Firms, lateral functions and the knowledge economy*

Eric Mengus Tomasz Michalski

November 9, 2021

VERY PRELIMINARY – PLEASE DO NOT CIRCULATE

Abstract

We document that more than one third of employment in French manufacturing firms is within *lateral* functions — tasks that are neither in production nor management. We show that such functions are heterogeneous in importance and composition, with less routine lateral functions being relatively more prevalent in larger firms, and that their higher shares in employment are correlated with higher productivity, intangible capital, measures of product complexity and innovation, and higher markups. We provide thus evidence suggesting that these functions generate information using specialized labor – a critical resource within knowledge-intensive organizations – relevant for the production of complex goods. We rationalize these findings by a simple model where firms decide on the complexity of goods that they produce and on the production of information to reduce the uncertainty they face associated with complexity.

JEL Classification:

Keywords: firm organization, functions, productivity, information production

*Mengus: HEC Paris and CEPR. Email: mengus@hec.fr. Michalski: HEC Paris and GREGHEC. Email: michalski@hec.fr. We thank Charles Angelucci, Giacomo Calzolari, Gregory Corcos, Johan Hombert, Raphaël Lévy, Denisa Mindruta, Ferdinando Monte, Tomasz Obloj, Luc Paugam, Fabiano Schivardi, Carlos Serrano, Claudia Steinwender, Yanos Zylberberg and the participants at seminars at Université de Lille for helpful comments. All remaining errors are ours.

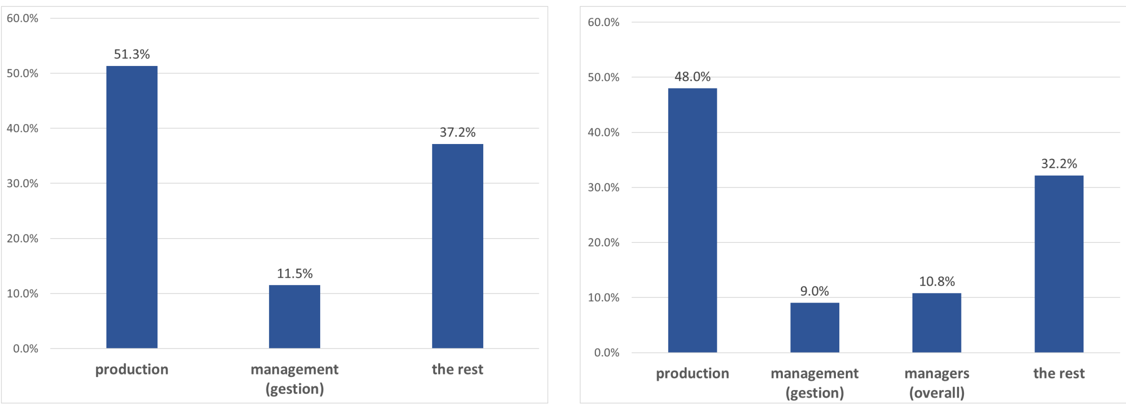
1 Introduction

[...] Just what, then, are the functions of the executives responsible for the fortunes of the enterprise? They coordinate, appraise and plan. They may, at the same time, do the actual buying, selling, advertising, accounting, manufacturing, engineering, or research, but in the modern enterprise the execution or carrying out of these functions is usually left to such employees as salesmen, buyers, production supervisors and foremen, technicians, and designers. [...]

Chandler (1962), p.8.

Using a classification of jobs detailing functions, we identify that 37.2% of hours worked *within* manufacturing firms in France[1] (see the left-hand panel of Figure 1) are performing functions other than production or management. This constitutes a large fraction of total hours worked and hence the non-production and non-management functions must be important to successful firm operations.

Figure 1: Shares of workers in different functions.



The left-hand panel shows the share of hours worked in production, management ("gestion" or administration in French) functions and the rest while the right-hand panel gives these shares and after isolating managers. Sample: firms in manufacturing with employment >50 people in 2015.

To date, however, they remain largely absent from the theories of the firm, even if they are mentioned in heuristic discussions or are invoked as an explanation of empirical patterns (Atalay et al., 2014, —auxiliary functions in their language). As envisioned by Chandler (1962) in the quote above, these non-production and non-management functions escape the hierarchical

[1] Sample of manufacturing firms with >50 employees in 2015. The categorization of functions is done by the INSEE, the French statistical agency. As the right-hand panel of Figure 1 shows, excluding jobs within lateral functions that have managerial tasks reduces this fraction only to 32.2% of hours.

or vertical view of the firm (advanced by e.g. Radner, 1993; Garicano, 2000; Caliendo et al., 2015):[2] we shall call them *lateral* functions.

In this paper, we provide some theory and evidence to understand the role of such lateral functions within organizations. We argue that these lateral functions — and in particular the *non-routine ones* such as B-2-B (purchases or sales), Intellectual services (legal services, IT, marketing among others), and R&D — allow firms to generate information to resolve uncertainty related to the different stages of the production processes from sourcing inputs to final good sales and branding. The resulting capabilities become the source of the firm's comparative advantage to supply complex goods – which we understand as goods that are more uncertain to produce.[3] More precisely, a firm needs to consider more payoff-relevant states in the production of the complex good, a cardinality-based notion of complexity (see Rubinstein, 1986).

To start with, we build a simple model of firms' technology to produce complex goods using information. In our model, firms observe their productivity draws and select whether to produce either a simple but low-value good or a high-value but complex good using a set of inputs that they source using labor. The production of the complex good requires to select one specific input, in contrast with the simple good which can be produced with any.[4] However, firms are ex ante not informed about which input to select but they can reduce this uncertainty by employing labor dedicated to information generation: more precisely, as in the rational inattention literature, firms face an information constraint that can be relieved by increasing specialized information-generating labor. From this model, we derive empirical implications. More productive firms, relative to less productive ones 1) produce more complex goods, 2) have a higher share of labor specialized in information generation, 3) sell with higher markups and, to the extent that management is complement to information production, 4) have a higher share of management labor. Our model, through various interpretations, indicates that B-2-B, Intellectual services and R&D functions should be especially important in information generation.

Next, we generate new facts about functions in organizations using a sample of all French manufacturing firms above 50 employees in 2015 and interpret them through the lens of our

[2] Moreover, if, given the skill content of some of those functions we would assign them a place within a hierarchy, hierarchies of many firms would appear to be bell-shaped instead of pyramid-like as required by management theories. This is important, because our approach points how empirical study of organizations such as Caliendo et al. (2015) could be refined.

[3] See for example Nedopil et al. (2011) for numerous case studies on the issue.

[4] Our framework can be restated e.g. as firms producing complex goods searching for the "ideal" consumer variety or quality.

model. We focus on manufacturing because it offers a rather homogenous sector where the output is strongly linked to physical goods – hence it is easier to distinguish the "production" types of occupations from those performing lateral functions. To examine functions, we use the detailed classification ("PCS"), produced by the French statistical office (INSEE), that allocates 486 different occupations into 15 distinct functions.

First, we show that lateral functions correspond to an important share of employment – as mentioned, 37.2% of hours worked. Furthermore, these functions are present in almost all firms. In particular, this holds particularly true for business relations (B-2-B), R&D, maintenance, transport and logistics and, to some extent, intellectual services (marketing, consulting, IT, legal services etc.).

Second, the subset of lateral functions identified by our model as important for information generation coincides with non-routine tasks according to the routineness measure from Autor et al. (2003): these functions are B-2-B; R&D; Intellectual services. We show that larger and/or more productive firms are relatively richer in these non-routine lateral functions – this share of employment in non-routine lateral function increases from an average of 12% for the smallest firms of our sample to more than 30% for the largest ones. In contrast, the shares of hours in routine lateral functions such as logistics or other functions' (such as retail sales) are uncorrelated with productivity or size. Our findings are robust controlling for the share of the management (as a function) and the share of managers overall and, also, on top of the (projected) skill composition of jobs. Functional composition of a firm workforce in terms of lateral functions along management is an important correlate of TFP.

Third, we provide evidence that suggesting that firms with relatively more non-routine lateral functions 1) generate more information, 2) produce more complex goods and 3) have higher markups. In particular, we show that higher shares of non-routine lateral workers are associated with measures of information production such as more intangible capital (per hour worked or as a share of total capital) or sales volatility but also with higher levels of self-reported product, process, marketing and logistics innovation and intellectual property protection. The share of non-routine lateral functions is also positively correlated with measures of product scope, complexity, and markups.

Fourth, we scrutinize the importance of particular subfunctions for TFP. We obtain that some subfunctions are of particular importance but our findings also suggest that R&D is only one component in the generation of relevant information for the firm. For example, other non-routine functions are correlated with intangible capital or product innovation measures, or e.g. marketing innovation. Moreover, the share of workforce related to input purchases or marketing appear to be strongly correlated with productivity. The former is strongly correlated with a higher share of materials in production, an indication that a successful outsourcing strategy may be key for the most productive manufacturing firms, a finding consistent with Bernard and Fort (2015).

Overall, we argue that non-routine lateral functions are essential for firms producing complex goods. They are not only important because of task specialization, but particularly vital in generating information about the economic environment which increases complex good production efficiency. Information produced by non-routine lateral workers that may possess specific human capital is retained within an organization, creating a critical resource asset (see Rajan and Zingales (1998)) for knowledge-based firms. Some of this inalienable information can be assessed and valued by outsiders, using accounting methods – such as intangible capital, while a large part may be unquantifiable and inherently connected with each firms' specific operations, creating its organizational capital. While effective management may be important in administering, exercising authority, coordinating and monitoring workers, managers are not necessarily the ones responsible in organizations to resolve uncertainty about markets, customers, inputs or technological processes. Thus, non-routine lateral workers play a key function alongside production workers and managers in successful firms that are producing complex and knowledge-based goods.

We view our contribution as complementary to the crucial themes of organization economics such as firm hierarchies or centralization-decentralization tradeoffs, and expanding the questions in this strand of research. While hierarchies exist in lateral functions, they may be flatter, especially as most non-routine lateral functions comprise of professionals (witnessed by low degree of routineness) that may work in teams.[5] Importantly, however, not all knowledge is generated within hierarchies. Information acquisition resolving uncertainty may be entrusted to specialized lateral functions' employees. At the same time, the need to generate information to produce complex goods may increase the need for coordination (Becker and Murphy, 1992), and be complementary with more intensive management, while successful experimentation by non-routine lateral workers may require autonomy that in turn invites decentralization and adaptation (Dessein and Santos, 2006).

[5]The increase over time in the shares of lateral functions in firms may be another reason for the observed flattening of hierarchies documented in Rajan and Wulf (2006).

Related literature. The paper is connected to different strands of the literature.

First, the role of lateral functions to produce information that is useful for the firms is connected to the resource-view of the firm (see Wernerfelt, 1984; Lockett et al., 2009, for a review), the dynamic capabilities theory of the firm (Teece, 1982; Teece et al., 1997) or the knowledge-based theory of the firm (Kogut and Zander, 1992).[6] Within this literature, we are close to Rajan and Zingales (1998) formulate a theory of the firm centered around access to a critical resource (which may be a machine, and idea etc.). Agents employed within a firm specialize their human capital to work with the resource. In our model, agents specialize in producing information about a particular function and jointly create the critical resource of the firm: information. Because of the problem of appropriability in information sharing, the ability to keep valuable acquired information within the organization is a source of its comparative advantage and a developed capability (Cohen and Levinthal, 1990). In particular, as in Rajan and Zingales (1998), we do not explain the presence of lateral functions through the lens of the property-rights theory (Grossman and Hart, 1986; Hart and Moore, 1990), given that we are not concerned by the allocation of assets but of workers, on which the firm cannot have residual rights. In addition, the view that producing and sharing information is key for the firms' borders is also forwarded by Atalay et al. (2014). We contribute to this literature by providing evidence on the type of intangibles that firms may produce, using the way firms specialize their workers.

Second, our focus is different from the firm-specific human capital literature such as Becker (1962) or Lazear (2009). Development of specific skills while employed may be needed to generate knowledge for firms to be more productive in complex goods. We abstain from studying skill acquisition by employees on the job and the potential frictions this may entail. The uses of general human capital may be firm specific, and firm-specific human capital in the sense of Becker that is generated during employment may not be easily transferable to other firms. In contrast, we concentrate on information production in the firm that allows the firm to create its competitive advantage as long as this information remains within the firm. In particular, workers with the same type of general human capital could be used by different firms to generate disparate firm-specific *information* required by the firm to produce complex goods. But this information is potentially transferable to other firms if the employee leaves. For example, AI modelers could be used by distinct firms to uncover needed information in different areas:

[6] See also Sutton (2012) for a theory of industry competition with firms differing in capabilities – either in terms of product quality or productivity. He considers "capability building" by firms through sunk costs that can take multiple forms: R&D or advertising expenditures, reputation building via bearing opportunity costs, etc.

exchange rate market fluctuations, programming robot arm movement, or optimizing supply chains. From this perspective, our paper is closer to Tambe et al. (2020) -who document the role of IT labor in accumulating digital capital –which is in turn a key determinant in future firm productivity– or, more recently, the role of sales managers when it comes to exporting as investigated by Patault and Lenoir (2021). We add to this paper a more systematic analysis of lateral functions and show the relative importance of all of these functions engaging into information generation and its role for the production of complex and higher-markups goods.

Third, our paper is connected with the literature on international trade and intra-firm trade with prominent examples as Helpman (1984) or Antràs (2003). This literature is particularly interested in the separation between headquarter services ("general purpose inputs") vs. production, and fragmentation of production processes, also enabled by ICT (Fort, 2016). We aim to understand better such "headquarter" services themselves, as certain functions performed within firms – such as management – received particular scrutiny in contemporary literature but the nature of the general purpose inputs produced within firms has so far received much less attention.[7]

Fourth, our interpretation that at least some lateral functions are about producing information to reduce uncertainty is related to the large literature about firm decision-making under different forms of uncertainty (e.g. Jovanovic, 1982; Zeira, 1987; Mitchell, 2000), mainly focused on learning and firm dynamics (see also Berman et al. (2019) on demand uncertainty in international trade). The idea that knowledge (that we take for an equivalent of information production) is about reducing uncertainty and that it has consequences on the (hierarchical) organization of the firm dates back to at least Radner (1993) with important contributions from Garicano (2000) and Caliendo et al. (2015) among others.[8] In contrast to this literature (discussed e.g. by Garicano and Van Zandt, 2013), we study information production (or knowledge production) not within a firm hierarchy involving different layers of management (that constitute knowledge hierarchies, solve team production or information processing problems) but through the lateral functions workers acquiring new information. We also show that these functions are able to produce multiple and potentially complementary "capabilities". Our approach that information production is costly and has to be traded off with potential gains has also received specific attention by Dessein et al. (2016).

[7]Some attempts to study these phenomena were made by Bernard and Fort (2015) focusing especially on input outsourcing and imports and by Defever (2006) in the context of multinationals.

[8]See also Garicano and Wu (2012) for an overview and a connection to the strategy literature.

From this perspective, our paper is also connected to the impact on management on firm organization. Note that we consider the impact of management through the use of labor. This differs from the approach by Bloom et al. (2014), Bloom et al. (2016) or Bender et al. (2018) who consider the impact of management practices on firms' productivity. Of course, the impact of good management practices may help to make the firm more productive and engage more into information-productive lateral functions by facilitating task coordination and information sharing.

Finally, our approach on costly information production is connected to the literature on costly information acquisition following Townsend (1979). In particular, our idea that complex goods are information sensitive parallels the idea that assets may also be information sensitive, thus affecting their design as argued by Dang et al. (2012). In addition, the use Shannon's entropy is connected with the literature on rational inattention as initiated by Sims (2003) (see Mackowiak et al., 2020, for an overview).

The paper is organized as follows. In Section 2 we lay out a simple model of firm employment structure that generates implications for data patterns. We also define good complexity that we shall consider. In part 3 we describe our data. Section 4 establishes the most salient facts about functions within firms and their relation with firm productivity and information production. Section 5 provides further discussion while 6 concludes.

2 A simple model

We start by building a model of heterogenous firms that decide on the complexity of the goods that they produce. In this decision, the trade-off is that more complex goods can be sold at higher prices but they also require more information. The main assumption of our approach is that experimenting, conception, acquiring and analyzing information to generate knowledge and resolve uncertainty requires specific labor corresponding to the lateral functions that we observe in the data.

2.1 The environment.

Consider a continuum of firms indexed by $i \in [0, 1]$. Each firm can produce a good that can either be simple or complex and we denote by $q \in \{simple, complex\}$ the corresponding complexity.

Production. To produce a good of complexity q, a firm has access to a set of potential inputs Ω and uses a production of the form $y_i = A_i \sum_{k\in\Omega} a_{k,q} x_k$, where A_i is firm's productivity and the $a_{k,q}$ are productivity parameters specific to a good of complexity q. All inputs are substitutes to produce a good, but they do not have the same productivity, so that substitutability is imperfect. We denote by $N = Card(\Omega)$ the number of potential inputs.

Importantly, we assume that the production of the complex good is more sensitive to the choice of inputs than the production of the simple good. As we will make this clearer afterward, this will mean that the production of the complex good is more uncertain that the one of the simple good. Formally, to make things simple, we assume an extreme form of uncertainty for the production of the complex good: there exists $k' \in \Omega$ such that $a_{k',complex} = 1$ and $a_{k,complex} = 0$ for any $k \neq k'$. In contrast, we assume that the production of the simple good does not face any uncertainty: $a_{k,simple} = 1$ for any $k \in \Omega$.[9]

Inputs are then produced internally only using labor. The production function of any input $k \in \Omega$ is $x_k = l_k^{\alpha}$, where l_k is the amount of labor used and $\alpha \in (0, 1)$ is a parameter. Finally, we denote by w the wage rate paid on labor.

Information. Firms cannot freely observe the productivities $a_{k,q}$. Instead, this requires to produce information. Formally, firms can decide on their information set $\mathcal{I}_i$ but this requires to hire labor within the firm.

Before acquiring any information on $\{a_{k,q}\}_{k\in\Omega,q\in Q}$, the information set of a firm that we denote by $\mathcal{I}_0$ is such that firms have uninformative priors on which input is the one that yields $a_{k,q} = 1$ and, for each $k \in \Omega$, they assign a priori probability $1/N$ that k is such that $a_{k,q} = 1$.

In the tradition opened by Sims (2003), we borrow from information theory the relative entropy $H(\mathcal{I}|\mathcal{I}_0)$ –also known as the Kullback-Leibler divergence– to measure the informational content of $\mathcal{I}$ relative to $\mathcal{I}_0$. We do not assume any constraints on the signals that firms can receive to update their information set.

Our key assumption is that the amount of additional information selected by the firm has to be produced by the firm using labor l_I. For simplicity, we assume that the production of information is linear in the labor used for this specific task. Overall, this leads to the constraint

[9] We use thus a cardinality-based notion of complexity similar to that in the literature on complexity in games as in e.g. Rubinstein (1986). Here, there are more payoff-relevant states (inputs) to consider in the production of the complex good.

on the amount of information used by the firm:

$$H(\mathcal{I}|\mathcal{I}_0) \leq l_I \tag{1}$$

Remark. Importantly, this assumption captures two aspects of information and the boundaries of the firm consistent with theories like the resource-view one. On the one hand, this assumption implies that information acquisition always requires the use of specialized labor within the firm and so it cannot be fully outsourced. On the other hand, the information acquired by the firm can then be used as an input for other production within the firm. Generated information becomes the critical resource of the firm and the source of its comparative advantage in producing the complex good.

Demand for goods. Finally, we need to detail the demand for the complex and the simple goods. To make things simple, we assume that there is an infinite demand for these two goods for any prices $\pi \leq \pi(q)$, with $q \in \{complex, simple\}$, so that firms are always better selling good of complexity q at the price $\pi(q)$. We then make the following assumption:

Assumption 1. *More complex goods are sold at higher prices:* $\pi(complex) > \pi(simple)$.

As this will become clear later on, this is a necessary condition for complex goods to be produced, as complex goods require more costly information generation.

More involved microfoundations of higher markup for more complex goods are possible. An example would be that differentiated goods are more complex to produce than homogenous goods and only differentiated goods allow for some market power while homogenous goods are competitively traded. In this case, the characteristics of the good that differentiate it from the other are complex to produce.

Perfect information. As a benchmark, let us clarify what firms would do if productivities $a_{k,q}$ would be perfectly observable at no cost. As $\pi(complex) > \pi(simple)$, it is straightforward that all firms, no matter their productivity level A_i, would prefer to produce the complex good. Indeed, all firms are perfectly able to select the right input $k' \in \Omega$ such that $a_{k,complex} = 1$. In addition, no labor is required to produce any information. In the end, the production of all firms satisfies $l_i = l_i(complex) = (\pi(complex)A_i/w)^{\frac{1}{1-\alpha}}$.

Interpreting the model. In this setup, the complexity of producing a good stems from the uncertainty on the set of inputs that are useful for production. The input purchasing (B-2-B, finding and maintaining supplier relations), R&D (trial and error), IT and legal functions (e.g. providing due diligence) may be seen as important in discerning such "right" inputs to produce the complex good.

Our approach can be recast to target other problems than procurement that firms face while producing products of differing complexity that exhibit similar structure. For example, consider a firm searching the right product characteristics to meet uncertain demand. In this example, simple products customers would not care about the particular characteristic of the good offered by the firms; hence all characteristics are perfect substitutes and there is no uncertainty faced by the firm. In contrast, for complex products, customers would desire one and only characteristic that the firm would need to discover through B-2-B, R&D and marketing effort.

More formally, in this model, the firm would have the option to produce a simple good and a set Ω of complex goods. The demand for the simple good would be at a price $p(simple)$ and the demand for complex goods would be peaked at the good $k \in \Omega$ with a price $p(complex)$ – so there is no demand for any other complex good $k' \neq k$. As in our benchmark model, the exact complex good for which there is a positive demand is not observable ex ante and firms need to generate information to discover this demand.

2.2 Optimal information production

Let us now turn to the case where productivities $a_{k,q}$ cannot be freely observed by firms. The problem faced by firms is then to select a level of complexity, the input, the amount of labor and its allocation between production and information production. More formally:

$$\max_{q \in Q, \{l_k\}_{k \in \Omega}, l^I, \mathcal{I}} \pi(q) A_i E\left[\sum_{k \in \Omega} a_{k,q}(l_k)^{\alpha} | \mathcal{I}\right] - w\left(\sum_{k \in \Omega} l_k + l_I\right),$$
$$\text{s.t. } H(\mathcal{I}|\mathcal{I}_0) \leq l_I$$

where $E(.|\mathcal{I})$ is the expectation operator conditional on the information set $\mathcal{I}$.

Information production. Let us first discuss the incentives by firms to produce information given a choice of complexity.

First, let us note that Constraint (1) is always binding as, otherwise, the firm would reduce its amount of labor dedicated to information production $l_{I,i}$ and strictly increase its profits.

Second, a firm deciding to produce the simple good is better off not producing information. It would imply a cost of $wl^I > 0$ and there is no gain to produce such an information for the simple good as any input has the same productivity.

In contrast, not producing information to produce the complex good may not be optimal. In this case, the firm would face an extreme form of uncertainty: when selecting an input $k' \in \Omega$, the firm expects a production

$$\pi(complex)A_i E\left[\sum_{k\in\Omega} a_{k,q}(l_k)^\alpha|\mathcal{I}_0\right] = \frac{\pi(complex)A_i}{N}(l_{k'})^\alpha.$$

The more inputs there are, the lower is the expected productivity of producing the complex good *in the absence* of information production.

On the other hand, acquiring information is costly. Let us start with an example. Suppose that the firm wants to have perfect information on the production function of the complex good. Given its prior set of information, the relative entropy of the new information set is:

$$H(\mathcal{I}|\mathcal{I}_0) = \sum_{k\in\Omega} P(k)\log\left(\frac{P(k)}{Q(k)}\right).$$

where $Q(k)$ is the probability of input k being the right one based on $\mathcal{I}_0$ and $P(k)$ is this probability based on $\mathcal{I}$. By assumption, $Q(k) = 1/N$ and under perfect information $P(k) = 1$ for the right input k' and equals 0 otherwise. As a result, the relative entropy in this case is:[10]

$$H(\mathcal{I}|\mathcal{I}_0) = \log N > 0.$$

There is then a need to produce information due to (1) and select a strictly positive l_I.

The following Lemma formally shows when firms choose to produce information as a function of the level of complexity of their production:

Lemma 1 (Information Production). *A firm producing the complex good produces information: $l_{I,i} > 0$. This contrasts with firm producing the simple good, which does not produce information: $\mathcal{I} = \mathcal{I}_0$ and $l_{I,i} = 0$.*

[10]Note that we use here the fact that $\lim_{x\to 0} x\log x = 0$.

Proof. See Appendix A.1. □

No information generation is optimal for the simple good as its production entails no uncertainty but a little bit of information is always desirable for the complex good. To produce this information, some specific labor l_I is necessary.

Note, however, that perfect information is not necessarily optimal when producing the complex good: the firm may be better off still facing some uncertainty. We will illustrate this point in what follows.

To make the problem tractable, we consider the information structure $\mathcal{I}(p)$ so that the posterior distribution is as follows. A given k is the right input for producing the complex good with probability $p \geq 1/N$ and all the other k are the right inputs with probability $1/N - (p - 1/N)/(N - 1)$. We obtain a continuum between $p = 1/N$ and $p = 1$.

Lemma 2 (Increasing information production)**.** *There is no loss of generality to focus on the information sets* $\{\mathcal{I}(p)\}_{p\in[1/N,1]}$*. As a result:*

(i) *Information labor* $l_{I,i}$ *and the probability* p *are increasing with firm's productivity* A_i*.*

(ii) *The probability* p *is an increasing and concave function of information labor* $l_{I,i}$*.*

Proof. See Appendix A.2. □

First of all, as we noted, we do not make assumption on the set of signals that firms can receive and so, without loss of generality, we can directly focus on posterior beliefs.

In the left panel of Figure 2, we illustrate Lemma 2's result by plotting the optimal probability p as a function of firm's productivity A_i, conditional on producing the complex good. Our calibration is such that $N = 2$ and so, the probability increases from $1/N = .5$ to 1. The right panel of Figure 2 illustrates the "production function" of information: by increasing the amount of labor dedicated to information production, a firm increases its probability to select the right input to produce the complex good. This production function features decreasing returns: this stems from the convexity in p of the conditional entropy.

Good selection and firm's structure. In the end, information production is tied to the production of the complex good so that a firm i's decision to produce the complex good boils down to compare:

$$\pi(complex)A_iE\left(a_k|\mathcal{I}\right)l_i(complex)^{\alpha}-wl_i(complex)-wl_{I,i}\geq\cdots$$
$$\cdots\pi(simple)A_il_i(simple)^{\alpha}-wl_i(simple),$$

with $l_i(complex)=\left(A_iE\left(a_k|\mathcal{I}\right)\pi(complex)/w\right)^{\frac{1}{1-\alpha}}$ the optimal amount of labor in production when producing the complex good and selecting the input with a productivity $a_{k,complex}=1$ and $l_i(simple)=\left(A_i\pi(simple)/w\right)^{\frac{1}{1-\alpha}}$ the optimal amount of labor in production when producing the simple good – in this case, the exact input that is selected does not matter.

As $\pi(complex)>\pi(simple)$, the marginal value of production is potentially larger for the complex good but, at the same time, information production leads to a larger cost for producing this good. This comparison of higher marginal value with larger cost leads to the following proposition:

Proposition 3 (Optimal firm structure and good production). *There exists $\bar{A}$ so that any firm with $A_i\geq\bar{A}$ produces information and the complex good. Otherwise, firms with productivity $A_i<\bar{A}$ do not produce information and they produce the simple good.*

Proof. See Appendix A.3. □

Only sufficiently productive firms engage into information production and produce the complex good. In contrast, less productive firms specialize in the simple good and, accordingly, does not produce any information.

Per se, the result that more productive firms engage into higher value activities is not new.[11] However, this self-selection of higher-productivity firms into the production of the complex good does not stem from a *fixed cost* of producing the complex good but from the comparison of the marginal gain to produce such good: due to endogenous information production, a low-productivity firm is relatively more productive for the simple good than for the complex good. This pattern is reversed for high-productivity firms that acquire information and benefit from a higher probability to find the right input for production. In a way, the need for information acquisition leads to a form of an adjustment cost to allow the organization to produce the complex good.

To illustrate this finding, we plot in Figure 3 profits from producing the simple and the complex goods as a function of productivity. As it can be observed, both goods yield 0 profits

[11] See Melitz (2003) among others and the general conditions for this to happen in Mrázová and Neary (2019).

when productivity equals 0. However, profits when producing the complex good are more convex than when producing the simple good. This difference in convexity happens despite the production function is the same for the two goods but only due to the *endogenous* information choice on the probability p – the stronger increase in the slope results from p increasing with productivity (left panel of Figure 2).

The role of management. Let us now extend our model to think about the role of management. To this purpose, we consider management labor l_M. Management is arguably complement to production but it is also complement to information production as management, consistently with the literature, plays an important role in gathering, disseminating, processing (Radner, 1993) or coordinating knowledge (i.e. information produced within the firm). From this perspective, adding lateral functions may contribute to increasing the need for coordinating different tasks: marketing, R&D and production for example.

To model these complementarities, we focus on the following modified problem for the firm:

$$\max_{q\in Q,\{l_k\}_{k\in\Omega}l_M l_I,\mathcal{I}} \pi(q)A_iE\left[\sum_{k\in\Omega} a_{k,q}(l_k)^\alpha|\mathcal{I}\right] l_M^\beta - w\left(\sum_{k\in\Omega} l_k + l_I + l_M\right),$$
$$\text{s.t. } H(\mathcal{I}|\mathcal{I}_0) \leq l_I^\gamma l_M^\delta$$

with α, β, γ and δ positive coefficients such that $\alpha+\beta<1$ and $\gamma+\delta\leq 1$.[12]

The first order condition with respect to management writes:

$$\pi(q)A_iE\left[\sum_{k\in\Omega} a_{k,q}(l_k)^\alpha|\mathcal{I}\right]\beta l_M^{\beta-1} + \lambda(l_I)^\gamma\delta l_M^{\delta-1} = w$$

with λ the Lagrange multiplier associated with the information constraint. Inspecting this condition, one can observe that management labor l_M increases with production labor l_k and firm's productivity A_i but l_M also increases with labor dedicated to information production and the shadow value of information production as measured by the Lagrange multiplier λ. The rest of the analysis is not modified with respect to the previous paragraph as in the previous paragraph.

In such a setting, higher productivity leads to more management labor all the more when it also leads to more labor dedicated to information production:

[12]This formulation encompasses many approaches in the literature. For example, if $\gamma=\delta$, $\alpha=\beta$ the wage bill for management is equivalent to a coordination cost as in Becker and Murphy (1992).

Corollary 4. *When management is complement to information production, firms producing more information hire relatively more management labor.*

We illustrate this finding in Figure 4 where we plot information and management labor as a function of productivity for a calibrated version of the model. Consistently with our results, only the most productive firms are producing the complex good and then also produce information and hire specific labor – this can be observed in the Figure as information labor is plotted by the red dashed line. Such presence of information labor leads to a higher demand for management labor as in Corollary 4, which can be observed in the Figure by the larger elasticity of management labor with respect to productivity for firms producing information – management labor is plotted by the black plain line.

Remark. In this paragraph, we have left unmodeled the precise motive for the complementarity between information and management labor. In models of the organisation of the firm, analyzing such complementarity in more details would allow to investigate how information labor should be organized: should it be centralized at the level of the firm, e.g. to benefit from increasing returns, or decentralized to adapt to local conditions. We leave the related questions to future research.

2.3 Empirical implications and further discussion

Let us now use our model to derive a set of empirical implications that we will confront with data in the next sections. To this purpose, let us consider two firms with two different productivities levels $A_{low} < A_{high}$. Using our previous results, we obtain the following proposition that makes predictions on the difference between these two firms.

Proposition 5. *Suppose that* $A_{low} < \bar{A} < A_{high}$. *Then:*

(i) *The high-productivity firm produces a more complex good than the low-productivity one.*

(ii) *Its share of information labor is larger.*

(iii) *Its share of management labor is higher.*

(iv) *Its information production is higher.*

(v) *Its markup is higher.*

More productive firms engage into the production of more complex goods, hire more information labor and, concomitantly, more management –under the assumption that information production is complement to management.

What kind of workers are employed in information generation? To connect our results to data, it is also useful to make more precise what we mean by labor engaged in information generation. In our benchmark model, labor responsible for producing information reduces the uncertainty regarding the selection of inputs for producing a complex good. Two functions within firms seem relevant for this role: R&D and B-2-B (purchases). The former is about designing the right product, i.e. identifying the right set of inputs that one needs to assemble in order to produce a good, and the latter is about making sure to have the actual sourcing of (high quality) inputs.

As we discussed, our model can also encompass demand uncertainty for complex goods and so, information generation may be important in finding the ideal variety desired by consumers or informing customers about firm products. In our data, jobs in advertising, marketing, sales or economic consultants that may critical for assessing the precise demand are gathered in the intellectual services or B-2-B (sales) functions. R&D workers will be key in resolving uncertainty about technological uncertainty while lawyers on the legal challenges (e.g. driverless cars, intellectual property protection) on the feasibility of producing different products. All in all, we expect workers in B-2-B, R&D and intellectual services perform important roles in complex good production.

In the following, we investigate how much these different functions are indeed connected to information generation and whether the implications of Proposition 5 are actually verified in the data.

Our model and theories of the firm. Before exploring data, let us discuss our modeling choice concerning the theory of the firm. In particular, an alternative for explaining why these non-routine lateral functions are within firms would be the property-right theory.

Indeed, lateral functions with low routineness scores that produce information involve by definition tasks that are less standardizable, requiring more customized actions than other functions like production. This means that for employees performing them, by the nature of the task or their skill, their effort and final output may not be easily measurable and therefore monitored. The way these functions are performed may require firm-specific investments on the side of workers but and/or yield firm-specific output. That naturally gives rise to contractual incompleteness (see e.g. Costinot et al., 2011) in the provision of non-routine labor services.

These functions, however, also require high human capital and may not require many physical assets. The understanding of why such functions are kept within firms is thus largely outside of the scope of the property-rights theory (see Rajan and Zingales, 1998): one of the contractual parties cannot *own* employees, and the mere fact of employing them within the organization as opposed to sourcing their services as outside contractors may not solve any hold-up problems.[13]

One answer to this can be that of the critical resource theories of the firm going back to Wernerfelt (1984) — that employment within the firm provides access to some critical resource. While Rajan and Zingales (1998) provide an explanation why employees with high human capital may be retained within the borders of organizations, it does not explain why larger or more productive firms would acquire a more *diverse* workforce, where workers have multiple functions; furthermore, they consider the "critical resource" to be exogenously given. In our framework, we abstain from modeling the contractual relations between owners and workers, but focus on the creation of the critical resource in the form of generated information.

3 Data description

In this section, we present our sources of data and how functions in firms are measured.

Sources. We rely on two main sources of data. We first use French matched employer-employee data (DADS – "Déclarations Annuelles de Données Sociales") that gives use worker-level information such as occupation, wage, hours. Occupations are coded following the 2003 PCS French classification at the 4-digit level.[14] Second, we use the FARE data set which is built from mandatory income statements of firms to tax authorities.[15] From this database, we extract firm-level information such as capital, output, sales and value added. We use the 2015 vintage of DADS-Postes (to obtain measures of compensation etc.) and FARE.

To generate additional measures on the complexity of production of firms we use the Eurostat's PRODCOM database and EAP data sets of the Insee that track detailed products of firms and their value.

[13]See also comments by Hart (2017), p. 1735.
[14]See Caliendo et al. (2015) among others for a use of this classification to study firm organization.
[15]The database FARE replaced the database FICUS in 2008.

The detailed description of data sources and variables used is given in Appendix B.

Sample. We identify a firm as a legal entity with a unique SIREN number.[16] We retain firms in the manufacturing sector (sectors in Section C according to the French NAF, rev. 2 classification), with employment in terms of hours from DADS-Postes (with full time equivalent of 1680 hours worked/year x 50) and FARE above 50 employees. One reason to apply such a threshold is to keep only the largest firms that may have a diversified workforce and hence multiple functions within firms. Another is that, given additional legal requirements on firms with more than 50 employees in France, there might be a discontinuity in productivity among firms while passing this threshold (see Garicano et al., 2016), confounding the analysis.[17] In the end, we are left with a sample of 6,715 firms. The sample statistics are shown in Table 2. The median firm has an employment of 126 full-time-equivalent (1680 hours/year) positions.

Functions. To analyze employment by functions that are performed in firms, we rely on the classification of functions by the French statistical agency, the INSEE. Based on the French PCS classification of occupations, this classification was developed to study the different tasks conducted within firms and which may involve different level of skills. More precisely, it allocates 486 existing 4-digit occupation codes into 15 distinct functions such as e.g. production, management, transport and logistics, business-to-business sales and purchases. We provide a more detailed description of functions in Table 1 as well as examples of jobs corresponding to each of these functions.[18]

Such defined functions are transverse and do not overlap with industries: a research engineer can occupy the same function (R&D) either in aircraft manufacturing or aluminum producing firms. In addition, they are not tied either to jobs' specific contractual terms (independent contractor, public or private entity, temporary or permanent employment). Importantly, they may combine very different levels of skills and distinct jobs focused on a particular function. For example, the function of "production" bundles together directly involved engineers (typically with college education), technicians (e.g. foremen, that might have some college and/or

[16] We also repeated our analysis using a sample where some of these legal entities are consolidated at a group level ("enterprises profilées" in French) obtaining qualitatively and quantitatively similar results. Available upon request.

[17] We repeated our analysis with different thresholds at 10 or 25 employees, and also for 2010 with qualitatively similar results.

[18] Some of these functions such as agriculture and fishing; health and social work or public administration will be less prevalent in the set of firms that we consider.

technical education) and skilled or unskilled blue-collar assembly line workers. On the other hand, "management" combines CEOs, managers of different levels, assistants, secretaries and regular office workers.

Intangibles. Another important variable of interest is intangibles. The stock of intangibles at the firm level is constructed by INSEE and released in the FARE data sets as the cumulated sum of expenditures related to intangibles such as R&D, patents, brands, goodwill, etc.[19]

4 Facts about functions

In this section, we document facts about the use of lateral functions within firms. We first show that the lateral functions are an important share of firms' employment and some lateral functions are close to ubiquitous. Second, lateral functions are heterogeneous across firms, with larger firms being more intensive in *non-routine* lateral functions. Third, we provide evidence on the link between these non-routine lateral functions and productivity. We then provide evidence that non-routine lateral functions are related with producing information that is used as inputs for production.

4.1 Lateral functions are an important component of firms

In Table 3, we report statistics on the distribution of functions across firms. The two main functions, typically considered in the literature, are clearly "management" and "production" that jointly account for more than 62.8% of hours worked in our sample and are present in more than 99% of the manufacturing firms studied. However, this also means that 37.2% of hours worked are unaccounted for by these base functions.

A close inspection of Table 3 reveals that some functions are close to ubiquitous, present in more than 80% of firms and account individually for more than 5% of total hours worked in manufacturing. This set of functions gathers handling business to business relations (B-2-B), R&D, maintenance and transport and logistics. We can add to this set "intellectual services" that are present in more than the majority of firms but correspond to a smaller share in total hours worked (2.4% of total). These functions group occupations that allow carrying tasks in

[19] The exact list is what is registered as expenditures linked to intangible assets (category 20) as listed by the French generally accepted accounting principles or "Plan comptable général".

the firm at different production stages, that could be associated as being transverse throughout the firm. They escape the traditional vertical management-production plant or hierarchical dichotomies. For example, Chandler (1962), p.8 dissociates “administration” functions (that would correspond to “management” in our classification) from those of “buying, selling, advertising, accounting, manufacturing, engineering, or research [...]” which would be encompassed by B-2-B, intellectual services, production and R&D functions. We shall call them thus lateral functions.

Consider the following examples. B-2-B involve purchases of inputs (and managing effectively outsourcing) but also sales of final products. Maintenance involves functions such as servicing equipment and buildings, cleaning premises or treatment of pollution. Transport and logistics involves warehousing and the movement of inputs, final goods or people – also within the firm. Intellectual services comprise of lawyers, marketing or IT professionals and different consultants.

Some other functions like construction and public works, culture and leisure, retail, health (e.g. company doctors) and social work or local services (e.g. cooks) are much less present in firms. Finally, public administration and agriculture and fishing are almost absent from our sample of manufacturing firms. Together they account only for 3.3% of total hours worked. We will group all these additional functions as "other" and disregard them in our analysis given their diverse nature.

Despite the fact that many lateral functions are present in a majority of firms, their employment shares within organizations differ greatly, as revealed by the coefficients of variation that are typically larger than 1. We turn next to functional firm heterogeneity.

4.2 Lateral function heterogeneity

In this section, we identify that lateral functions markedly differ in terms of routineness and, on top of management and production, we identify two groups of lateral functions that, accordingly, we label as routine functions and non-routine functions.

More precisely, from the perspective of organization economics one important measure is that of routineness, that is the extent to which a given function involves tasks that are repetitive, standardized and can follow codified procedures. Employees executing routine duties are much easier to manage, monitor and appraise. Conversely, the nature of non-routine tasks *par excellence* requires employees to have more own initiative, deal with non-standard problems, produce information that may be specific to the unique issue at hand.[20]

To provide insight into the nature of functions, we turn to readily available measures of routineness — the Routine Task Intensity (RTI) index of Autor et al. (2003) that classify occupations according to the ease of their automation and transpose these measures into functions.[21]

As can be seen in Table 4, functions differ markedly in such a measure of routineness. Those requiring higher skills – such as intellectual services, R&D or B-2-B tasks – are typically much less routine with RTI scores around -0.6. Management and production are the most routine among all functions with the former on average the most routine of them all. This may be surprising at first, but the bulk of hours worked in that function is performed by office workers (2-digit occupation code CS 54), among the most routine occupations. This is because the "management" function doesn't capture the hierarchical share of hours worked by managers in general, but the share of hours dedicated to administration tasks within each firm. Most of these are performed by workers that are at the bottom of the firm hierarchy.

Firms may differ substantially in how routine their functions are as witnessed by the standard deviations within categories (e.g. transport and logistics), an issue we discuss further below.

Table 4 suggests a partition of the different functions considered into 4 major distinct categories. First, we want to treat management and production, the functions traditionally discussed in the literature separately. There seems to be also a difference among the lateral functions among those that are more and less routine. Incidentally, the more non-routine lateral functions — intellectual services, R&D or B-2-B — are also the ones that our model points to as being responsible for information generation within firms (see Section 2.3). This squares well with the intuition that non-routine tasks require experimentation and non-standard worker actions. We shall pay particular attention to these functions and label them "non-routine lateral" functions, while maintenance and transport and logistics as routine and lateral. The summary statistics for such groupings of functions is shown in Table 3, lower panel.

Figure 5 shows the extensive margins of each category (whether they are present in firms or not) with firm size measured by hours worked.[22] It is clear from Figure 5 that the presence of

[20] We do not address any potential incentive provision issues in this paper because of lack of suitable data.

[21] To translate these indices and obtain exposure to automation we merge the exposure classifications of Goos et al. (2014) (that include RTI in their dataset) based on 2-digit ISCO occupation classification into the 2015 4-digit PCS classification. Function assignment is available at the 4-digit CS level, so we obtain routinness measures for functions by weighting hours worked in occupations within the function different RTI indexes. More details in the Online Appendix.

[22] Figure 9, top panel, depicts the relation between the logarithm of the number of all 15 functions present in an

different categories of functions is related with size: large firms have all types of functions. The shares of these functions within firms of different sizes (their intensity) are shown in Figure 6. We observe that there is a negative relationship between firm size and the share of production and routine lateral functions. The share of management is constant while that of non-routine lateral functions increasing with firm size.

Clearly, the composition of different functions differs markedly within firms, and there are systematic differences across firms of disparate sizes. By itself, the aforementioned evidence could be associated with more task specialization within larger firms that is recorded in our data. But this raises questions whether the composition of functions plays any further role *controlling* for the size of organizations, which we pursue in Section 4.4 below.

4.3 Hierarchy and functions

The INSEE classification that we use to discern between different functions or occupations performed by workers in firms does not inform about within-organization hierarchy. It is important thus to inspect whether the lateral functions are not hiding a large fraction of workers that perform managerial roles.

We proceed in the following way. The DADS data at our disposal does not directly trace hierarchical ties in firms. But the detailed description of jobs by 4-digit occupation codes from the PCS along with the most typical job titles allow to approximate the share of managers in a given occupation. For each 4-digit occupation we code an index that is an equally weighted measure of two subindexes. The first is an indicator whether "manager" or similar role is mentioned in the occupation title – as an example, with this approach, foremen are coded as managers. The second is based on whether all (=1) or some (=0.5) of the typical jobs within the occupation have explicitly managerial title roles or not. This index takes thus values of $\{0, 0.25, 0.5, 075, 1\}$, and we apply it directly to the share of the workforce in a given occupation to approximate the share of managers.

In Table 3, lowest panel, we show the resulting shares of lateral and other functions within firms without managers. Even after our adjustment, non-manager and non-production workers constitute 32.2% of the hours worked in firms. Given with the share of 37.2% of hours in lateral functions, we conclude that a high fraction of hours worked in lateral and other functions is not related to the preponderance of managers. Employees performing non-management and

organization and firm size.

non-production functions in firms are not merely "relabeled" managers dedicated to solving non-administration and non-production problems.

4.4 Non-routine lateral functions and productivity

We start with the correlations of functional composition of firms and their productivity. We investigate whether the *shares* of different functions in employment are correlated with standard measures of firm productivity. Our main finding is that the share of non-routine lateral functions is strongly correlated with productivity which is consistent with our model in Section 2.

Approach. To address this question, we proceed in two steps. In a first step, we estimate firm productivity as the residual of the following OLS regression within each 2-digit sector:

$$LN(VA_i) = \alpha + \beta_1 LN(Capital_i) + \beta_2 LN(Hours_i) + \beta_2 LN(PredictedAverageWage_i) + \epsilon_i \tag{2}$$

where *LN(VA)* is the logarithm of value added; capital: LN(Capital) is the logarithm of the value of property, plant and equipment (ppe) capital of the firm in 2015; LN(Hours) is the logarithm of hours worked; LN(Predicted Average Wage) is the logarithm of the ratio of the predicted wage bill and hours worked[23][24] and ϵ is an error term. We use the predicted instead of the actual wage bill to account for worker skill but at the same time avoid the problem of the correlation of a regressor with the error term: as is known in the literature, more productive firms may pay their workers more due to different rent-sharing practices.

Note that the first-stage inclusion of the projected wage bill in TFP estimation accounts indirectly for projected employed worker skill.

In a second step, to investigate the correlation of function shares on TFP we then regress obtained productivity estimates on the shares of management and lateral functions and industry fixed effects. Given that some firms do not have all functions, we cannot use logarithms of hours worked directly and need to use shares. Since shares necessarily sum to 1, we choose

[23] To obtain the projected wage bill, we first regress individual remuneration within firms in 2015 on hours worked, age, age square, sex, 2-digit occupation X function and industry fixed effects in the manufacturing sector. Then we calculate for each firm the predicted wage bill given the characteristics of its employees.

[24] We tried different specifications with different definitions of capital or including the wage bill directly without a large difference in the results.

"Production" as the base function of a manufacturing company. As a result, the interpretation of the presented results involves how much a share of a function is correlated with TFP relative to the share attributed to Production. We estimate the following regression by OLS:

$$LN(TFP_i) = \alpha + \sum \gamma_j share_j + \sum \zeta_k \theta_k + \varepsilon_i \tag{3}$$

where $share_i$ denotes the employment shares of functions considered (apart from production) and θ_i are 2-digit industry effects.

The share of non-routine functions increases with firm's productivity. We report the results in Table 5. Our preferred specification is the one in column 2, with the sample winsorized in terms of TFP at 0.5% from above and below to exclude outliers. The relations between the major function categories' employment shares and TFP are also shown graphically in Figure 8.

Our main finding in this table is that, depending on the specification, the share of non-routine lateral functions is higher in more productive firms. In particular a 1 percentage point higher share of non-routine functions is correlated with a 0.21% higher TFP. For the median firm in our sample (126 employees), a shift in hours from production to non-routine lateral functions by approximately 12.6 jobs is on average equivalent to an increase of productivity of 2.08%. This finding is consistent with the logic of our model: more productive firms hire more employees into non-routine lateral tasks that provide information.

We also find, consistent with our model but also the empirical result of Bender et al. (2018) on the importance of management on TFP[25], that a higher share of management function in employment is correlated with higher TFP. An increase in the share of management in employment by 1 percentage point at the expense of production is correlated with an increase of productivity of 0.57%.

In another version of Table 5 – the Appendix Table C.1 we explicitly include the share of managers (calculated in the way described in Section 4.3) in all functions bar for those overseeing production. We find that our correlations of different function shares with productivity are qualitatively the same, and the share of managers in the workforce is significantly correlated with TFP. Both functional division and hierarchy are related to productivity.[26]

[25] These authors particularly focus on management quality. We do not have similar measures to theirs for our administrative data. However, in separate sets of regressions shown in Table C.7 we find that higher management hours shares, especially among CEOs and "cadres" – top managers strongly correlate with productivity measures.

[26] Further investigation is reported in Section C.1 of the Appendix.

Further results. To complete the picture, we find that no single non-routine function is driving the correlation with productivity and that this connection does not simply result from the number of distinct functions firms have.

First, we show that no particular non-routine function is driving this correlation. To this end, we work directly with the main functions as determined by INSEE, and display the results in Table 6. B-2-B, R&D and maintenance (routine function in our classification, but much less than production, management or transport and logistics) are statistically significantly correlated with productivity and intellectual services are so in the sample with 95% of observations (last column). An increase of 1 percentage point in the employment shares in any of these functions at the firm level correlates with a higher TFP at least of 0.1%. The only exception is Transport and Logistics that is not correlated with productivity in any of our specifications. We note that the patterns discussed above are often even starker within multi-plant firms.

Second, we obtain that the number of distinct functions in the firm is not correlated with productivity (Figure 9, lower panel) in contrast with a strong correlation with size (Figure 9, upper panel). This, along with the evidence presented above, shows that it is not the number of functions within the firm but the employment share structure that is correlated with productivity.

Given that routine lateral functions turn out not to be correlated with productivity, and for most firm sizes (e.g. below the 95% percentile their share is constant), we will concentrate in further investigations on non-routine lateral functions.

4.5 Lateral functions, productivity and information

In this subsection, we discuss and provide suggestive evidence about why firms keep lateral functions – and, especially non-routine lateral ones such as B-2-B, intellectual services and R&D – within their borders.

We argue that these functions are key to produce relevant information that is required for the production of more complex goods. To show this, we first provide evidence that firms that are relatively more intensive in non-routine lateral functions are also relatively richer in intangible capital – we take intangibles a proxy for the intensity of information in one firm's production. Second we provide evidence that such firms engage into more complex productions defined in different ways. We also provide evidence that such firms are able to sell their products at higher markups. Overall, we obtain that the role of non-routine lateral functions exceeds R&D and also concerns other non-routine lateral functions such as B-to-B or intellectual services.

Intangible capital production. To provide evidence in favor of this interpretation, we investigate how non-routine lateral functions correlate with intangibles at the firm level. We take intangibles as a proxy for the importance of information as an input for the firm's production and so, how much information-sensitive this production is. We report in Table 7 the outcomes of regressions of different measures of the intensity of intangibles (for example, intangible capital per worker or the share of intangibles in total capital).

We first obtain the share non-routine lateral functions is strongly correlated with the different measures of intangible intensity. Note also that the share of management is also correlated with these measures.

Importantly, this correlation is not driven solely by R&D. This can be observed in column 2, where we also obtain that other non-routine lateral functions than R&D are also strongly correlated with intangibles to the same extent as R&D. When considering alternative measures of intangible intensity as in columns 4 and 5, we even obtain that R&D is actually *less* important than other non-routine lateral functions.

Second, we investigate whether intangibles help to explain the connection between productivity and non-routine lateral functions. To this end, we reestimate equation (3) with the logarithm of intangible capital in lieu of shares of functions and show the estimates in Table 8. Clearly intangible capital is positively correlated with firm productivity.[27] The question arises thus whether the inclusion of intangible capital in initial TFP estimation (equation (2)) and rerunning equation (3) still will show correlation of non-routine lateral functions with productivity. As can be seen in Table C.4, we still find that non-lateral functions' shares are correlated with productivity, albeit the coefficients (especially for the management function) are reduced.

Remark. Furthering the view that information production is correlated with TFP, we also obtain that lower routineness of the firm labor force is correlated with higher productivity (Table C.8 and Figure 10), and this is true within many of the considered functions as well.

Product complexity and markups. There are many other ways than intangibles — and, in particular, the measure of intangibles that we are using — in which information production may impact TFP measures, and where there may be an important role to play for non-lateral functions. For example, the production of complex products may require many nonstandardized tasks provided by non-routine lateral functions. In turn, the high margins that firms earn may

[27] We note that intangible capital values that we have are possibly imperfectly measuring the true extent of the concept as it retains only special investments within firms from the accounting perspective.

be important drivers of TFP.

We investigate these notions with firm-product-level data. We capture the complexity of the product portfolio of a firm through five measures. First, we compute the weighted (by shares of product sales) volatility of production. Greater uncertainty in product sales would require more lateral experimentation and specialized knowledge. Second, we calculate a weighted product complexity measure (based on the PCI indicators from the Harvard Atlas of Economic Complexity).[28] Third, we compute firm-level sales-weighted share of differentiated products according to the Rauch (1999) classification. Differentiated products require R&D to allow a firm to differentiate its products from other firms and also searching for and handling buyers. Fourth, we simply count the product lines (at the 4-digit NACE level) that a firm produces. Handling more distinct products within a firm requires more production of information. Finally, we calculate how concentrated the product sales are: the more dispersed are the sales, the more difficult the task to manufacture them. Hence we equate more complex goods as such that have a higher volatility, and the scope of the product lines of the firm with higher information requirements. We measure markups by dividing total revenue by total costs from firms' income statements.

We then correlate these different measures with the share of non-routine lateral workers, controlling by firms' size (measured by employment).[29] We report the results in Table 9, without (top panel) and with 2-digit NACE fixed effects (lower panel) to control for industry-level determinants. We uncover that there is substantial between industry-level variation in these measures, with some industries (not shown) scoring considerably higher than others in terms of our complexity proxies. This is especially true for the PCI and product differentiation measures, where 2-digit industry effects can explain even more than 40% of overall variation. Overall, we find that higher shares of non-routine lateral workers in organizations are correlated with higher product sales volatility, higher product complexity and differentiation, a larger scope of products, a greater dispersion of sales among distinct product lines but also with higher markups. These findings are consistent with our model that firms with more non-routine lateral worker shares would produce more complex goods and obtain higher markups, being able to charge higher prices.

[28] The Product Complexity Index (PCI) is a ranking of product's know-how diversity and complexity based on country characteristics that make them.

[29] Correlations with extended firms' employment structure available upon request. Findings on the share of non-routine lateral unchanged qualitatively.

Innovation activity. Information production by workers in non-routine lateral functions in our view is related to non-routine experimentation and should result in innovative activity.

We observe self-reported measures of different types of innovation for a subset of firms that responded to the Community Innovation Survey for 2016. There are overall 29 questions that directly pertain to different types of innovation, grouped thematically: innovations in products, processes, marketing, intellectual property, organizations and logistics. The correlations of the share of non-routine lateral workers with these measures are in Table 10 and in the Appendix Table C.5 (without industry fixed effects). Top panels show the correlates of overall non-routine lateral shares, while lower panels present a distinction between R&D and other non-routine lateral functions' shares.

In the top panel of Table 10 we observe that the share of non-routine lateral workers in firms is positively correlated with all innovation measures (product, process, marketing, intellectual property and logistics) except for organizational innovations. The lower panel, where a distinction between the two different types of non-routine functions (R&D and non-R&D) is made, shows that both types of workers are important in generating innovation. In particular, there exists innovation where R&D is not critical: the share of non-routine non-R&D lateral workers is positively correlated with marketing or logistics innovations, while that of R&D shares are not.

5 Further discussion

5.1 Firm size, outsourcing and the number of functions.

The fact that non-routine functions have lower shares in employment for smaller or less productive firms does not mean that e.g. R&D, purchases of inputs or sales, marketing etc. are not required by those firms in production.

One explanation of this phenomenon is that small or less productive firms use outsourcing more. In particular, information generation may well take place outside the firm. In favor of this possibility, we do observe outsourcing by firms not only in low- but also high-skilled (non-core in their terminology, i.e. with high codifiability and low weight in firm production) tasks as documented by Bergeaud et al. (2021) among others. However, in our data we also observe that outsourcing intensity[30] is in general positively correlated with measures of firm's size and TFP

[30]Unfortunately, we do not have a finer breakdown of exact firm input purchases by category nor function.

(see Figure C.1), and with the employment shares of some non-routine lateral categories (input purchasing) – see Table C.6. Put together with the facts that we document on the propensity of firms to engage in the production of complex goods –in the end, more productive firms produce more complex goods and generate more information–, this suggests that there is a complementarity between outsourcing high-skilled tasks and information generation within the firms: firms outsource some of their non-core high-skilled tasks to focus on their more critical high-skilled tasks. There might be also increasing returns in information generation which would favor emergence of specialized firms providing such services.

Another explanation why small firms have lower shares of employment of explicitly non-routine functions is that workers in those firms perform many more unrelated tasks on their job. Indeed, e.g. managers in smaller firms may need to perform several functions at the same time that in a larger firm are taken care of by workers dedicated to them specifically, while managers retain their base functions (in the words of Chandler) such as coordinating, appraising and planning. We do not see large or productive firms with only managers (which, according to the naive interpretation of our estimates would be the most productivity "enhancing" thing to do) or production workers, but a rather a much more diverse workforce. This suggests complementarities among different functions as in our model. Firms that are more productive have specialized workers (which means they are not easily substitutable between the functions). The question thus appears why such a specialization among the more productive firms is needed. Given that the number of functions in organizations is not correlated with productivity (Figure 9, lower panel) we can argue that productive firms specialize their workforce in some particular (and not all) functions.

5.2 Which lateral *sub*functions are particularly important in firms?

We proceed with further characterization including subfunctions within the non-routine lateral functions and rerunning the regression 3, with the results shown in the Appendix Table C.2.

For B-2-B into sales and purchases, only occupations related with input purchases are correlated with productivity across the different specifications. As there is a strong correlation with the share of purchasing personnel with the share of purchased materials in total cost (including labor) in Table C.6, this is further a strong indication that more productive firms outsource more as exhibited in the lower panel of Figure C.1. Marketing comes out strongly as a non-lateral function that is very strongly correlated with productivity. Within the sample containing core 95% of observations, the shares of legal services and operations management cadres (a routine lateral function) turn out to have statistically significant correlations with TFP.

Our analysis shows also that some topics such as marketing, operations management, purchasing management taught in business schools may be especially important for developing skills to acquire specialized information that is crucial for the functioning of firms.

6 Conclusion

In this paper, we provide new facts on the structure of firms and on lateral functions that constitute an important fraction of employment in manufacturing firms. We rationalize these facts by a model where firms can produce information resolving uncertainty to produce higher-value complex goods using specific labor. Model predictions are consistent with the data; higher shares of non-routine lateral functions and management are correlated with higher productivity and measures of information production and product complexity. Our results suggest that functional composition of the workforce is another important driver of TFP.

Our description of lateral functions is mainly in the cross-section. A natural question is about the time evolution of lateral functions. First, the nature of some of those functions may have changed as well; for example, some IT services became standardized, codifiable and therefore could be outsourced. The development of business services in many countries is a witness to that. Moreover, the relative importance of these functions may have changed over time, either for some firms or for all the firms, as a result of a need to generate more information to produce ever more complex goods. From this perspective, an interesting question is whether the resulting evolution of the ability of firms to engage into more complex production has allowed only some firms to increase their market power, consistently with the rise in markups explored by De Loecker et al. (2020). Causal inference of the role of functions in firms would be important as well. We leave these crucial questions for future research.

Bibliography

ANTRÀS, P. (2003): "Firms, Contracts, and Trade Structure," *Quarterly Journal of Economics*, 118, 1375–1418.

ATALAY, E., A. HORTAÇSU, AND C. SYVERSON (2014): "Vertical Integration and Input Flows," *American Economic Review*, 104, 1120–1148.

AUTOR, D. H., F. LEVY, AND R. J. MURNANE (2003): "The skill content of recent technological change: An empirical exploration," *Quarterly journal of economics*, 118, 1279–1333.

BECKER, G. S. (1962): "Investment in Human Capital: A Theoretical Analysis," *Journal of Political Economy*, 70, 9–49.

BECKER, G. S. AND K. M. MURPHY (1992): "The Division of Labor, Coordination Costs, and Knowledge," *Quarterly Journal of Economics*, 107, 1137–1160.

BENDER, S., N. BLOOM, D. CARD, J. V. REENEN, AND S. WOLTER (2018): "Management Practices, Workforce Selection, and Productivity," *Journal of Labor Economics*, 36, 371–409.

BERGEAUD, A., C. MAZET-SONILHAC, C. MALGOUYRES, AND S. SIGNORELLI (2021): "Technological Change and Domestic Outsourcing," IZA Discussion Papers 14603, Institute of Labor Economics (IZA).

BERMAN, N., V. REBEYROL, AND V. VICARD (2019): "Demand Learning and Firm Dynamics: Evidence from Exporters," *The Review of Economics and Statistics*, 101, 91–106.

BERNARD, A. B. AND T. C. FORT (2015): "Factoryless Goods Producing Firms," *American Economic Review*, 105, 518–23.

BLOOM, N., L. GARICANO, R. SADUN, AND J. V. REENEN (2014): "The Distinct Effects of Information Technology and Communication Technology on Firm Organization," *Management Science*, 60, 2859–2885.

BLOOM, N., R. SADUN, AND J. V. REENEN (2016): "Management as a Technology?" NBER Working Papers 22327, National Bureau of Economic Research, Inc.

CALIENDO, L., G. MION, L. D. OPROMOLLA, AND E. ROSSI-HANSBERG (2020): "Productivity and Organization in Portuguese Firms," *Journal of Political Economy*, 128, 4211–4257.

CALIENDO, L., F. MONTE, AND E. ROSSI-HANSBERG (2015): "The anatomy of French production hierarchies," *Journal of Political Economy*, 123, 809–852.

CHANDLER, A. D. (1962): *Strategy and Structure*, MIT Press.

COHEN, W. M. AND D. A. LEVINTHAL (1990): "Absorptive Capacity: A New Perspective on Learning and Innovation," *Administrative Science Quarterly*, 35, 128–152.

COSTINOT, A., L. OLDENSKI, AND J. RAUCH (2011): "Adaptation and the Boundary of Multinational Firms," *The Review of Economics and Statistics*, 93, 298–308.

DANG, T. V., G. GORTON, AND B. HOLMSTRÖM (2012): "Ignorance, debt and financial crises," Mimeo.

DE LOECKER, J., J. EECKHOUT, AND G. UNGER (2020): "The rise of market power and the macroeconomic implications," *The Quarterly Journal of Economics*, 135, 561–644.

DEFEVER, F. (2006): "Functional fragmentation and the location of multinational firms in the enlarged Europe," *Regional Science and Urban Economics*, 36, 658–677.

DESSEIN, W., A. GALEOTTI, AND T. SANTOS (2016): "Rational Inattention and Organizational Focus," *American Economic Review*, 106, 1522–36.

DESSEIN, W. AND T. SANTOS (2006): "Adaptive Organizations," *Journal of Political Economy*, 114, 956–985.

FORT, T. C. (2016): "Technology and Production Fragmentation: Domestic versus Foreign Sourcing," *The Review of Economic Studies*, 84, 650–687.

GARICANO, L. (2000): "Hierarchies and the Organization of Knowledge in Production," *Journal of Political Economy*, 108, 874–904.

GARICANO, L., C. LELARGE, AND J. V. REENEN (2016): "Firm Size Distortions and the Productivity Distribution: Evidence from France," *American Economic Review*, 106, 3439–3479.

Garicano, L. and T. Van Zandt (2013): "Hierarchies and the Division of Labor," in *The Handbook of Organizational Economics*, ed. by R. Gibbons and J. Roberts, Princeton: Princeton University Press, chap. 15, 604–654.

Garicano, L. and Y. Wu (2012): "Knowledge, Communication, and Organizational Capabilities," *Organization Science*, 23, 1382–1397.

Goos, M., A. Manning, and A. Salomons (2014): "Explaining job polarization: Routine-biased technological change and offshoring," *American Economic Review*, 104, 2509–26.

Grossman, S. J. and O. D. Hart (1986): "The Costs and Benefits of Ownership: A Theory of Vertical and Lateral Integration," *Journal of Political Economy*, 94, 691–719.

Hart, O. (2017): "Incomplete Contracts and Control," *American Economic Review*, 107, 1731–52.

Hart, O. and J. Moore (1990): "Property Rights and the Nature of the Firm," *Journal of Political Economy*, 98, 1119–1158.

Helpman, E. (1984): "A Simple Theory of International Trade with Multinational Corporations," *Journal of Political Economy*, 92, 451–471.

Jovanovic, B. (1982): "Selection and the Evolution of Industry," *Econometrica*, 50, 649–670.

Kogut, B. and U. Zander (1992): "Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology," *Organization Science*, 3, 383–397.

Lazear, E. P. (2009): "Firm-Specific Human Capital: A Skill-Weights Approach," *Journal of Political Economy*, 117, 914–940.

Lockett, A., S. Thompson, and U. Morgenstern (2009): "The development of the resource-based view of the firm: A critical appraisal." *International Journal of Management Reviews*, 11, 9 – 28.

Mackowiak, B. A., F. Matejka, and M. Wiederholt (2020): "Rational Inattention: A Review," CEPR Discussion Papers 15408, C.E.P.R.

MELITZ, M. J. (2003): “The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity,” *Econometrica*, 71, 1695–1725.

MITCHELL, M. F. (2000): “The Scope and Organization of Production: Firm Dynamics Over the Learning Curve,” *RAND Journal of Economics*, 31, 180–205.

MRÁZOVÁ, M. AND J. P. NEARY (2019): “Selection Effects with Heterogeneous Firms,” *Journal of the European Economic Association*, 17, 1294–1334.

NEDOPIL, C., U. STEGER, AND W. AMANN (2011): *Managing Complexity in Organizations*, Palgrave Macmillan.

PATAULT, B. AND C. LENOIR (2021): “How valuable are business networks? Evidence from sales managers in international markets,” Mimeo, University of Amsterdam and Insee.

RADNER, R. (1993): “The Organization of Decentralized Information Processing,” *Econometrica*, 61, 1109–1146.

RAJAN, R. G. AND J. WULF (2006): “The Flattening Firm: Evidence from Panel Data on the Changing Nature of Corporate Hierarchies,” *The Review of Economics and Statistics*, 88, 759–773.

RAJAN, R. G. AND L. ZINGALES (1998): “Power in a Theory of the Firm,” *Quarterly Journal of Economics*, 113, 387–432.

RAUCH, J. E. (1999): “Networks versus markets in international trade,” *Journal of International Economics*, 48, 7–35.

RUBINSTEIN, A. (1986): “Finite automata play the repeated prisoner’s dilemma,” *Journal of Economic Theory*, 39, 83–96.

SIMS, C. A. (2003): “Implications of rational inattention,” *Journal of monetary Economics*, 50, 665–690.

SUTTON, J. (2012): *Competing in Capabilities*, Oxford University Press.

TAMBE, P., L. HITT, D. ROCK, AND E. BRYNJOLFSSON (2020): “Digital Capital and Superstar Firms,” NBER Working Papers 28285, National Bureau of Economic Research, Inc.

TEECE, D. J. (1982): "Towards an economic theory of the multiproduct firm," *Journal of Economic Behavior & Organization*, 3, 39–63.

TEECE, D. J., G. PISANO, AND A. SHUEN (1997): "Dynamic capabilities and strategic management," *Strategic Management Journal*, 18, 509–533.

TOWNSEND, R. M. (1979): "Optimal contracts and competitive markets with costly state verification," *Journal of Economic Theory*, 21, 265–293.

WERNERFELT, B. (1984): "A resource-based view of the firm," *Strategic Management Journal*, 5, 171–180.

ZEIRA, J. (1987): "Investment as a Process of Search," *Journal of Political Economy*, 95, 204–210.

Tables and Figures

Table 1: Further description of functions using INSEE documentation

Code	Function	Further description	Example of occupations
CONREC	R&D	Jobs in conception, research and innovation.	Engineers and technicians in R&D.
PREINT	Intellectual services	Jobs providing specific knowledge for consulting, expertise, etc.	Lawyers, advertising, communication, IT, architects, etc.
AGRICU	Agriculture and fishing	Jobs in agriculture, fishing, lumbering	Farmer, Farm hands, etc.
BTP	Construction and public works	–	Engineers, technicians in construction, builder, carpenters, etc.
FABRIC	Production	Jobs connected to any process involved in the production of tangible goods and energy.	Engineers, technicians and workers in production.
COMINT	B-to-B	wholesale and business-to-business trade, both sales and purchases.	Buyers, salespersons, sales executives, etc.
GESTIO	Management	CEOs, management and administrative staff.	–
LOGIST	Transport and logistics	Both passenger and good transport	Engineers in logistics, drivers, handlers, dockers, etc.
ENTREP	Maintenance	Jobs for maintenance and repair (excluding construction)	Repair mechanics, cleaners, gardeners, etc.
DISTRI	Retail	–	Cashiers, butchers, salespersons, etc.
SERPRO	Local services	Daily life services (excluding transport, retail, education and health).	Hairdressers, cooks, real estate agents, etc.
EDUFOR	Education and formation	Jobs in primary, secondary and upper education and professional training.	Teachers, education trainers, etc.
SANSOC	Health and social work	–	Medical doctors, pharmacists, nurses, childcare, social worker, etc.
CULLO	Culture and leisure	–	Librarians, journalists, artists, sports instructors, etc.
ADMPUB	Public administration	All jobs related to public administration (excluding health and education but including security and justice).	–

Note: See https://www.insee.fr/fr/statistiques/1893116 for further documentation.

Table 2: Sample statistics

Variable	Source	unit	Mean	Std. Dev	Min.	Max.
property, plant and equipment	FARE	1000 euros	47120.87	262488.6	1.319	1.42e+07
intangible capital	FARE	1000 euros	7659.016	56802.75	-.162	2352462
capital	FARE	1000 euros	54779.89	290688.9	1.465	1.45E+07
value added	FARE	1000 euros	22856.92	86871.67	34.705	2895507
sales	FARE	1000 euros	88459.83	423847.3	1109.17	2.01E+07
output	FARE	1000 euros	77682.19	390757.2	12.79	2.00E+07
total wages paid	DADS	euros	1.07E+07	3.41E+07	1065385	1.07E+09
projected wages	DADS	euros	9663794	2.88E+07	1090598	9.27E+08
total hours worked	DADS	hours	475824.2	1214838	88166	3.75E+07
Distinct product lines (8 digit)	EAP		2.9106	4.292801	1	119
Hhi of sales of products	EAP		0.756131	0.271374	0.054292	1
Weighted volatility of sales growth	PRODCOM		0.172628	0.102032	0.024402	2.117789
Raw markup	FARE		0.037564	0.100719	-0.66804	2.067379

Table 3: Distribution of basic functions across firms

Variable	Mean	Std. Dev.	Min	Max	Median	Share of firms with function	Share in total hours worked
Public administration	0.0%	0.4%	0.0%	12.5%	0.0%	2.3%	0.0%
Agriculture and fishing	0.1%	1.2%	0.0%	54.2%	0.0%	7.3%	0.1%
Construction and public works	1.1%	4.3%	0.0%	79.2%	0.0%	38.6%	0.9%
B-2-B	6.4%	7.1%	0.0%	84.6%	4.1%	90.0%	6.3%
R&D	5.7%	7.7%	0.0%	75.8%	3.1%	82.0%	9.3%
Culture and leisure	0.2%	1.2%	0.0%	44.0%	0.0%	20.9%	0.2%
Retail	1.5%	7.1%	0.0%	97.0%	0.0%	37.0%	1.4%
Education and training	0.0%	0.8%	0.0%	58.6%	0.0%	6.9%	0.1%
Maintenance	7.0%	8.5%	0.0%	96.5%	4.9%	94.4%	7.1%
Production	54.9%	20.0%	0.0%	100.0%	57.5%	99.8%	51.3%
Management	11.6%	7.3%	0.0%	94.6%	10.2%	99.3%	11.5%
Transport and logistics	9.2%	8.5%	0.0%	87.2%	7.1%	96.8%	8.6%
Intellectual services	1.7%	3.2%	0.0%	75.1%	0.9%	65.5%	2.4%
Health and social work	0.2%	1.0%	0.0%	40.2%	0.0%	26.7%	0.3%
Local services	0.3%	1.7%	0.0%	64.0%	0.0%	25.0%	0.4%
Non-routine lateral	13.8%	12.2%	0.0%	84.8%	10.5%	96.5%	18.0%
Routine lateral	16.3%	11.8%	0.0%	97.6%	13.8%	99.1%	15.7%
Other functions	3.5%	9.0%	0.0%	98.2%	1.1%	86.2%	3.4%
Non-routine lateral without R&D	8.1%	8.3%	0.0%	84.8%	5.7%	93.1%	8.7%
Shares without manager positions							
Non-routine lateral	11.0%	10.3%	0.0%	82.0%	8.2%	96.5%	14.9%
Routine lateral	14.8%	11.2%	0.0%	92.4%	12.4%	98.7%	14.2%
Other functions	3.1%	8.5%	0.0%	97.1%	0.9%	84.9%	3.1%
Non-routine lateral without R&D	5.8%	6.6%	0.0%	76.5%	4.0%	93.1%	6.5%

The first five columns reports statistics on the within-firm shares of functions. The share is defined by the number of hours worked in a given function divided by the total number of hours. The sixth column reports the share of firms that has a given function in-house. The last column gives the share of the hours worked in the function in total hours worked for the entire sample.

Table 4: Summary of routinness measures for different functions

Variable	Observations	Mean	Std. Dev	Min	Max
Construction and public works	2589	-0.10	0.29	-1.50	0.46
B-2-B	6042	-0.67	0.11	-0.82	0.05
R&D	5436	-0.59	0.15	-0.82	-0.40
Culture and leisure	1303	-0.19	0.30	-0.73	1.24
Retail	2483	0.25	0.83	-1.52	1.41
Maintenance	6330	0.07	0.32	-1.00	1.59
Production	6699	0.34	0.32	-0.82	2.24
Management	6668	0.68	0.66	-0.75	2.24
Transport and logistics	6502	0.24	0.92	-1.50	2.24
Intellectual services	4396	-0.58	0.16	-1.00	-0.33
Health and social work	1725	-0.49	0.22	-1.00	-0.33
Local services	1681	-0.35	0.28	-0.75	0.03

Table 5: Productivity and functions

	No FE	2-digit-NACE FE	Multi-plant firms	2-digit-NACE FE
Management	0.524***	0.570***	0.628***	0.437***
	(0.058)	(0.069)	(0.065)	(0.067)
Non-routine lateral	0.155***	0.208***	0.309***	0.220***
	(0.036)	(0.051)	(0.074)	(0.038)
Routine lateral	0.031	0.046	0.058	0.047
	(0.022)	(0.036)	(0.034)	(0.031)
Other functions	0.094**	0.101**	0.152***	0.112**
	(0.041)	(0.048)	(0.026)	(0.047)
CONSTANT	-0.084***	-0.084***	-0.140***	-0.065***
	(0.010)	(0.012)	(0.011)	(0.012)
N	6648	6648	2917	6380
clusters	24	24	24	24
R^2	0.0183	0.0223	0.0363	0.0267
trim	1%	1%	1%	5%

Table 6: Productivity and functions

	No FE	2-digit-NACE FE	Multi-plant firms	2-digit-NACE FE
Management	0.536***	0.586***	0.624***	0.446***
	(0.063)	(0.070)	(0.087)	(0.066)
B-2-B	0.118	0.177**	0.329***	0.188***
	(0.078)	(0.079)	(0.111)	(0.054)
R&D	0.167***	0.236**	0.278**	0.215***
	(0.060)	(0.089)	(0.123)	(0.062)
Intellectual services	0.209	0.262	0.363	0.403***
	(0.177)	(0.193)	(0.228)	(0.142)
Maintenance	0.050	0.120**	0.134*	0.131***
	(0.039)	(0.044)	(0.070)	(0.039)
Transport and logistics	0.014	-0.009	-0.011	-0.014
	(0.034)	(0.041)	(0.054)	(0.039)
Other functions	0.095**	0.104**	0.150***	0.112**
	(0.039)	(0.046)	(0.025)	(0.043)
CONSTANT	-0.085***	-0.083***	-0.137***	-0.064***
	(0.011)	(0.011)	(0.013)	(0.011)
N	6648	6648	2917	6380
clusters	24	24	24	24
R^2	0.0185	0.0228	0.0369	0.0278
trim	1%	1%	1%	5%

Table 7: Intangibles and functions

	intangible capital / hour worked	intangible capital / hour worked	intangible capital / hour worked	intangible capital / (ppe + intangible capital)	intangible capital / total capital
Management	4.150***	4.183***	4.412***	3.758***	3.208***
	(0.513)	(0.466)	(0.513)	(0.251)	(0.257)
Non-routine lateral	4.260***		4.258***		
	(0.382)		(0.342)		
Routine lateral	0.012	0.016	-0.000	-0.850**	-0.844**
	(0.443)	(0.440)	(0.441)	(0.335)	(0.316)
R&D		4.360***		2.712***	2.314***
		(0.462)		(0.398)	(0.401)
Other non-routine lateral		4.185***		4.156***	3.802***
		(0.484)		(0.390)	(0.393)
Other functions	1.980***	1.985***	1.923***	2.674***	2.618***
	(0.511)	(0.511)	(0.504)	(0.323)	(0.334)
CONSTANT	-7.068***	-7.069***	-7.106***	-4.056***	-4.050***
	(0.156)	(0.155)	(0.151)	(0.082)	(0.082)
N	6565	6565	6305	6565	6565
clusters	24	24	24	24	24
R^2	0.2077	0.2077	0.2138	0.2450	0.2142
trim	1%	1%	5%	1%	1%

Table 8: Intangible capital and TFP

	2-digit-NACE FE	Multi-plant firms	2-digit-NACE FE
Logarithm of intangible capital	0.010***	0.011*	0.009***
	(0.002)	(0.006)	(0.002)
CONSTANT	-0.064***	-0.089**	-0.043***
	(0.014)	(0.041)	(0.012)
N	6565	2897	6305
N_clust	24	24	24
R^2	0.0044	0.0074	0.0074
trim	1%	1%	5%

Table 9: Non-routine lateral functions, product complexity and markups

	Sales growth volatility	Product complexity (PCI)	PCI*(PCI >0)	Rauch product differentiation	Rauch product differentiation <1	Log of number of products	Product sales concentration	Markup
Non-routine lateral	0.098**	1.761***	1.341***	0.344**	0.533**	0.761***	-0.241***	0.059**
	(0.036)	(0.427)	(0.346)	(0.152)	(0.209)	(0.176)	(0.039)	(0.023)
Ln of hours worked	0.005	-0.027	-0.023	-0.021**	-0.029	0.103***	-0.027***	0.003
	(0.003)	(0.030)	(0.021)	(0.009)	(0.026)	(0.015)	(0.005)	(0.002)
CONSTANT	0.083**	0.468	0.629**	1.120***	1.029**	-1.017***	1.248***	-0.014
	(0.037)	(0.379)	(0.252)	(0.085)	(0.413)	(0.182)	(0.056)	(0.027)
N	6233	5790	5790	5758	1957	6235	6233	6648
clusters	23	23	23	23	23	23	23	24
R^2	0.0177	0.0830	0.0969	0.0415	0.0374	0.0736	0.0421	0.0082
industry FE	N	N	N	N	N	N	N	N
trim	1%	1%	1%	1%	1%	1%	1%	1%
Non-routine lateral	0.033**	0.102	0.170*	0.066*	0.218***	0.532***	-0.170***	0.048**
	(0.015)	(0.203)	(0.087)	(0.035)	(0.066)	(0.145)	(0.043)	(0.020)
Ln of hours worked	0.005*	0.009	0.003	-0.006**	0.009*	0.104***	-0.030***	0.002
	(0.003)	(0.012)	(0.009)	(0.002)	(0.005)	(0.014)	(0.004)	(0.002)
CONSTANT	0.053	-0.480***	-0.003	0.726***	0.388***	-0.998***	1.292***	0.011
	(0.034)	(0.146)	(0.112)	(0.028)	(0.062)	(0.172)	(0.052)	(0.021)
N	6233	5790	5790	5758	1957	6235	6233	6648
clusters	23	23	23	23	23	23	23	24
R^2	0.1436	0.5425	0.5005	0.4143	0.5501	0.1058	0.0726	0.0463
industry FE	Y	Y	Y	Y	Y	Y	Y	Y
trim	1%	1%	1%	1%	1%	1%	1%	1%

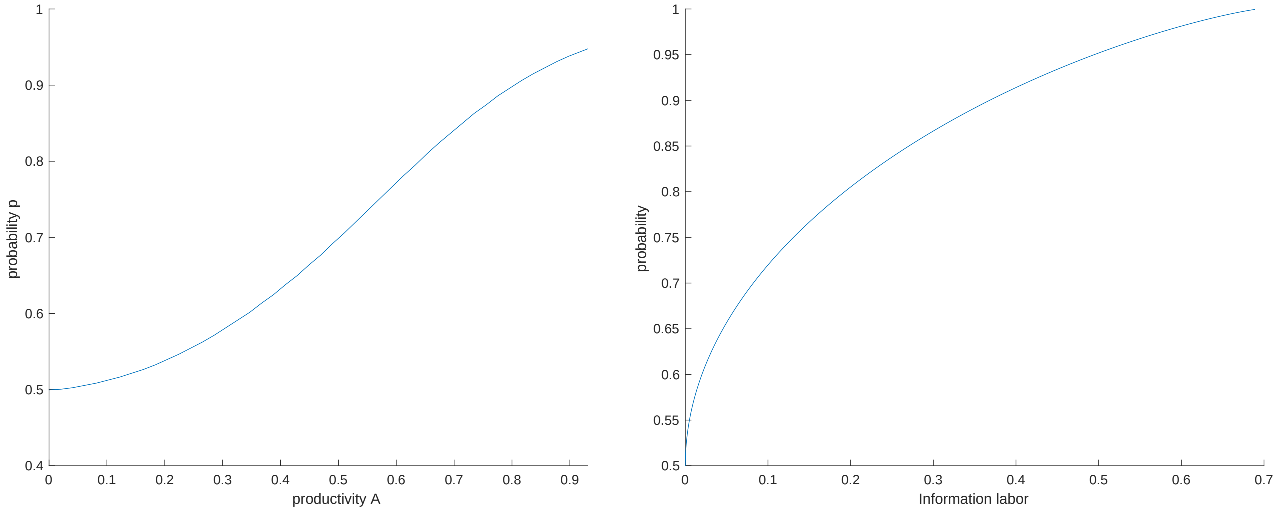
Top panel: correlations without 2-digit industry level effects. Lower panel: with 2-digit industry level effects.
"Sales growth volatility" is calculated as the standard deviation of (log)growth of 8-digit products sales in the EU 27 (EU 28 without France) over the period 2005-2014 weighted by firm sales.
"Product complexity (PCI)" is the firm-level sales-weighted (at the 8-digit product level) 2015 measure of product complexity from the Harvard Atlas of Economic Complexity.
"PCI*(PCI >0)" is the PCI index for PCI>0 and zero otherwise.
"Rauch product differentiation" is the sales-weighted (at the 8-digit product level) measure of product differentiation from Rauch (1999) where homogenous goods are coded as "0", reference priced products are coded as "0.5", and differentiated as "1". We adopt the "conservative" classification with results similar while using the "liberal" one.
"Rauch product differentiation < 1" retains firms that produce some non-differentiated products.
"Log of number of products" measures the number of distinct 4-digit product lines that a firm produces.
"Product sales concentration" is calculated as the HHI of sales in different 4-digit products.
"Markup" is total revenue/total cost at the firm level.
Data for the calculation of firm-level measures of product count and concentration from EAP 2015 and Eurostat PRODCOM database of sold production (for volatility of sales growth at the 8-digit NACE Rev. 2 code). Data for two sectors – NACE 10 and 11 from a different EAP data.
Product-level volatility included for products that had at least 5 years of data in the period 2010-2015, but calculated over entire range 2005-2014. For 8-digit lines with less data, the volatility of sold production at the 2-digit NACE assigned.
Sample trimmed at 0.5% at each tail of estimated TFP.

Table 10: Innovation measures and non-routine lateral functions

	Product innovation	Process innovation	Organization innovation	Marketing innovation	Intellectual property development	Logistics innovation
Non-routine lateral	1.587***	0.473*	0.593	1.764***	4.563***	1.091**
	(0.216)	(0.257)	(0.348)	(0.213)	(0.564)	(0.458)
Ln of hours worked	0.166***	0.243***	0.218***	0.159***	0.626***	0.411***
	(0.016)	(0.025)	(0.028)	(0.044)	(0.056)	(0.059)
CONSTANT	-1.632***	-2.445***	-1.896***	-1.199*	-7.445***	-4.648***
	(0.215)	(0.329)	(0.374)	(0.592)	(0.744)	(0.769)
N	1818	1818	1818	1818	1818	1818
clusters	24	24	24	24	24	24
R^2	0.2149	0.1000	0.0812	0.1007	0.2796	0.1075
industry FE	Y	Y	Y	Y	Y	Y
R&D	1.339***	0.648	0.668*	0.214	5.800***	0.846
	(0.406)	(0.488)	(0.346)	(0.420)	(1.150)	(0.800)
Other non-routine lateral	1.783***	0.334	0.533	2.995***	3.581***	1.286**
	(0.222)	(0.265)	(0.556)	(0.454)	(0.820)	(0.582)
Ln of hours worked	0.169***	0.241***	0.217***	0.178***	0.610***	0.414***
	(0.016)	(0.026)	(0.027)	(0.041)	(0.054)	(0.059)
CONSTANT	-1.681***	-2.409***	-1.881***	-1.510**	-7.197***	-4.697***
	(0.213)	(0.340)	(0.349)	(0.538)	(0.708)	(0.771)
N	1818	1818	1818	1818	1818	1818
clusters	24	24	24	24	24	24
R^2	0.2158	0.1002	0.0812	0.1145	0.2824	0.1076
industry FE	Y	Y	Y	Y	Y	Y

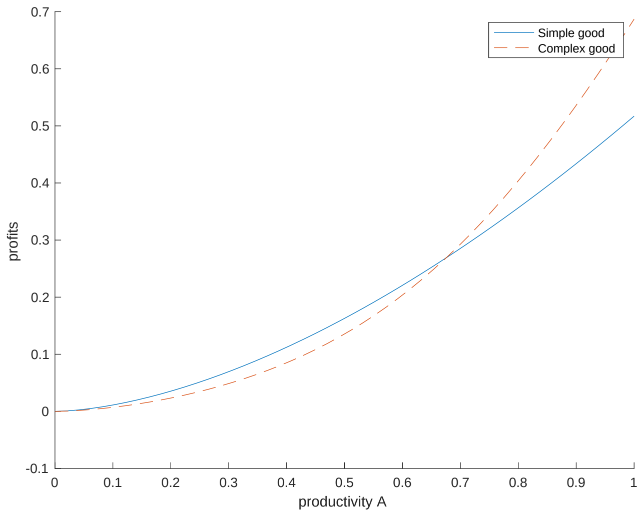
Top panel: correlations with overall share of non-routine lateral functions. Lower panel: with a distinction between R&D and other non-routine lateral. 2-digit industry level effects in all specifications.
Innovation measures from 2016 the French version of the Community Innovation Survey (CIS). We grouped yes(=1)/no answers to 29 questions into distinct groups.
"Product innovation" is the sum of indicator variables whether the firm conducted product or process innovation (maximum value = 2).
"Process innovation" is the sum of indicator variables whether the firm had any process innovation (maximum value = 3).
"Organization innovation" is the sum of indicator variables whether the firm had any changes in work organization – in production, procedures and decision making or external relations (maximum value = 3)..
"Marketing innovation" is the sum of indicator variables whether the firm changed its marketing practices – either in presentation, marketing, sales or pricing (maximum value = 4).
"Intellectual property development" is the sum of indicator variables on different aspects of intellectual property – patents, trade secrets etc. (maximum value = 8).
"Logistics innovation" is the of sum of indicator variables whether the firm changed its logistics practices (maximum value = 3).
Sample trimmed at 0.5% at each tail of estimated TFP for all firms.

Figure 2: Probability p as a function of productivity and information labor



Figures show the optimal probability as a function of productivity and as function of information labor l_I. The calibrated parameters are $N = 2$, $\alpha = .4$, $\pi(complex) = 1.5$, $\pi(simple) = 1$ and $w = .5$.

Figure 3: Optimal profits as a function of productivity.



The figure shows profits as a function of productivity. The calibrated parameters are $N = 2$, $\alpha = .4$, $\pi(complex) = 1.5$, $\pi(simple) = 1$ and $w = .5$.

Figure 4: Management and information labor as a function of productivity.

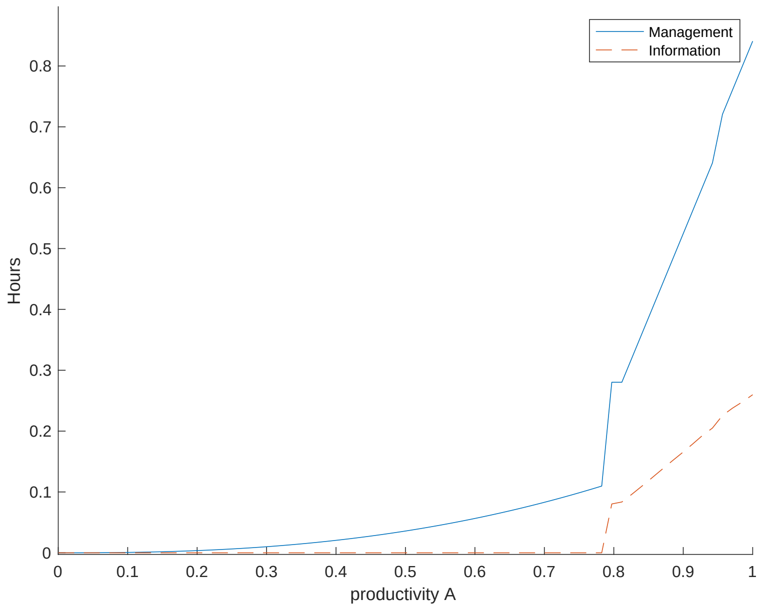
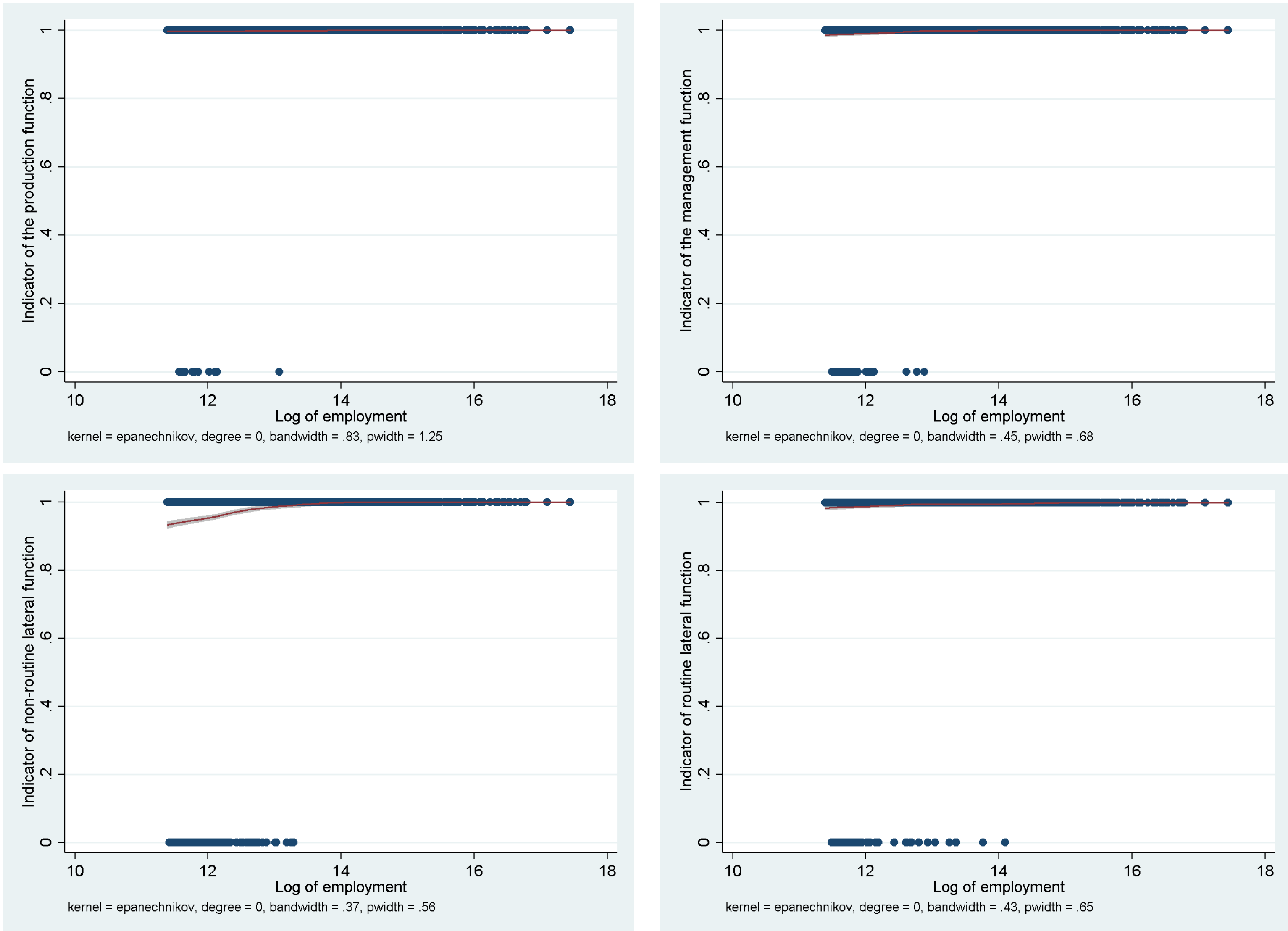


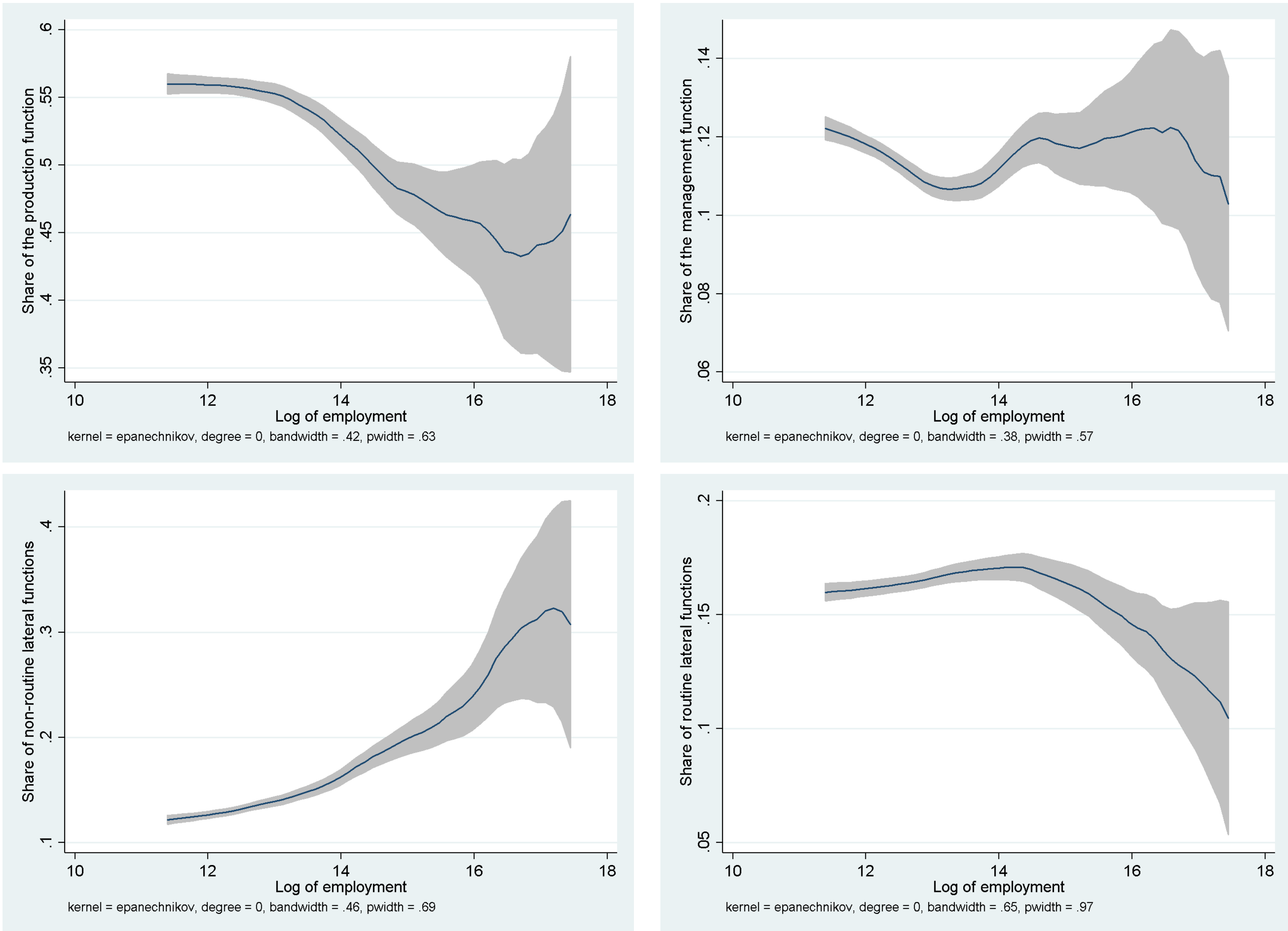
Figure shows labor in management and information production as a function of productivity. The calibrated parameters are $N = 2$, $\alpha = .4$, $\beta = .2$, $\gamma = \delta = .5$, $\pi(complex) = 1.5$, $\pi(simple) = 1$ and $w = .5$.

Figure 5: Firm employment and the presence of different functions within firms.



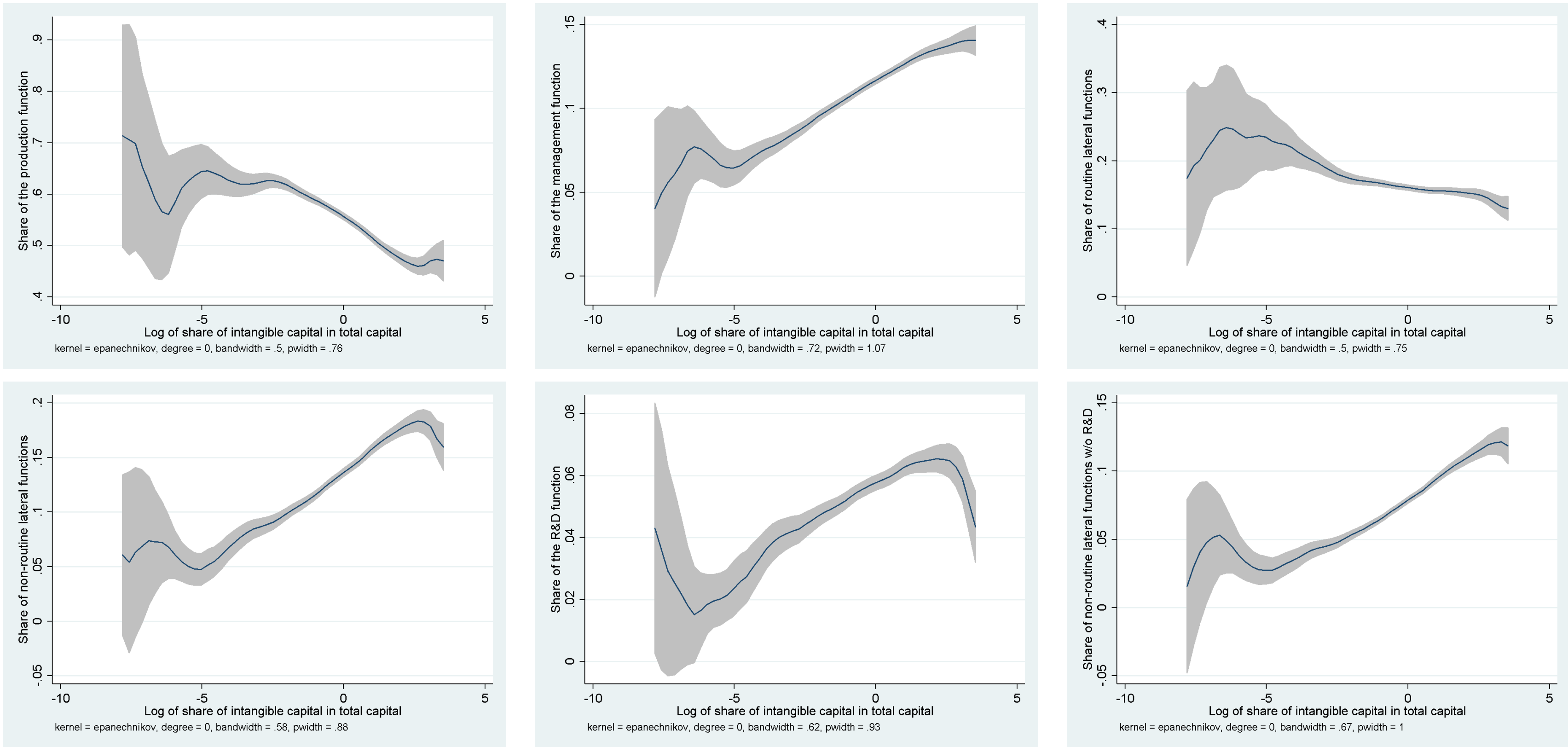
Figures show a kernel estimate of the relationship between firm employment (measured in full position equivalent hours) and an indicator whether a function is represented within a firm. 95% confidence intervals around the estimate are shown. Sample trimmed at the top and bottom 2.5% estimate of TFP.
Larger firms have more functions present within firms and size is an important predictor of whether a function is within a firm or not. See also the top panel of Figure 9.

Figure 6: Firm employment and share of different functions.



Figures show a kernel estimate of the relationship between firm employment (measured in full position equivalent hours) and the employment share within different functions. The values may not sum to one as “other functions” category is not depicted. 95% confidence intervals around the estimate are shown. Sample trimmed at the top and bottom 2.5% estimate of TFP.

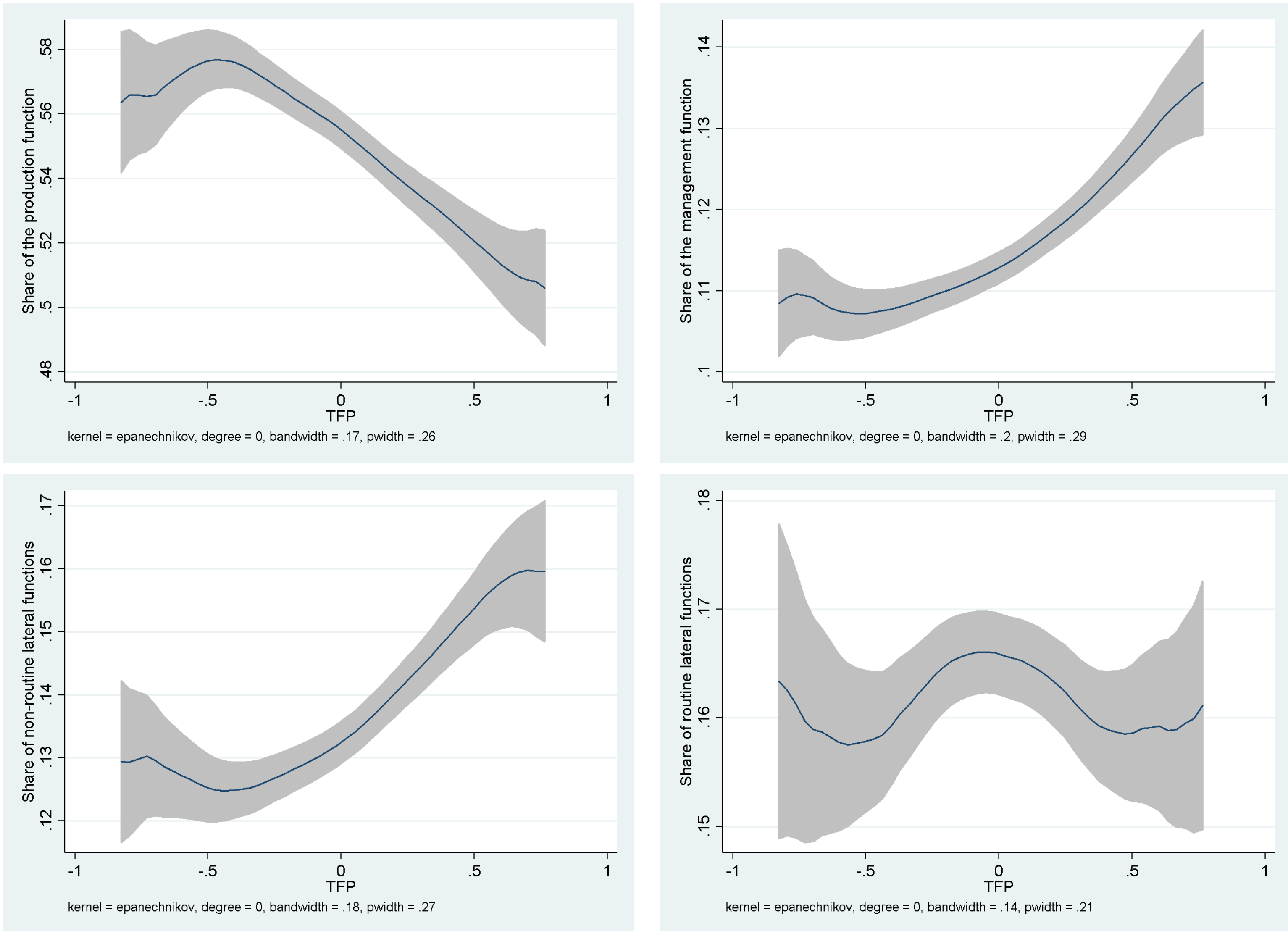
Figure 7: Share of intangibles in total capital and the presence of different functions within firms.



Figures show a kernel estimate of the relationship between the logarithm of the share of intangible capital in total capital and shares of different functions represented within a firm. 95% confidence intervals around the estimate are shown. Sample trimmed at the top and bottom 2.5% estimate of TFP, fixed effects included.

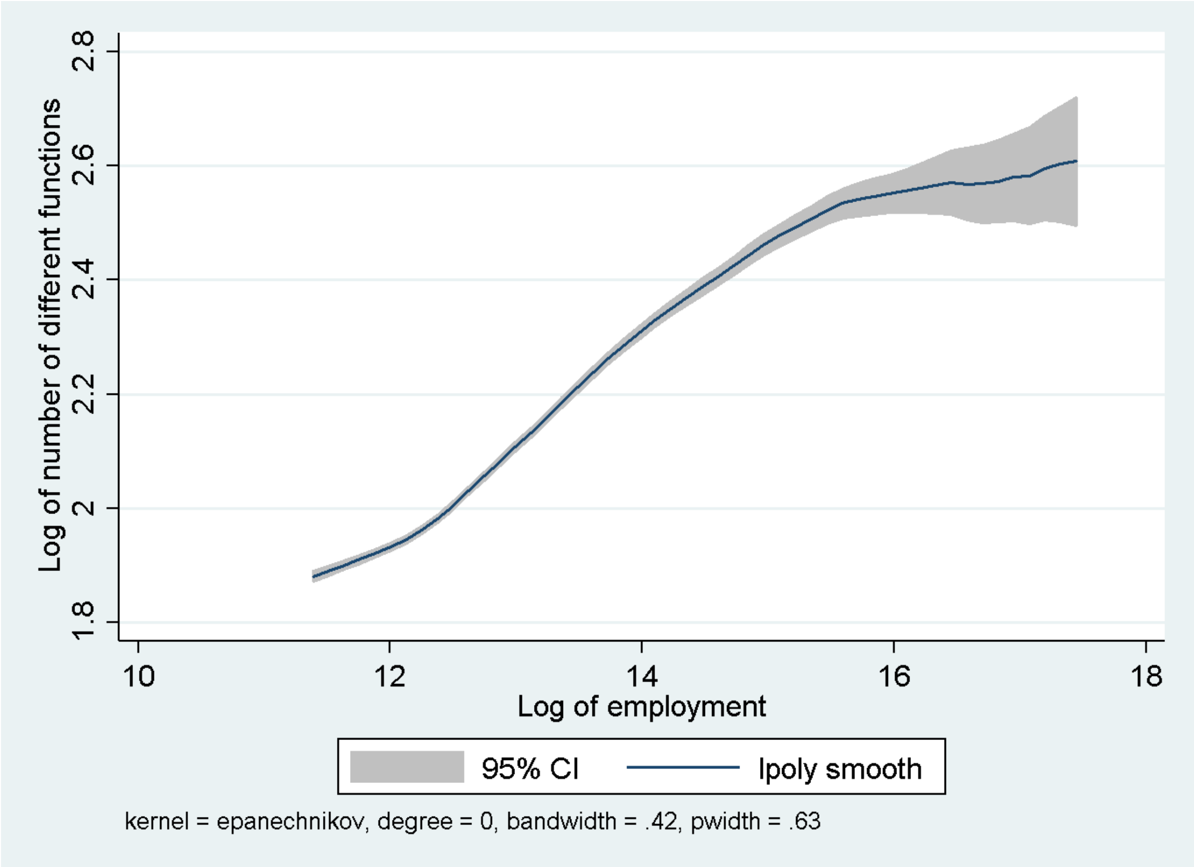
Firms with higher shares of management and non-routine lateral functions have higher shares of intangible capital within total capital. The relationship is inverse for the production function and flat for the routine functions.

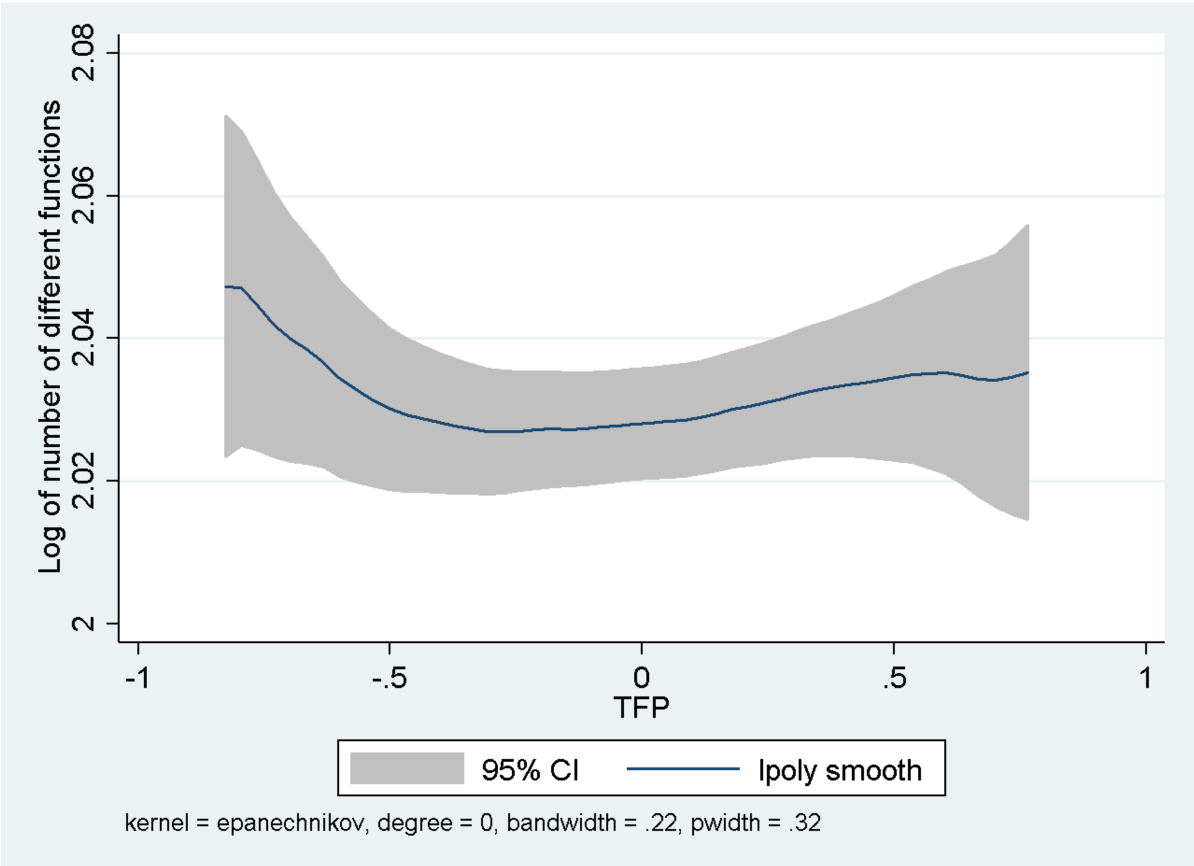
Figure 8: Firm TFP and share of different functions.



Figures show a kernel estimate of the relationship between firm TFP and the employment share within different functions. The values may not sum to one as “other functions” category is not depicted. 95% confidence intervals around the estimate are shown. Sample trimmed at the top and bottom 2.5% estimate of TFP.

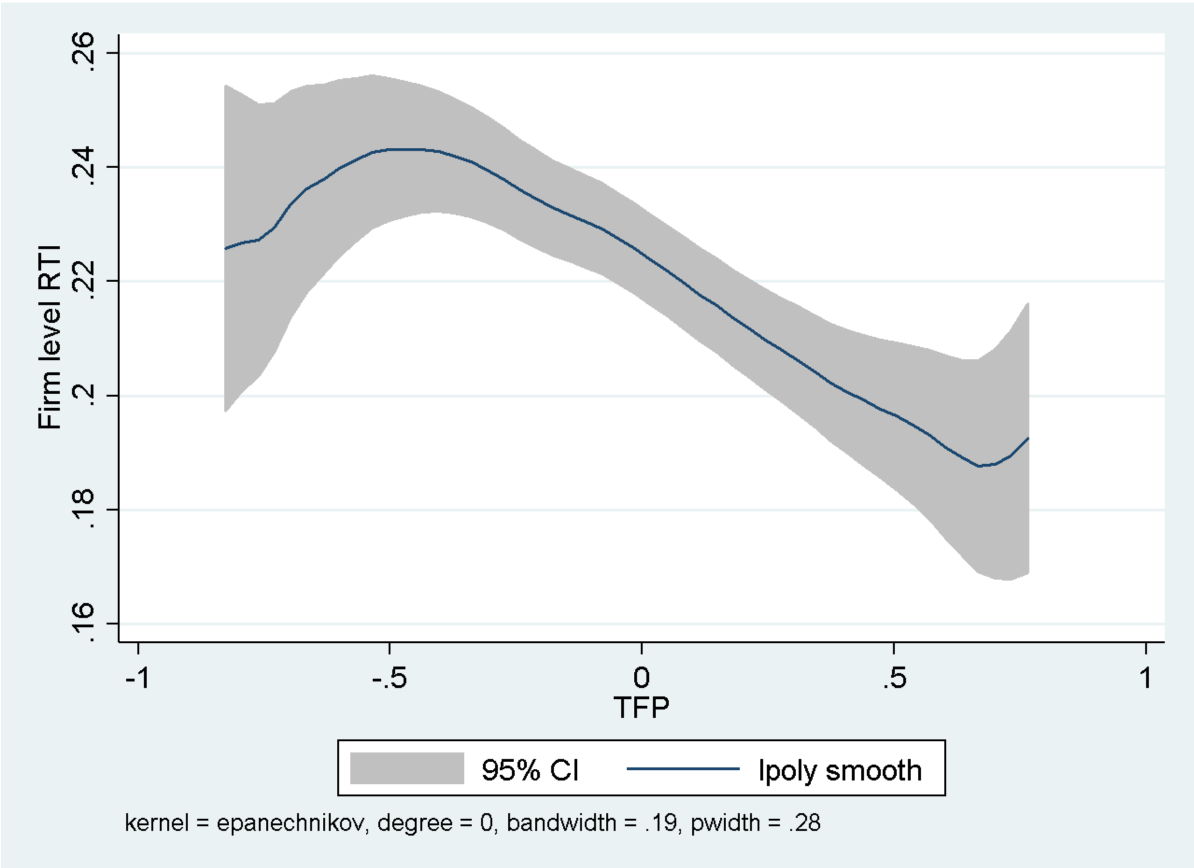
Figure 9: Number of functions vs. employment and TFP.





Figures show a kernel estimate of the relationship between respectively firm employment or TFP and the logarithm of the number of different functions. 95% confidence intervals around the estimate are shown. Sample trimmed at the top and bottom 2.5% estimate of TFP.

Figure 10: Firm-level routinness vs. employment and TFP.



Figures show a kernel estimate of the relationship between respectively firm employment or TFP and the routineness measure at the firm level. 95% confidence intervals around the estimate are shown. Sample trimmed at the top and bottom 2.5% estimate of TFP.

A Proofs

A.1 Proof of Lemma 1.

The first part of the proof directly follows the discussion in the text.

For the second part of the proof, let us consider a probability distribution such that k' has now probability $1/N + \epsilon$ and all the other inputs have probability $1/N - \epsilon/(N-1)$, with ϵ arbitrarily small. The amount of information of such distribution is such that:

$$H(\mathcal{I}|\mathcal{I}_0) = (1/N + \epsilon) \log \frac{1/N + \epsilon}{1/N} + (N-1)(1/N - \epsilon/(N-1)) \log \frac{1/N - \epsilon/(N-1)}{1/N}$$

When ϵ is small enough:

$$H(\mathcal{I}|\mathcal{I}_0) = N\epsilon^2/2 + N\epsilon^2/(2(N-1)) = \Gamma(N)\epsilon^2$$

The problem solved locally by the firm is then:

$$\max_{\epsilon} \max_{l} \left\{ \pi(complex) A_i \left(\frac{1}{N} + \epsilon \right) (l)^{\alpha} - wl_2 - w1/2\Gamma(N)\epsilon^2 \right\}$$

We have l satisfying:

$$\alpha\pi(complex) A_i \left(\frac{1}{N} + \epsilon \right) l^{\alpha-1} = w.$$

The optimal ϵ then satisfies:

$$\begin{aligned} \pi(complex) A_i \left(l^{\alpha} + \left(\frac{1}{N} + \epsilon \right) \alpha l^{\alpha-1} \frac{\partial l}{\partial \epsilon} \right) &= w\Gamma(N)\epsilon \\ \pi(complex) A_i l^{\alpha} + w \frac{\partial l}{\partial \epsilon} &= w\Gamma(N)\epsilon \end{aligned}$$

As the left hand term is strictly positive, we have $\epsilon > 0$.

A.2 Proof of Lemma 2.

First, let us consider a probability distribution such that the probability of k' is p. The probability distribution for all the other $i \in \Omega$ that minimizes

$$p \log p - \log N + \sum_{i \neq k'} p_i \log p_i$$

is the uniform distribution. As the distribution on all other $i \in \Omega$ is payoff irrelevant, it is then without loss of generality to consider the $\mathcal{I}(p)$.

Second, let us note that any distribution such that the probability of k' is $p \geq 1/N$ and other probabilities are $f_i(p)$, with $\sum_i f_i(p) = 1 - p$ and $f_i(p)$ decreasing, we have that $H(\mathcal{I}|\mathcal{I}_0)$ is increasing and convex in p. Indeed, the derivative of $H(\mathcal{I}|\mathcal{I}_0)$ with such distribution is:

$$\log p + \sum_i \frac{\partial f_i}{\partial p} \log f_i(p) > 0,$$

and the second order derivative is:

$$\frac{1}{p} + \sum_i \left(\frac{\partial f_i}{\partial p}\right)^2 \frac{1}{f_i(p)} > 0$$

The problem solved by firms is then:

$$\max_p \max_l \{\pi(complex) A_i p l^\alpha - wl - wC(p)\}$$

with $H(\mathcal{I}|\mathcal{I}_0) = C(p)$. Clearly, p is increasing in A_i and, as $C(p)$ is increasing and convex in p, we have $l_{I,i}$ increasing in A_i.

Finally, as $H(\mathcal{I}(p)|\mathcal{I}_0)$ is increasing in p and the information constraint binds, we have p is increasing in l_I. As $H(\mathcal{I}(p)|\mathcal{I}_0)$ is strictly increasing and convex, we also have that the inverse function, that is p as a function of l_I is concave, which proves (ii).

A.3 Proof of Proposition 3.

First of all, note that ultimately $l_{I,i} = \log N$ and the firm operates under perfect information. As $\pi(complex) > \pi(simple)$, this implies that when $A_i \geq \bar{A}$, the production of the complex good dominates the production of the simple good.

Using the enveloppe theorem, the derivative of profits with respect to A_i is

$$\pi(complex)pl_i(complex)^\alpha$$
$$\pi(simple)l_i(simple)^\alpha.$$

Using the first order condition for labor, the difference between these two derivatives are:

$$\frac{w}{A_i}(l_i(complex) - l_i(simple)) = \left(\frac{w}{A_i}\right)^{\frac{2-\alpha}{1-\alpha}} \left([\pi(complex)p]^{\frac{1}{1-\alpha}} - [\pi(simple)]^{\frac{1}{1-\alpha}}\right).$$

As p is continuously increasing from $1/N$ to 1 when A_i increases from 0 to ∞, we obtain the proposition from the intermediary value theorem.

B Data sources and variables used

Data on functions: https://www.insee.fr/fr/statistiques/1893116

Data on employment (by occupation), wage bill at the SIREN level: DADS-Postes 2015.

Balance sheet data (tangible and intangible capital, sales, materials purchased, markups etc.): FICUS-FARE 2015.

Routineness measures from Goos et al. (2014) translated into two-digit PCS and then into individual functions.

PRODCOM: 8-digit product level data (sales) at the SIREN level to calculate product scope, concentration and sales growth variability. The latter calculated from pan-EU (excluding France) PRODCOM data from EUROSTAT.

Product complexity indexes at the SIREN level calculated from individual HS4 code indexes from the Atlas of Economic Complexity at Harvard University, using PRODCOM data.

Rauch product differentiation classification from Rauch (1999).

Community Innovation Survey, 2016 for product innovation measures at the SIREN level.

C Additional figures and tables

Table C.1: Productivity, functions and managers

	No FE	2-digit-APEN FE	Multi-plant firms	2-digit-APEN FE
Management (function)	0.529***	0.559***	0.576***	0.407***
	(0.083)	(0.087)	(0.087)	(0.079)
Non-routine lateral	0.148***	0.202***	0.275***	0.203***
	(0.040)	(0.055)	(0.080)	(0.046)
Routine lateral	0.027	0.042	0.039	0.036
	(0.025)	(0.036)	(0.039)	(0.031)
Other functions	0.095**	0.099*	0.147***	0.111**
	(0.043)	(0.050)	(0.025)	(0.047)
Managers (share)	0.225**	0.300***	0.519***	0.332***
	(0.106)	(0.093)	(0.166)	(0.099)
CONSTANT	-0.082***	-0.084***	-0.141***	-0.065***
	(0.010)	(0.011)	(0.012)	(0.011)
N	6648	6648	2917	6380
N_clust	24	24	24	24
R^2	0.0176	0.0215	0.0359	0.0264
trim	1%	1%	1%	5%

Table C.2: Productivity and detailed functions

	2-digit-NACE FE	Multi-plant firms	2-digit-NACE FE
Management: CEOs	1.353***	1.635**	1.560***
	(0.420)	(0.708)	(0.382)
Management: cadres	0.590**	0.533	0.501**
	(0.269)	(0.423)	(0.241)
Managers: mid-level	0.470**	0.544*	0.312*
	(0.208)	(0.286)	(0.175)
Managers: office workers	0.491***	0.498***	0.322***
	(0.123)	(0.125)	(0.111)
B-2-B: purchases	0.895**	0.804*	1.014***
	(0.336)	(0.392)	(0.270)
B-2-B: sales	0.093	0.237*	0.105*
	(0.088)	(0.124)	(0.056)
R&D	0.145*	0.154	0.108**
	(0.079)	(0.105)	(0.050)
Intellectual services: IT	0.277	0.458	0.289
	(0.191)	(0.315)	(0.180)
Intellectual services: legal services	5.105	5.892	6.241**
	(4.454)	(5.436)	(2.824)
Intellectual services: marketing	4.336***	4.689**	3.534***
	(1.034)	(1.671)	(1.246)
Intellectual services: economic consulting	-0.879	1.152	0.747
	(0.920)	(0.690)	(0.732)
Intellectual services: other	0.008	-0.335	0.049
	(0.293)	(0.528)	(0.196)
Maintenance: cadres	0.663***	0.770**	0.629***
	(0.147)	(0.326)	(0.145)
Maintenance: technicians	0.057	0.052	0.060
	(0.053)	(0.103)	(0.052)
Maintenance: lowest level	0.103	0.121*	0.113*
	(0.061)	(0.061)	(0.055)
Transport and logistics: cadres	0.286	0.783	0.809*
	(0.580)	(0.862)	(0.447)
Transport and logistics: mid-level	0.205	0.397	0.070
	(0.301)	(0.340)	(0.274)
Transport and logistics: lowest-level	-0.011	-0.042	-0.018
	(0.042)	(0.069)	(0.039)
Production: cadres	0.428***	0.370	0.388***
	(0.125)	(0.225)	(0.105)
Production: technicians and foremen	-0.041	-0.098	-0.012
	(0.047)	(0.093)	(0.035)
Other functions	0.103**	0.145***	0.116**
	(0.047)	(0.030)	(0.044)
CONSTANT	-0.093***	-0.138***	-0.075***
	(0.014)	(0.019)	(0.014)
N	6648	2917	6380
clusters	24	24	24
R^2	0.0306	0.0494	0.0385
trim	1%	1%	5%

Table C.3: Summary statistics on detailed functions

Variable	Mean	Std. Dev.	Min	Max	Median	Share of firms with function	Share in total hours worked
Public administration	0.0%	0.4%	0.0%	12.5%	0.0%	2.3%	0.0%
Agriculture and fishing	0.1%	1.2%	0.0%	54.2%	0.0%	7.3%	0.1%
Construction and public works	1.1%	4.3%	0.0%	79.2%	0.0%	38.6%	0.9%
B-2-B	6.4%	7.1%	0.0%	84.6%	4.1%	90.0%	6.3%
R&D	5.7%	7.7%	0.0%	75.8%	3.1%	82.0%	9.3%
Culture and leisure	0.2%	1.2%	0.0%	44.0%	0.0%	20.9%	0.2%
Retail	1.5%	7.1%	0.0%	97.0%	0.0%	37.0%	1.4%
Education and training	0.0%	0.8%	0.0%	58.6%	0.0%	6.9%	0.1%
Maintenance	7.0%	8.5%	0.0%	96.5%	4.9%	94.4%	7.1%
Production	54.9%	20.0%	0.0%	100.0%	57.5%	99.8%	51.3%
Management	11.6%	7.3%	0.0%	94.6%	10.2%	99.3%	11.5%
Transport and logistics	9.2%	8.5%	0.0%	87.2%	7.1%	96.8%	8.6%
Intellectual services	1.7%	3.2%	0.0%	75.1%	0.9%	65.5%	2.4%
Health and social work	0.2%	1.0%	0.0%	40.2%	0.0%	26.7%	0.3%
Local services	0.3%	1.7%	0.0%	64.0%	0.0%	25.0%	0.4%
B-2-B: sales	5.3%	6.8%	0.0%	84.6%	3.0%	87.1%	5.1%
B-2-B: purchases	1.1%	1.5%	0.0%	46.6%	0.7%	62.6%	1.2%
Maintenance: cadres	0.5%	1.5%	0.0%	82.2%	0.0%	43.4%	0.7%
Maintenance: technicians	2.6%	5.3%	0.0%	83.3%	1.4%	71.7%	3.0%
Maintenance: low-skilled	3.9%	6.0%	0.0%	86.3%	2.1%	81.5%	3.4%
Management: CEOs	0.6%	0.9%	0.0%	11.5%	0.0%	45.8%	0.3%
Management: cadres	2.3%	2.6%	0.0%	47.6%	1.7%	83.3%	3.2%
Management: middle managers	1.7%	2.2%	0.0%	25.2%	1.1%	69.2%	2.1%
Management: office workers	7.1%	5.7%	0.0%	92.2%	5.8%	97.6%	5.9%
Intellectual services: IT high skill	0.4%	1.6%	0.0%	55.3%	0.0%	31.8%	0.6%
Intellectual services: IT medium skill	0.4%	1.2%	0.0%	33.8%	0.0%	34.9%	0.5%
Intellectual services: legal services	0.0%	0.2%	0.0%	5.1%	0.0%	8.1%	0.1%
Intellectual services: economic consulting	0.2%	0.8%	0.0%	34.2%	0.0%	18.2%	0.3%
Intellectual services: marketing and communication	0.1%	0.4%	0.0%	7.7%	0.0%	15.7%	0.2%
Intellectual services: other	0.6%	2.0%	0.0%	74.2%	0.0%	48.6%	0.7%

Table C.4: Productivity and functions: TFP estimated with intangible capital

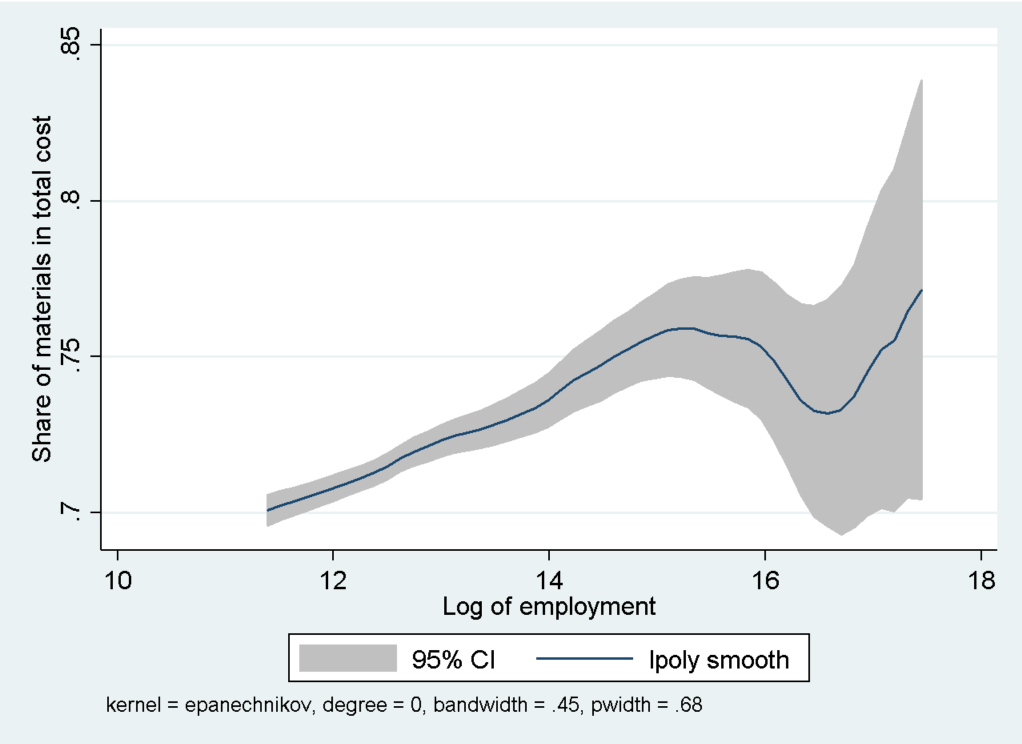
	2-digit- NACE FE	Multi-plant firms	2-digit- NACE FE
Management	0.514***	0.518***	0.364***
	(0.071)	(0.149)	(0.062)
Non-routine lateral	0.203***	0.218***	0.210***
	(0.049)	(0.071)	(0.039)
Routine lateral	0.060	0.110*	0.051
	(0.039)	(0.062)	(0.036)
Other functions	0.040	0.149	0.067
	(0.043)	(0.147)	(0.044)
CONSTANT	-0.078***	-0.058**	-0.050***
	(0.014)	(0.022)	(0.014)
N	6564	3668	6300
clusters	24	24	24
R^2	0.0189	0.0218	0.0212
trim	1%	1%	5%

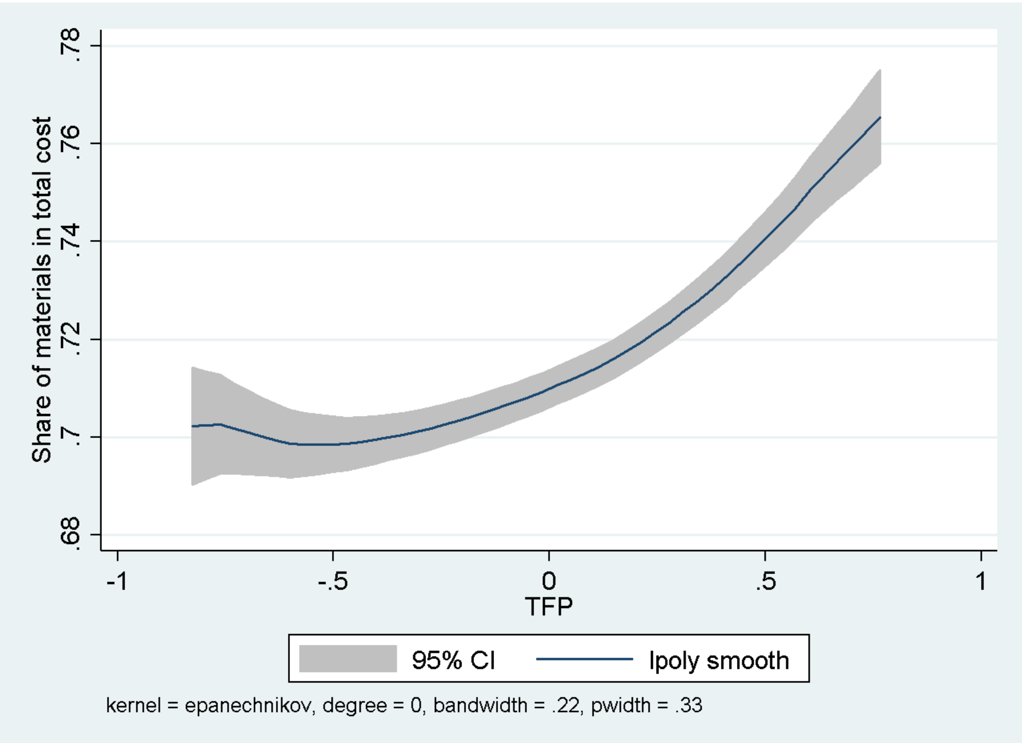
Table C.5: Innovation measures and non-routine lateral functions

	Product innovation	Process innovation	Organization innovation	Marketing innovation	Intellectual property development	Logistics innovation
Non-routine lateral	1.560***	0.589**	0.964***	1.067***	4.798***	0.931**
	(0.217)	(0.260)	(0.314)	(0.291)	(0.630)	(0.371)
Ln of hours worked	0.167***	0.248***	0.221***	0.166***	0.636***	0.430***
	(0.017)	(0.024)	(0.030)	(0.047)	(0.060)	(0.057)
CONSTANT	-1.666***	-2.448***	-1.927***	-1.556***	-7.451***	-4.822***
	(0.225)	(0.306)	(0.386)	(0.549)	(0.743)	(0.710)
N	1818	1818	1818	1818	1818	1818
clusters	24	24	24	24	24	24
R^2	0.1739	0.0805	0.0611	0.0460	0.2487	0.0912
industry FE	N	N	N	N	N	N
R&D	1.532***	0.867**	1.359***	-0.555	6.352***	0.717
	(0.243)	(0.381)	(0.250)	(0.502)	(0.710)	(0.616)
Other non-routine lateral	1.591***	0.277	0.519	2.887***	3.053***	1.171**
	(0.316)	(0.267)	(0.537)	(0.564)	(0.946)	(0.441)
Ln of hours worked	0.167***	0.243***	0.215***	0.192***	0.612***	0.433***
	(0.017)	(0.024)	(0.027)	(0.043)	(0.055)	(0.057)
CONSTANT	-1.673***	-2.384***	-1.836***	-1.928***	-7.095***	-4.871***
	(0.221)	(0.302)	(0.360)	(0.497)	(0.681)	(0.710)
N	1818	1818	1818	1818	1818	1818
clusters	24	24	24	24	24	24
R^2	0.1739	0.0815	0.0627	0.0723	0.2565	0.0915
industry FE	N	N	N	N	N	N

Top panel: correlations with overall share of non-routine lateral functions. Lower panel: with a distinction between R&D and other non-routine lateral. No industry level effects in all specifications.
Innovation measures from 2016 the French version of the Community Innovation Survey (CIS). We grouped yes(=1)/no answers to 29 questions into distinct groups.
"Product innovation" is the sum of indicator variables whether the firm conducted product or process innovation (maximum value = 2).
"Process innovation" is the sum of indicator variables whether the firm had any process innovation (maximum value = 3).
"Organization innovation" is the sum of indicator variables whether the firm had any changes in work organization – in production, procedures and decision making or external relations (maximum value = 3)..
"Marketing innovation" is the sum of indicator variables whether the firm changed its marketing practices – either in presentation, marketing, sales or pricing (maximum value = 4).
"Intellectual property development" is the sum of indicator variables on different aspects of intellectual property – patents, trade secrets etc. (maximum value = 8).
"Logistics innovation" is the of sum of indicator variables whether the firm changed its logistics practices (maximum value = 3).
Sample trimmed at 0.5% at each tail of estimated TFP for all firms.

Figure C.1: Share of materials in total cost vs. employment and TFP.





Figures show a kernel estimate of the relationship between respectively firm employment or TFP and the share in total cost of materials and services purchased outside of the firm. 95% confidence intervals around the estimate are shown. Sample trimmed at the top and bottom 2.5% estimate of TFP.

Table C.6: Share of purchased materials in total cost and the share of B-2-B purchase function

	2-digit-NACE FE >49 employees	Multi-plant firms >49 employees	2-digit-NACE FE >99 employees	Multi-plant firms >99 employees	2-digit-NACE FE >249 employees	Multi-plant firms >249 employees
B-2-B: purchases	0.976***	0.735	1.417***	1.447***	1.773***	1.917***
	(0.300)	(0.458)	(0.286)	(0.331)	(0.526)	(0.517)
Constant	0.786***	0.793***	0.795***	0.795***	0.802***	0.809***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.004)
N	6580	2889	3567	1955	1340	969
clusters	24	24	24	24	24	24
R^2	0.1693	0.1741	0.1907	0.2014	0.1965	0.2384

Regression: $materialsshare = \alpha + \beta \times$ share of particular labor in purchases $+\epsilon$ where materials share is the ratio of materials and (materials+wages).

C.1 More on lateral functions and hierarchies

In this section, we provide evidence that the role of non-routine lateral functions differ from the hierarchical knowledge production discussed in the literature (see Garicano, 2000; Caliendo et al., 2015, among others) and provide a complementary view of firm organization. Non-routine lateral functions typically do not have workers in the lowest skill layers (CS 5 and 6), but not all e.g. at the hierarchical level of "cadres" performing them are also managers.

To investigate this issue, we split further the lateral functions into distinct subfunctions imposing the hierarchical structure used by Caliendo et al. (2015)[31] and investigate e.g. the correlation of different subfunctions shares with firm productivity.[32] If the hierarchical-vertical view would account purely for productivity differentials between firms, the obtained coefficients for all functions on the same hierarchical layer should be of the same sign and magnitude — and the nature of the tasks performed at each layer would not matter.

We superimpose functions with hierarchical layers. Results are shown in Table C.7, with employment shares of lowest-ranking employees and workers (CS 5 and 6 as the base category). We focus our attention on the first column. Interestingly, only few of the functions X hierarchy levels shares' come out as statistically significant. It is not necessarily true that shares of subfunctions with higher skilled workers (as witnessed by the PCS classification) are always correlated with higher firm productivity. Higher CEO (a management function) share in hours worked is strongly correlated with productivity. Higher shares of cadres (the second-highest level layer after the CEO) in management, B-2-B, maintenance and production are correlated with TFP, while those in all other are not.[33] Among functions in middle- and lowest hierarchical levels we find that the shares of hours worked in total employment of lowest level (CS 5 or 6) B-2-B and management (e.g. office clerks) workers are positively related with TFP. We reject the Wald tests of equality of coefficients for the "cadres" (CS3) layer at 1% and for the mid-level (CS4) at 2% level. These results suggest that – as R&D or intellectual services functions' shares come as statistically significant overall as shown in Table 6 and discussed in Section 4.4 – it may be the team output of a function that matters and not the hierarchical structure. We also observe that the "management" function at all levels is an important correlate of

[31] These authors use the 1 digit PCS classification of occupations and group jobs into 4 hierarchy layers: CEOs (CS code "2"); senior staff or management positions (CS "3"); employees at a supervisor level (CS "4"); other qualified or non-qualified white and blue-collar workers (heterogenous group of CS "5" and "6" codes)

[32] This is possible by using the 4-digit PCS classification.

[33] Statistical significance of the correlation of these functions is unrelated to the size of particular subfunction in overall workforce (Table C.3).

productivity, confirming the notions advanced e.g. in Bender et al. (2018). We conclude that although hierarchy structure is correlated with productivity overall as argued in Caliendo et al. (2020), functional composition of the workforce may matter as well.

Table C.7: Productivity and detailed functions

	2-digit-NACE FE	Multi-plant firms	2-digit-NACE FE
Management: CEOs	1.375***	1.676**	1.582***
	(0.405)	(0.699)	(0.370)
Management: cadres	0.727**	0.652	0.610**
	(0.262)	(0.410)	(0.239)
Managers: mid-level	0.582**	0.706**	0.454**
	(0.211)	(0.318)	(0.174)
Managers: office workers	0.488***	0.493***	0.321***
	(0.126)	(0.130)	(0.113)
B-2-B: cadres	0.317***	0.512***	0.294***
	(0.106)	(0.149)	(0.078)
B-2-B: mid-level	0.006	0.017	0.059
	(0.122)	(0.150)	(0.097)
B-2-B: lowest level	1.650**	1.873**	1.015
	(0.769)	(0.872)	(0.692)
R&D: cadres	0.202	0.176	0.171
	(0.121)	(0.160)	(0.107)
R&D: technicians	0.110	0.171	0.095
	(0.114)	(0.181)	(0.108)
Intellectual services: cadres	0.062	0.726**	0.420
	(0.382)	(0.324)	(0.341)
Intellectual services: mid-level workers	0.305	-0.087	0.262
	(0.269)	(0.407)	(0.203)
Maintenance: cadres	0.683***	0.763**	0.659***
	(0.151)	(0.324)	(0.148)
Maintenance: technicians	0.041	0.040	0.048
	(0.053)	(0.102)	(0.050)
Maintenance: lowest level	0.104	0.117**	0.113*
	(0.064)	(0.053)	(0.058)
Transport and logistics: cadres	0.313	0.780	0.846*
	(0.593)	(0.840)	(0.480)
Transport and logistics: mid-level	0.232	0.447	0.099
	(0.301)	(0.367)	(0.275)
Transport and logistics: lowest-level	-0.017	-0.046	-0.022
	(0.042)	(0.068)	(0.037)
Production: cadres	0.429***	0.334	0.398***
	(0.136)	(0.233)	(0.108)
Production: technicians and foremen	-0.041	-0.094	-0.011
	(0.047)	(0.091)	(0.035)
Other functions	0.112**	0.154***	0.124***
	(0.044)	(0.026)	(0.043)
CONSTANT	-0.095***	-0.141***	-0.077***
	(0.014)	(0.017)	(0.014)
N	6648	2917	6380
clusters	24	24	24
R^2	0.0273	0.0460	0.0346
trim	1%	1%	5%

Table C.8: Routineness and productivity

Item	col 1	col 2	col 3	col 4	col 5	col 6	col 7	col 8
Firm-level	-0.056***							
	(0.017)							
B-2-B		-0.085**						
		(0.031)						
R&D			-0.068***					
			(0.024)					
Maintenance				-0.026*				
				(0.013)				
Production					-0.057***			
					(0.014)			
Management						-0.000		
						(0.011)		
Transport and logistics							0.004	
							(0.005)	
Intellectual services								-0.066**
								(0.030)
CONSTANT	0.029***	-0.040*	-0.024	0.009***	0.037***	0.010	0.008***	-0.025
	(0.005)	(0.020)	(0.015)	(0.001)	(0.006)	(0.007)	(0.000)	(0.018)
N	6580	5918	5327	6202	6564	6535	6371	4293
clusters	24	24	24	24	24	24	24	24
R^2	0.0043	0.0036	0.0045	0.0039	0.0044	0.0026	0.0031	0.0045