productivity (in logs)	623	11.24	0.65	9.02	
Total factor productivity (in logs)	612	11.61	1.01	7.24	
Price mark-up	611	0.90	0.53	6.43	

Notes: See equation (1) for measurement of firm's functional specialization, and equation (2) for calculation of firms' upstreamness and downstreamness. TFP is estimated using the Wooldridge (2009) approach specifying a Cobb-Douglas value added production function. Labor productivity is real value added divided by persons engaged. The price mark-up over marginal costs is estimated using the approach suggested by De Loecker and Warzynski (2012). Min and max are not disclosed for productivity and mark-ups for reasons of confidentiality.

Table 3 compares functional specialization to the input-output based measure of upstreamness (U_k). The comparison is made for the sample of 623 manufacturing firms. The upstreamness measure U_k is continuous. Yet, to allow comparison, we group firms into terciles in the columns of Table 3. One third of firms with the highest (lowest) upstreamness measure U_k are considered more upstream (more downstream) and shown in the first (third) column.

[8] The minimum value corresponds with a firm that only exports products of the industry 'Manufacture of furniture; other manufacturing' for which we calculated an upstreamness value of 1.63 (see Appendix Table 1). The maximum corresponds to a firm only exporting products related to the industry 'manufacture of basic metals'.

If the upstreamness measure U_k aligns closely with the measure of functional specialization, most observations will be ordered along the main diagonal. This is not the case. There appears no relation between the upstreamness value U_k and the specialization of firms in R&D, fabrication, and marketing.[9] This provides suggestive evidence that input-output based measures of upstreamness do not relate to what firms do, which is tested more formally in the next section.

Table 3. Comparison between functional specialization and upstreamness for manufacturing firms

		Firm position based on the upstreamness measure $\mathbf{U}_k$			
		More upstream	Middle	More downstream	**Sum**
Functional special-ization of firm in:	R&D	**9.5 *(59)***	8.3 *(52)*	9.6 *(60)*	27.6 *(171)*
	Fabrication	10.8 *(67)*	**11.6 *(72)***	10.6 *(66)*	32.6 *(205)*
	Marketing	13.2 *(82)*	13.5 *(84)*	**13.0 *(81)***	39.9 *(247)*
	Sum	33.4 *(208)*	33.4 *(208)*	33.2 *(207)*	**100 *(623)***

Notes: Percentage share of the number of firms in the total number of firms (number of firms in brackets). Manufacturing firms only. Firms are allocated to terciles in the columns using the upstreamness measure U_k. Shares may not sum due to rounding.

5. Results

This section examines the relation between functional specialization, measures of upstreamness, productivity, and mark-ups. We consider regression specifications that take the following form:

$$Y_{kst} = \alpha + \beta SI_{kst} + \gamma X_{kst} + \lambda_s + \lambda_t + \varepsilon_{kst}, \qquad (7)$$

where Y is either productivity or the price mark-up over costs. The variable for functional specialization, SI, is a dummy variable. We include dummies for firms specialized in R&D and marketing and exclude the dummy for fabrication, so the β-coefficient estimates are relative to this excluded function. X includes a set of other variables such as upstreamness and control variables. Upstreamness is also a dummy variable based on the grouping of firms into terciles (see previous section). The middle group is excluded in the regressions, so the coefficient estimates are obtained

[9] We also do not observe a relation between downstreamness (D_k) and functional specialization.

for firms that are more upstream or more downstream relative to the excluded group. The variables λ_s and λ_t are industry and time fixed-effects.

Section 5.1 presents the baseline results. Section 5.2 examines robustness of the main results to including other explanatory variables.

5.1 Functional specialization, upstreamness, productivity, and mark-ups

Table 4 presents regression results using equation (7) with firm TFP as the dependent variable. Regression results in column 1 include dummies for the functional specialization of firms. Columns 2 and 3 add dummies for upstreamness and downstreamness respectively. In columns 4 and 5 the measures are included simultaneously.

Results in column 1 suggest firms specialized in R&D and marketing activities are associated with a significantly higher TFP level compared to firms specialized in fabrication, which is the excluded dummy in the regressions. We observe a similar positive and significant relation if we consider real value added divided by employment (i.e. labor productivity).[10] The coefficient estimates suggest that on average, firms specialized in R&D have a 20 percent higher TFP level compared to firms that specialize in fabrication.[11] Firms that have relatively more workers involved in marketing are estimated to be 12 percent more productive on average.

Higher productivity for firms specialized in R&D and marketing is consistent with findings in related literature. Innovation in products and processes often positively relates to productivity performance (see e.g. Raymond et al. 2015). One would therefore expect that firms specializing in R&D have higher TFP levels. Similarly, marketing may generate higher returns, for instance from nurturing brand names.

The findings in columns (2) and (3) of Table 4 suggest that input-output based measures of upstreamness are not significantly related to firm TFP. That is, firms in the upper or lower tercile of the upstreamness measure (U_k) do not have a significantly higher productivity level (the middling tercile is the excluded dummy category). The downstreamness measure (D_k) also does not significantly relate to TFP. This is consistent with findings by Chor et al. (2014) who calculate input-output based upstreamness and downstreamness measures for Chinese manufacturing firms and find no significant relation to productivity.

In columns (4) and (5) we include both measures of firm specialization simultaneously. Functional specialization still relates significantly to productivity. Measures of upstreamness and downstreamness are not significantly related to TFP. Moreover, adding upstreamness and downstreamness measures hardly affects the coefficient estimates for the relation between firm

[10] Results not shown but available upon request.

[11] We calculate the percentage impact of the dummy variable on TFP using Kennedy (1981). Assuming errors are normally distributed, we calculate $(\exp(\beta\text{-}0.5\,variance(\beta))\ \text{-}1) \times 100\%$, where the variance is the square of the standard error for the estimate of β.

specialization and TFP. This suggests that input-output based upstreamness measures are largely orthogonal to functional specialization.

Table 4. Relation firm TFP and functional specialization

	(1)	(2)	(3)	(4)	(5)
Specialized in R&D	0.216***			0.219***	0.217***
	(0.072)			(0.073)	(0.073)
Specialized in Marketing	0.143**			0.146**	0.146**
	(0.066)			(0.067)	(0.066)
More upstream, U_k		-0.066		-0.054	
		(0.075)		(0.075)	
More downstream, U_k		0.090		0.106	
		(0.065)		(0.066)	
More upstream, D_k			-0.031		-0.043
			(0.066)		(0.067)
More downstream, D_k			9.85e-05		-0.004
			(0.076)		0.076)
Constant	11.65***	11.76***	11.73***	11.67***	11.65***
	(0.085)	(0.083)	(0.087)	(0.090)	(0.090)
Time fixed-effects	Yes	Yes	Yes	Yes	Yes
Industry fixed-effects	Yes	Yes	Yes	Yes	Yes
Observations	611	611	611	611	611
R^2	0.744	0.741	0.740	0.745	0.744

Notes: Dependent variable is firm TFP estimated from a value added production function using the Wooldridge approach and adjusted for mark-ups, see section 3. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Next, we examine the relation between functional specialization and mark-ups. Table 5 reports regressions with (the natural logarithm of) mark-ups as the dependent variable. These mark-ups are estimated following the approach suggested by De Loecker and Warzynski (2012), where a mark-up is obtained for a firm as the wedge between labor's expenditure share in revenue (directly observed in the data) and labor's output elasticity obtained by estimating the associated production function.

Scholars argue the creation of intangibles may generate (temporary) market power (De Loecker and Eeckhout, 2017). For example, R&D may result in the development of new knowledge. Marketing may help establish brand names. This suggests a positive relation between mark-ups and functional specialization.

On the other hand, our descriptive analysis suggested that there are no price mark-ups over marginal costs (the mark-ups are generally below one, see Table 2). The firms covered in the analysis are likely heavily exposed to international competition as the Netherlands is a very open

economy with most larger firms actively engaged in international trade.[12] This puts pressure not to charge prices above marginal costs. Indeed, the results in Table 5 suggest no significant relation between mark-ups and functional specialization. The absence of a significant relation is also found for alternative approaches to estimate the mark-up, including the price-cost margin.[13] If anything, our results suggest a negative relation between mark-ups and specialization, but this is at the border of common levels of statistical significance.[14]

Table 5. Relation between mark-ups and functional specialization

	(1)	(2)	(3)	(4)	(5)
Specialized in R&D	-0.0649*			-0.0631	-0.0678*
	(0.0391)			(0.0397)	(0.0393)
Specialized in Marketing	-0.0484			-0.0465	-0.0574*
	(0.0338)			(0.0344)	(0.0336)
More upstream, $\mathbf{U_k}$		0.0454		0.0417	
		(0.0383)		(0.0388)	
More downstream, $\mathbf{U_k}$		0.0178		0.0130	
		(0.0373)		(0.0376)	
More upstream, $\mathbf{D_k}$			-0.0188		-0.0181
			(0.0351)		(0.0350)
More downstream, $\mathbf{D_k}$			0.0945**		0.0992***
			(0.0368)		(0.0369)
Constant	-0.333***	-0.381***	-0.351***	-0.353***	-0.320***
	(0.0412)	(0.0407)	(0.0395)	(0.0470)	(0.0429)
Time fixed-effects	Yes	Yes	Yes	Yes	Yes
Industry fixed-effects	Yes	Yes	Yes	Yes	Yes
Observations	611	611	611	611	611
R^2	0.440	0.438	0.445	0.441	0.449

Notes: Dependent variable is the (natural logarithm of the) mark-up using the labor elasticities from the value added production function estimates in the Wooldridge approach and the labor share, see section 3. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The survey also asks firms about the nature of their business. One possible response is that the firm indicates it 'does not produce goods, but contracts-out the production completely and has developed the goods or owns the intellectual property rights of the produced goods.' These are the so-called Factory-Less Goods Producing (FLGP) firms (Bernard and Fort, 2015). Classic examples

[12] In 2017, 88 percent of large enterprises (250+ employees) in the Netherlands were trading internationally (Lammertsma and Bruls, 2019). Out of every euro earned by the Dutch manufacturing industry, about 70 euro cents is generated by exports (https://www.cbs.nl/en-gb/news/2017/16/growing-export-dependence-dutch-manufacturing-industry).

[13] Results not reported but available upon request.

[14] The results in table 6 suggest a significant positive relation between mark-ups and more downstream firms for the measure D_k. This significant relation is not observed for other measures of the price mark-up and thus might be spurious.

are Apple, Nike and Reebok, which have contracted out their fabrication activities. In the surveys, 32 out of 1,272 Dutch firms indicated being FLGP firms.[15]

Table 6 examines all firms, both manufacturing and non-manufacturing, in the survey. Column (1) includes a dummy if a firm is an FLGP. We find a positive relation with TFP, but the result is not significant at conventional levels of significance. This might be due to the limited number of observations for FLGP firms.[16]

The other columns in Table 6 examine the relation between specialization and TFP for the full sample. As before, firms that have a relatively higher share of workers involved in R&D are significantly more productive. The relation with TFP for firms specialized in marketing is not significant in column (4). Using the coefficient estimate in column (2), firms specialized in R&D have a 16 percent higher TFP on average.[17]

Table 6. Factory-less Goods Producing Firms and Productivity

	(1)	(2)	(3)	(4)	(5)
Factory-less goods producing firm	0.148				
	(0.114)				
Specialized in R&D		0.170***			0.210***
		(0.045)			(0.050)
Specialized in Fabrication			-0.145**		
			(0.045)		
Specialized in Marketing				0.011	0.092*
				(0.048)	(0.054)
Constant	11.74***	11.70***	11.79***	11.74***	11.65***
	(0.078)	(0.077)	(0.077)	(0.082)	(0.083)
Time fixed-effects	Yes	Yes	Yes	Yes	Yes
Industry fixed-effects	Yes	Yes	Yes	Yes	Yes
Observations	1,268	1,268	1,268	1,268	1,268
R^2	0.655	0.659	0.658	0.655	0.660

Notes: Dependent variable is firm TFP estimated from a value added production function using the Wooldridge approach, with mark-up subtracted. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 7 explores the relation between functional specialization and other measures of firm performance. The first column in Table 7 examines the relation between functional specialization and wages. These results suggest that specialization in R&D positively relates to wages. This finding is consistent with specialization requiring relatively more and better paid knowledge and

[15] Note that we consider the full sample of 1,272 observations, since FLGP firms are often not classified in manufacturing (Bernard et al. 2017). By definition, FLGP do not have factories and we therefore expect them to be specialized in R&D or marketing. Out of the 32 FLGP firms, 29 firms are identified as being specialized in either R&D or marketing using equation (1). This supports our approach.

[16] Results are also not significant if we consider labor productivity as the dependent variable.

[17] For the full sample, we also do not observe a significant relation between input-output based measures of upstreamness and firm TFP. Results not shown but available upon request.

innovation workers.

The second column considers the relation to the return on sales (RoS), measured as earnings before tax as a share in total turnover. Although we find a positive relation to functional specialization in R&D or marketing (as before, the excluded dummy is fabrication), these results are not significant. In column (3), we express earnings before tax as a share in value added (RoVA). Again we observe a positive (but insignificant) relation to functional specialization in R&D and marketing. Moreover, three year moving averages for return on sales or value added also suggests a positive (and insignificant) relation (not shown).

The column (4) in Table 7 examines the relation between intellectual property investment (IP inv) and functional specialization. Also here, we do not observe a significant relation, but the coefficients suggest a positive relation for firms specialized in R&D or marketing.

Table 7. Relation functional specialization and other measures of firm performance

	(1)	(2)	(3)	(4)
	Wages	RoS	RoVA	IP inv
Specialized in R&D	0.105***	0.051	3.230	0.015
	(0.035)	(0.033)	(3.032)	(0.012)
Specialized in Marketing	0.051*	0.016	2.082	0.012
	(0.031)	(0.021)	(1.933)	(0.013)
Constant	3.660***	0.053*	-0.119	0.041
	(0.038)	(0.028)	(0.419)	(0.027)
Time fixed-effects	Yes	Yes	Yes	Yes
Industry fixed-effects	Yes	Yes	Yes	Yes
Observations	627	628	628	628
R^2	0.210	0.055	0.027	0.010

Notes: Dependent variable is the average wage in logs (column 1); Return on Sales (column 2); Return on value added (column 3); and Intellectual Property investment as a share in value added (column 4). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5.2 Robustness analysis

Table 8 examines sensitivity of the results to controlling for other firm characteristics. A potential concern is that the baseline results on functional specialization are driven by confounding variables. There is a long list of variables that may relate to firm productivity such as investment in innovation or the firms' scope of activities (Syverson, 2011). As a result we cannot exclude the possibility of confounding variables, but we can examine whether the results are affected by control variables that are available in the dataset we constructed.

In Table 8, we include the size of the firm approximated by the number of employees, investment in software and intellectual property as a share in firm value added, the age of the firm,

and the trade share which is the log of (gross exports plus imports divided by gross output).[18]

Firm size and engagement in international trade correlate positively with firm productivity. This correlation is widely documented and consistent with Melitz (2003) where larger firms are more productive and more likely to trade. Investment in intellectual property relates positively to productivity as well. For software investment we observe a significant negative relation. Investment in software typically requires company reorganization (Brynjolffson and Hitt, 2000). Therefore, productivity effects from software investment are likely better captured in studies that exploit the panel dimension of the data.[19]

The regressions reported in Table 8 are demanding in terms of the number of variables included relative to the number of observations, because we include a set of control variables besides the year and industry fixed-effects. Our findings suggest that the relation between functional specialization and productivity is still observed. R&D and marketing positively relate to higher TFP, although at the border of common levels of statistical significance.

In comparison to the baseline findings in Table 4, the coefficients in column (1) of Table 8 suggest that firms specialized in R&D have a 9 percent higher TFP level compared to firms that specialize in fabrication. Firms that have relatively more workers involved in marketing are on average 8 percent more productive. As before, we do not observe a significant relation between firm productivity and input-output based upstreamness and downstreamness measures.[20]

Table 8. Relation TFP and functional specialization, including control variables

	(1)	(2)	(3)	(4)	(5)
Specialized in R&D	0.113**			0.118*	0.111*
	(0.056)			(0.056)	(0.056)
Specialized in Marketing	0.098*			0.105**	0.094*
	(0.051)			(0.052)	(0.051)
More upstream, $\mathbf{U_k}$		-0.009		-0.0001	
		(0.056)		(0.056)	
More downstream, $\mathbf{U_k}$		0.129**		0.139**	
		(0.054)		(0.055)	
More upstream, $\mathbf{D_k}$			0.065		0.057
			(0.056)		(0.056)
More downstream, $\mathbf{D_k}$			0.012		0.057
			(0.061)		(0.056)

[18] The structural business statistics do not provide information on the educational attainment of the firm's workforce. Hence, we cannot include human capital as a control variable. Note that we observe a positive relation between specialization in R&D and wages, see Table 7.

[19] We also ran regressions where we used the three-year average software and intellectual property investment as a share in value added. This helps address the issue that investments are lumpy, i.e. typically investments are concentrated in a particular year with no investments for several years thereafter (Levinsohn and Petrin, 2003). Results are similar if we use a three-year average.

[20] The results reported in Table 8 are qualitatively similar if we use labor productivity instead of TFP as the dependent variable. Using $\mathbf{U_k}$, more downstream firms are related to higher TFP levels, see columns (2) and (4) of Table 8. This result is not significant if we use labor productivity as the dependent variable. The significance of this relation is affected by the control variables included in the analysis.

Employment (thousands)	0.380***	0.384***	0.381***	0.379***	0.376***
	(0.077)	(0.079)	(0.077)	(0.078)	(0.077)
Investment in intellectual property	0.259***	0.269***	0.266***	0.263***	0.260***
	(0.099)	(0.103)	(0.099)	(0.102)	(0.098)
Software investment	-2.247***	-2.225***	-2.220***	-2.253***	-2.247***
	(0.772)	(0.770)	(0.771)	(0.769)	(0.771)
Age of firm (year/1000)	0.976	0.916	0.889	0.934	0.917
	(1.04)	(1.04)	(1.05)	(1.03)	(1.05)
Trade share	0.048***	0.049***	0.051***	0.046**	0.048***
	(0.034)	(0.032)	(0.03)	(0.033)	(0.034)
Constant	11.12***	11.17***	11.17***	11.11***	11.12***
	(0.079)	(0.076)	(0.081)	(0.082)	(0.084)
Time fixed-effects	Yes	Yes	Yes	Yes	Yes
Industry fixed-effects	Yes	Yes	Yes	Yes	Yes
Observations	611	611	611	611	611
R^2	0.764	0.764	0.762	0.766	0.764

Notes: Dependent variable is firm TFP estimated from a value added production function using the Wooldridge approach and adjusted for mark-ups. Age of the firm refers to year of inception. Trade share is the log of gross exports plus imports divided by gross output. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

6. Concluding remarks

This paper proposed to measure functional specialization of firms and considered it a determinant of productivity and mark-ups. Based on the firm's employment composition in business functions, we distinguished firms that are specialized in R&D, fabrication or marketing. Functional specialization aims to capture *what* firms do. It differs from upstreamness and downstreamness that measures *where* products are positioned in the production line. The difference was confirmed by the empirical analysis, which indicated that functional specialization is not related to upstreamness. Moreover, we found that firms specialized in R&D and marketing are more productive compared to firms specialized in fabrication. Upstreamness and downstreamness do not significantly relate to firm productivity.

Our findings inform an important debate. The decline of manufacturing employment and its implications for socio-economic outcomes such as wages and (un)employment are an important and often discussed issue in society. Recent work has documented that continuing firms may transition from manufacturing to services, and studied the implications for wages and employment conditional on the occupation of workers (Bernard et al. 2017). Ding et al. (2019) provide a model and empirical evidence whereby U.S. firms shift towards the provision of professional services in response to international competition of physical inputs. The findings presented in this paper suggest the shift away from physical production towards R&D and marketing relates positively to firm productivity.

Functional specialization can be measured for firms in countries that have administered the type of survey used in this paper. This includes several European countries (Nielsen, 2018), but also the National Organizations Survey for the U.S. (Sturgeon et al. 2013), and the Survey of Innovation

and Business Strategy for Canada. Alternatively, if information on the occupational composition of the firms' workforce is available, it can also be applied in situations where such surveys have not been held using the mapping between occupations and activities proposed in Timmer et al. (2019). This opens up further empirical research to study structural change within and across firms and their implications for aggregate productivity and other important socio-economic outcomes.

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Appendix A. Input-output based measures of upstreamness and downstreamness

In this appendix, we first outline a set of commonly used input-output based measures for up- and downstreamness. Second, we empirically implement the input-output based measures using world input-output tables.

Input-output based upstreamness and downstreamness measures: definition

To start the exposition, consider two accounting identities that form the basis for the input-output system.[21] First, gross output from each country ($i, j \in \{1,\ldots,N\}$) and good $s \in \{1,\ldots,S\}$ is used by final or intermediate purchasers, such that $y_i(s) = \sum_j f_{ij}(s) + \sum_j \sum_{s'} z_{ij}(s,s')$, where $y_i(s)$ is gross output of good s in country i, $f_{ij}(s)$ is the final output value of goods shipped from industry s in country i to country j, and $z_{ij}(s, s')$ are the values of intermediates from industry s in country i used by industry s' in country j.[22] Second, value added equals the value of gross output minus intermediate inputs: $v_i(s) = y_i(s) - \sum_j \sum_{s'} z_{ij}(s,s')$.

Both accounting equations can be stacked to create a global input-output system. That is, consider a gross output vector $\mathbf{y}$ with block elements $\mathbf{y}_i$ of dimension S x 1. Intermediate input flows are in a matrix $\mathbf{Z}$ with block elements $\mathbf{Z}_{ij}$ of dimension S x S. Final goods flows are in a matrix $\mathbf{F}$ with dimension NS x N that has block elements $\mathbf{f}_{ij}$ of dimension S x 1. And value added is in a vector $\mathbf{v}$ with S x 1 dimensional block elements $\mathbf{v}_i$. This can be used to define the global input-output matrix $\mathbf{A} = \mathbf{Z}\hat{\boldsymbol{y}}^{-1}$, with $\mathbf{A}_{ij} = \mathbf{Z}_{ij}\hat{\boldsymbol{y}}_j^{-1}$.[23] Rewriting the accounting identities in a global input-output system:

$$\mathbf{y} = \mathbf{A}\mathbf{y} + \mathbf{F}\iota, \tag{A1}$$

$$\mathbf{v}' = \mathbf{y}' - \iota'\mathbf{A}\hat{\boldsymbol{y}} = \mathbf{y}' - \iota'\hat{\boldsymbol{y}}\mathbf{B}, \tag{A2}$$

where ι is a summation vector of appropriate dimension, and $\mathbf{B} = \hat{\boldsymbol{y}}^{-1}\mathbf{A}\hat{\boldsymbol{y}}$ measures the share of good s used by a downstream industry to produce s'. Equations A1 and A2 can be re-written such that:

$$\mathbf{y} = [\mathbf{I} - \mathbf{A}]^{-1}\mathbf{f} = (\mathbf{I} + \mathbf{A} + \mathbf{A}^2 + \mathbf{A}^3 + \ldots)\mathbf{f}, \tag{A3}$$

$$\mathbf{y}' = \mathbf{v}'[\mathbf{I} - \mathbf{B}]^{-1} = \mathbf{v}'(\mathbf{I} + \mathbf{B} + \mathbf{B}^2 + \mathbf{B}^3 + \ldots). \tag{A4}$$

Where $\mathbf{f} = \mathbf{F}\iota$. Note that $[\mathbf{I} - \mathbf{A}]^{-1}$ and $[\mathbf{I} - \mathbf{B}]^{-1}$, the Leontief inverse and the Ghosh inverse (Miller and Blair, 2009), are the geometric expansions that trace the stages in a global value chain.

[21] We closely follow Johnson (2018) in the exposition of upstreamness and downstreamness measures. Note that these measures were initially developed by Dietzenbacher et al. (2005) to characterize 'distance' between industries, which they termed the average propagation length.
[22] In input-output analysis, industries are typically equated with products.
[23] A hat symbol '^' denotes a diagonal matrix with the vector along the diagonal.

Equation A3 shows that output is equal to the final good plus the value of intermediate inputs used to produce it, where **Af** are intermediate inputs directly used, $\mathbf{A}^2\mathbf{f}$ the intermediate inputs used to produce the intermediate inputs and so on. Similarly, in equation A4, output is equal to direct value added from the sector from which the good originates plus value added from other sectors from which inputs where sourced further up the global value chain. So **v**'**B** is one step back in the chain, $\mathbf{v}'\mathbf{B}^2$ is two steps back, and so on.

In this setup, a good that is used for final consumption or used as an input to produce a final good is more downstream. Likewise, a good is more upstream if it is used to produce intermediate inputs (that are used to produce intermediate inputs etcetera). Antràs and Chor (2013) count the number of steps away from final consumption and weight each stage by the output value. This results in the following upstreamness measure:

$$\mathbf{U} = 1\hat{\boldsymbol{y}}\mathbf{f} + 2\hat{\boldsymbol{y}}^{-1}\mathbf{A}\mathbf{f} + 3\hat{\boldsymbol{y}}^{-1}\mathbf{A}^2\mathbf{f} + \ldots = \hat{\boldsymbol{y}}^{-1}[\mathbf{I}-\mathbf{A}]^{-2}\mathbf{f}. \tag{A5}$$

It measures the average number of stages of production a good passes through before reaching the final consumer. Hence, this upstreamness measure is larger if a good is more upstream. For example, coltan is typically not used as a final product, but serves as an input for tantalum capacitors that are used in many electronic devices. By contrast, apparel is often sold to final consumers. Coltan would thus receive a higher upstreamness value than apparel.[24]

Fally (2012) developed an alternative measure of the position and length of global value chains. This measure counts the production stages for the production of a particular product backward:

$$\mathbf{D} = 1\mathbf{v}'\hat{\boldsymbol{y}}^{-1} + 2\mathbf{v}'\mathbf{B}\hat{\boldsymbol{y}}^{-1} + 3\mathbf{v}'\mathbf{B}^2\hat{\boldsymbol{y}}^{-1} + \ldots = \mathbf{v}'[\mathbf{I}-\mathbf{B}]^{-2}\hat{\boldsymbol{y}}^{-1} = \iota'[\mathbf{I}-\mathbf{A}]^{-1}. \tag{A6}$$

Thus, the length of an industry's value chain is equal to the column sum of the Leontief Inverse.[25] Fally (2012) shows **D** can be expressed as a weighted average of the number of stages required to produce good *s* in country *i*, weighted by how much each stage of production contributes to the final value of that good.

Using input-output tables, the upstreamness (U_s) and downstreamness (D_s) of a product can be measured. Typically, researchers have estimated these using national input-output tables.[26] This stands at odds with the 'global' in global value chains. That is, national input-output tables do not adequately reflect production networks fragmented across national borders since exports are not always the final stage. We therefore implement - upstreamness and downstreamness measures on

[24] In the input-output literature **U** is known to measure the strength of total forward linkages in a production process. To see this, note that $\mathbf{U} = \hat{\boldsymbol{y}}^{-1}[\mathbf{I}-\mathbf{A}]^{-2}\mathbf{f} = \hat{\boldsymbol{y}}^{-1}[\mathbf{I}-\mathbf{A}]^{-1}\hat{\boldsymbol{y}}\iota = [\mathbf{I}-\mathbf{B}]^{-1}\iota$. So **U** is the row sum of the Ghosh inverse matrix (Miller and Blair, 2009).

[25] The third equality follows from $\iota'\hat{\boldsymbol{y}} = \mathbf{v}'[\mathbf{I}-\mathbf{B}]^{-1}$ and $\hat{\boldsymbol{y}}[\mathbf{I}-\mathbf{B}]^{-1}\hat{\boldsymbol{y}}^{-1} = [\mathbf{I}-\mathbf{A}]^{-1}$. In the input-output literature this measure has commonly been used to measure total backward linkages.

[26] For example, Fally (2012) and Antràs et al. (2012) use an input-output table for the US. Chor et al. (2014) use an input-output table for China.

the basis of world input-output tables (as e.g. in Fally and Hillberry, 2017 and Antràs and Chor, 2018).

Measuring upstream and downstreamness using World Input-Output Tables

We use the 2016 release of World Input-Output Tables (WIOTs), which provide tables for the period from 2000 to 2014 (Timmer et al. 2016). In essence, WIOTs are constructed by merging harmonized national input-output tables with international trade statistics. These tables provide information on input purchases, the direct parent (downstream) industry and country, as well as direct source country and industry. Total production and input purchases is disaggregated for 56 sectors of the economy.

The $\mathbf{U}_{is}$ and $\mathbf{D}_{is}$ statistics are calculated at the level of country-industry (*i*; *s*) pairs. We focus on the length and position of industries for products that are finalized in the Netherlands. But we consider sensitivity of the results to alternative approaches such as a cross-country average measure of $\mathbf{U}_s$ and $\mathbf{D}_s$.

Appendix Table 1 shows upstreamness and downstreamness calculated according to equations (A5) and (A6) using the WIOT for 2014. Industries are ranked by their upstreamness in value chains from most upstream to least upstream.[27]

Typically, only values for manufacturing industries are reported (see e.g. Antràs et al. 2012; Fally, 2012). Instead, Appendix Table 1 shows upstreamness for all 54 sectors of the economy, including services. The WIOTs distinguish two services sectors that are of interest here, namely 'Scientific research and development' (R&D sector) and 'Advertising and market research (Advertising sector). On the face of it, these two sectors might be considered to be upstream and downstream in global value chains, as e.g. in Rungi and Del Prete (2018).[28] Thus one might expect that the R&D sector will show up as being upstream based on estimates of **U** and **D**, whereas the Advertising sector will be downstream based on **U** and **D**.

An interesting finding that emerges from Appendix Table 1 relates to the upstreamness, $\mathbf{U}_{is}$, of the R&D and Advertising sectors. We find that the R&D sector is one of the most downstream industries (the row is in italics in Appendix Table 1). It is ranked 47 out of 54. One reason why these findings do not conform with standard expectations is due to the definition of R&D in the System of National Accounts 2008 (SNA 2008, see UN et al. 2009), see section 2 for further

[27] Two industries are not reported, for which no data for the Netherlands is provided in the WIOT, so in total 54 sectors are distinguished. Dutch industries which are not separately distinguished in the WIOTs are: Activities of households as employers (ISIC revision 4 code T), and Activities of extraterritorial organizations and bodies (ISIC revision 4 code U). Industries T and U are typically small industries and for the Netherlands included in 'other service activities' (ISIC revision 4 code R-S).

[28] Antràs and Chor (2018) use the 2013 release of the WIOTs that do not distinguish R&D and advertising industries. Furthermore, this release is in SNA 1993 where R&D is commonly an intermediate input, whereas the 2016 WIOT is in SNA 2008, where R&D is commonly an investment.

discussion. The upstreamness measure $\mathbf{U}_{is}$ for the advertising sector suggests it is one of the most upstream industries (also in italics in Appendix Table 1). It ranks 6 out of 54.

These findings are also observed for the downstreamness measure, $\mathbf{D}_{is}$. The R&D sector is an upstream activity in a global value chain, so we would expect it would be ranked among the least downstream industries as it stimulates little upstream intermediate demand. In fact, it ranks 39 out of 54. For example, it is ranked more downstream than manufacturers of furniture products (ranked 42). Advertising is a very downstream activity, but it ranks only 24 out of 54, appearing less downstream than basic metal products (ranked 7) and chemical products (ranked 3).

Does this finding hold more generally? First, we calculated $\mathbf{U}_{is}$ for the Netherlands in other years using the WIOTs that are available annually from 2000 to 2014. The R&D industry in the Netherlands has a similar value for $\mathbf{U}_{is}$ in the years from 2009 to 2014, ranking between 40 and 49 out of 54.[29] Advertising consistently ranks among the most upstream industries (ranking between 2 and 6 over the period from 2000 to 2014).

Second, we calculated $\mathbf{U}_{is}$ for other country-industry pairs and calculated an unweighted average for each industry in the other 42 countries distinguished in the WIOTs. The R&D sector ranks between 38 and 49 out of 56 over the years from 2000 to 2014. The Advertising sector ranks between 12 and 19 out of 56 during these years. It suggests that the observations for the upstreamness and downstreamness of the R&D and advertising sectors hold more broadly.[30]

Appendix Table 1. Upstreamness and downstreamness, 2014

Code	Good/Industry *s*	U_{is}	rank	D_{is}	rank
B	Mining and quarrying	3.71	1	1.41	53
C24	Manufacture of basic metals	3.56	2	2.78	7
C20	Manufacture of chemicals and chemical products	3.55	3	2.99	3
C33	Repair and installation of machinery and equipment	3.50	4	2.40	21
E37-E39	Sewerage; waste collection and disposal activities	3.48	5	2.44	19
M73	*Advertising and market research*	*3.46*	*6*	*2.19*	*24*
M69_M70	Legal and accounting, head offices and consultancy activities	3.43	7	2.01	35
C17	Manufacture of paper and paper products	3.18	8	2.77	8
M74_M75	Other professional, scientific and technical activities	3.17	9	2.07	32
C18	Printing and reproduction of recorded media	3.15	10	2.44	20
K66	Activities auxiliary to financial services	3.14	11	1.62	50
C25	Manufacture of fabricated metal products	3.13	12	2.54	15
C23	Manufacture of other non-metallic mineral products	3.13	13	2.53	16
C19	Manufacture of coke and refined petroleum products	3.12	14	3.33	1

[29] In the years before 2009, we observe a much higher value for $\mathbf{U}_{is}$. It ranks between 5 and 8 out of 54 during the period from 2000 to 2008. This sudden change might be due to revisions in the data and appears specific to the Netherlands as they do not hold more generally. Due to the implementation of the new System of National Accounts, R&D is now considered an investment rather than intermediate input (UN et al., 2009).

[30] One may argue that industry classifications are too aggregated and create biases in computing $\mathbf{U}_{is}$ and $\mathbf{D}_{is}$ compared to what would be obtained with more disaggregated data. Fally (2012) examines the aggregation properties of indexes **U** and **D** and shows that aggregating industries does not substantially affect the average of **U** and **D** across industries.

C16	Manufacture of wood and of products of wood	3.04	15	2.47	18
H53	Postal and courier activities	3.04	16	1.97	38
H52	Warehousing and support activities for transportation	3.04	17	2.00	36
C22	Manufacture of rubber and plastic products	3.02	18	2.58	14
K64	Financial service activities	3.01	19	1.57	52
J59_J60	Film production, publishing and broadcasting	2.98	20	2.04	34
N	Administrative and support service activities	2.95	21	1.73	47
D35	Electricity, gas, steam and air conditioning supply	2.89	22	2.32	23
H49	Land transport and transport via pipelines	2.83	23	2.17	27
J58	Publishing activities	2.80	24	2.09	31
H51	Air transport	2.74	25	2.85	4
C27	Manufacture of electrical equipment	2.72	26	2.35	22
H50	Water transport	2.71	27	2.62	10
G46	Wholesale trade, except of vehicles and motorcycles	2.62	28	1.88	43
J62_J63	Computer programming, consultancy and related activities	2.60	29	1.85	45
A01	Crop and animal production and related service activities	2.46	30	2.48	17
C28	Manufacture of machinery and equipment n.e.c.	2.39	31	2.59	12
G45	Trade and repair of motor vehicles and motorcycles	2.37	32	2.14	28
M71	Architectural and engineering activities;	2.36	33	1.93	40
F	Construction	2.33	34	2.59	13
J61	Telecommunications	2.29	35	2.17	26
C26	Manufacture of computer, electronic and optical products	2.29	36	3.09	2
C10-C12	Manufacture of food products, beverages and tobacco products	2.22	37	2.85	5
E36	Water collection, treatment and supply	2.11	38	1.76	46
A03	Fishing and aquaculture	2.07	39	2.06	33
C30	Manufacture of other transport equipment	1.96	40	2.82	6
C21	Manufacture of pharmaceutical products	1.92	41	2.10	30
C29	Manufacture of motor vehicles	1.90	42	2.76	9
K65	Insurance, and pension funding	1.86	43	1.93	41
A02	Forestry and logging	1.86	44	2.18	25
C13-C15	Manufacture of textiles, wearing apparel and leather products	1.79	45	2.59	11
L68	Real estate activities	1.74	46	1.98	37
M72	*Scientific research and development*	*1.69*	*47*	*1.94*	*39*
R_S	Other service activities	1.65	48	1.88	44
C31_C32	Manufacture of furniture; other manufacturing	1.63	49	1.91	42
I	Accommodation and food service activities	1.54	50	2.14	29
O84	Public administration and defense; social security	1.47	51	1.73	48
P85	Education	1.26	52	1.37	54
G47	Retail trade, except of motor vehicles and motorcycles	1.21	53	1.71	49
Q	Human health and social work activities	1.09	54	1.58	51

Notes: Upstreamness, $\mathbf{U}_{is}$, according to equation (A5). Downstreamness, $\mathbf{D}_{is}$, according to equation (A6). Industry codes are the ISIC revision 4. Country-industry pairs for the Netherlands are reported. *Source*: Authors calculation based on World Input-Output Tables, 2016 release.