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# ABSTRACT

## The Influence of Value-Chain Governance on Innovation Performance: A Study of Italian Suppliers

This paper explores how value-chain governance affects the innovation performance of suppliers of intermediate products. We take advantage of a unique dataset of Italian firms to identify governance regimes along suppliers' technological capabilities and the level of explicit coordination in the value chain. Our results indicate that 'modular' value-chain governance is more conducive to innovation for suppliers, especially when these firms have medium capability levels. Conversely, market-based governance modes appear to strongly reduce the innovativeness of suppliers with low capability. These patterns are also reflected in export performances and sales of innovative products. Our results go partially against other findings in the GVC literature, whereby relational value chains are seen to provide the most favorable environment to learn and innovate. Interestingly, the highest levels of technological capabilities consistently reduce the correlation between supplying intermediates and innovation performance, which indicates that technology-gap is an important mediator of learning within value chains.

**JEL Classification:** F14, O30

**Keywords:** global value chains, export, suppliers, innovation, technological capabilities

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## 1. INTRODUCTION

Available data indicates that the vast majority of firms in the economy serve as suppliers to other companies.[1] Such relationships are not only relevant for their weight in total production, but especially because they create value chains that shape industries and national economies. Nonetheless, despite the clear importance of suppliers, only a small – albeit growing – share of the theoretical and empirical literature accounts for their peculiar nature and for the fact that they operate in environments that are distinct from firms selling to final markets. Consequently, their production, learning routines, and performance can also be substantially different.

This paper explores how value-chain governance regimes affect the innovation and export success of Italian suppliers.[2] Our analysis is motivated by the literature on Global Value Chains (hereinafter, GVC) largely emphasizing how firms' specific mode of participation can shape their growth prospects and the degree of technological exchange across the companies involved. When the complexity of the relationship becomes too high, GVC linkages tend to depart from arms-length market transactions (see for instance Gereffi et al, 2005; Giuliani et al, 2005; Humphrey & Schmitz, 2002) and firms have to rely on coordination mechanisms other than the mere setting of prices and quantities traditionally studied in economics. In 'relational' value chains, for example, complex transactions are managed through a high level of explicit coordination between buyers and suppliers, which tends to involve more enduring relationships and important exchanges of tacit knowledge across firms. On the other hand, companies in 'modular' value chains rely on technical standards and codification to exchange complex information, which provides them with higher flexibility and reduces switching costs,

[1] For instance, Dhyne & Rubínová (2016) report that 75% of Dutch firms sell products to other companies, with an average manufacturing firm relying on 48 buyers and 60 suppliers.

[2] The term 'governance' refers to the "authority and power relationships that determine how financial, material, and human resources are allocated and flow within a chain" (Gereffi, 1994).

as well as the level of explicit coordination needed between buyers and suppliers (a detailed discussion of governance regimes is provided in Sections 2 and 4).

Importantly, such governance modes are intrinsically connected to the level of explicit coordination and power asymmetry in the value chain, as well as to suppliers' internal technological capabilities. We take advantage of this argumentation to classify governance regimes and test whether 'relational' and 'modular' value chains – those forms of participation combining the highest levels of interfirm coordination and suppliers' capability – are the ones most conducive to innovations for suppliers of intermediate products. Our hypothesis relies on the notion that firms' learning and innovativeness are fostered by environments involving rich flows of information across firms, as well as enough supplier capability to understand and make use of this knowledge. While this is true in both relational and modular value chains, information flows within the latter tend to occur in a more codified form, so that learning is more dependent on suppliers' internal efforts compared to relational GVCs (wherein direct knowledge exchanges and assistance from buyers are more common).

A first challenge in tackling this research question is related to the direct unobservability of such characteristics. We overcome this issue by taking advantage of the 2009-to-2015 waves of the MET (*Monitoraggio, Economia e Territorio*) survey, which provide unique proxies for explicit coordination and power asymmetry in the value chain, as well as for suppliers' internal technological capabilities. We capture this last dimension with the *share of employees devoted to planning, research, and innovation* in the total workforce of the firm. This measure, which is quite specific to our dataset, includes not only R&D personnel, a commonly used proxy for absorptive capacity in the literature, but also a broader set of tasks and internal skills that are necessary for a company to produce, absorb, and make use of external knowledge. Its relevance is largely analyzed in the technological capabilities literature (Bell & Pavitt, 1993; Lall, 1992) and represents an important piece of information which we deem essential in classifying value-chain governance modes.

As for explicit coordination and power asymmetry in a chain, we employ firms' *share of sales from subcontracting* over total sales – i.e., products that are made-to-order based on the specifications of a client. Suppliers of intermediates that intensively engage in selling products made under the specifications of their customers can reasonably be expected to coordinate more closely with such buyers. They are also more likely to be reliant on their customers for advanced business capabilities (e.g., design, marketing, supply, and distribution) and tend to have fewer commercial alternatives (as we discuss in Section 4). Existing evidence indicates that buyers frequently share relevant knowledge with their suppliers, allowing their subcontracted companies to achieve higher standards and improve their innovation performance. At the same time, buyers also tend to be highly restrictive in regard to the independent use of this knowledge in other activities by the supplier (Alcacer & Oxley, 2013). These relationships therefore tend to involve high levels of explicit coordination – with learning opportunities for subcontracted firms – while jointly creating significant power asymmetries between the parties involved.

Overall, value-chain governance regimes can impose constraints on the activity of suppliers or, alternatively, create significant opportunities that can dramatically affect their learning and innovativeness. In this spirit, we focus on product and process innovations as our main outcome variables throughout this paper, which is consistent with the view that innovation is the main channel for suppliers to upgrade in value chains (Morrison et al., 2008). Indeed, firms normally move into higher value-added activities, products, and sectors through improvements in their goods and processes allowing them to keep up, or even overtake, their competitors (Giuliani et al., 2005). Such improvements are rarely radical and most often constitute marginal (evolutionary) steps towards higher value-added tasks. We explicitly take this issue into account by disentangling innovations that are *only new to the firm* (marginal or imitative) from those that are instead *also new to the market* (radical innovations). We then broaden our analysis to look at the possible influence of governance on exports and sales of innovative products, which are two critical outcomes of successful innovations. Finally, we always allow the effect of governance to be mediated by the intensity of firms' engagement in the value chain as a supplier, which we proxy with its share of revenues from intermediate/semi-finished goods.[3]

Our taxonomy for governance regimes, despite admittedly being an approximation, makes an important contribution to the existing literature. Most GVC studies using firm-level survey data tend to consider only a firm's position in value chains, combined with some notion of participation depth usually obtained by identifying additional indicators for trade (exporting, importing, or both), foreign direct investments, or self-declared engagement in networks (Accetturo & Giunta, 2018; Agostino et al., 2015; Agostino et al., 2016; Giovannetti et al., 2015). The idea of governance itself is hardly considered in the literature, with only a few comparable studies credibly creating governance typologies (Agostino et al., 2020; Brancati et al., 2017; Pietrobelli & Saliola, 2007).

Our work is also related to analyses on the role of subcontracting as a source of learning in GVCs, as well as to the growing literature on suppliers of intermediate goods (Agostino et al., 2015; Alcacer & Oxley, 2013). Within this framework, our paper provides an interesting key to interpretation by connecting the lower performance of suppliers relative to firms that sell final goods – a pattern that frequently emerged in this literature – to the effects of GVC governance upon innovation.

[3] The reader should note that this is *not* the same variable as the firms' share of sales-to-order in total sales cited above. Intermediates (or final goods) produced by firms may or may not be produced under a sales-to-order regime, i.e. under the clients' strict specifications.

Our results indicate that value-chain governance regimes that combine higher explicit coordination and sufficient supplier capability are the ones most conducive to innovation for suppliers. However, unlike most of the literature within this strand of research, we provide evidence that modular forms of GVC – and not relational ones – offer the best conditions for innovation to suppliers. At the same time, we show that market-based relationships tend to be problematic for firms with low capabilities, as they combine poor internal and external sources of learning.

Finally, we show that technology gaps have an important influence within this relationship by documenting an inverse-U relationship between firm capability and learning from the value chain. In particular, the effect of supplying intermediates on innovation is found to be reduced for highly capable firms, and this reduction is even stronger in case of a high dependence on subcontracting for their sales. This idea is better known in other streams of literature, such as studies on 'technology-gap' (Dosi et al., 1990; Verspagen, 1991) and knowledge spillover (Blalock & Gertler, 2009; Girma & Gorg, 2007). Within the GVC perspective, some analyses highlighted how foreign firms may become reluctant to supply knowledge to their suppliers if the latter achieve higher levels of capability and attempt to upgrade to more sophisticated tasks (Lebdioui et al., 2020).

The reminder of the paper is as follows. Section 2 reviews the related literature and contextualizes our contribution to empirical studies of suppliers. In Section 3, we present the dataset and the main variables employed, while Section 4 sets up our governance classification. In Section 5 we outline the empirical methodology, whose results are extensively discussed in Section 6. Finally, Section 7 concludes the paper, reviews possible policy implications, and discusses some limitations of our analysis.

## 2. RELATED LITERATURE

Suppliers have been the main focus of the GVC approach since its very outset (Gereffi et al, 2005; Giuliani et al, 2005; Humphrey & Schmitz, 2002). The emphasis of this strand of research on the existence of hierarchical relationships in value chains led to the identification of a rich taxonomy of governance modes regulating and coordinating production within such interactions. Following the literature on transaction costs (Antràs & Helpman, 2004; Coase 1937; Williamson, 1985), the complexity of transactions was seen as a major factor explaining the transition from arms-length market relationships to a full integration of the production tasks. In between these two extremes, however, the GVC literature identified several governance modes, all characterized by different levels of explicit coordination and power asymmetry. Three main forms of governance generally emerge within this framework: *captive*, *relational,* and *modular* value chains. Captive and relational governances typically emerge when products are not standardized, causing transactions to become too complex to be handled through arms-length relationships and market transactions. Due to their low level of capability, captive value chains suppliers are confined to narrow tasks (such as simple assembly), while being dependent on their buyers for more sophisticated complementary activities (such as design, logistics, and innovation). On the other hand, relational value chains tend to emerge when suppliers are endowed with adequate degrees of internal capabilities. These value chains are characterized by a high level of buyer engagement in the provision of tacit and explicit knowledge to suppliers, which may be mutually beneficial due to the presence of complementary competencies between buyers and sellers. As a result, most of the GVC literature tends to consider the relational governance as the ideal environment for upgrading. Conversely, suppliers receive assistance from their buyers in captive value chains, but may be hampered by their low level of competence, as well as their financial and technological dependence on their buyers (Giuliani et al., 2005; Humphrey & Schmitz, 2002; Pietrobelli, 2008; Pietrobelli & Rabellotti, 2007).

An intermediate position is found in *modular* value chains, that emerge when transactional complexity can be codified – for example, through standards and product specifications – and suppliers are capable enough to require lower monitoring and control by the buyers. Because relationship-specific investments and explicit coordination remain low, switching costs are negligible and the firms involved can operate in an environment that is similar to market-based transactions. Modular value chains are still considered as conducive to learning and spillovers due to the high content of non-price information flowing across firms and because of the pressure exerted by buyers in terms of quality, technology, and innovation (Pietrobelli et al., 2011). However, suppliers must develop higher capabilities without the assistance from buyers that could otherwise be available in relational or captive value chains.

This framework initially spawned a prolific literature of very detailed case studies[4] and, more recently, a growing empirical research at the firm-level focusing on suppliers' performance. While this strand of research is still hampered by the difficulties in identifying suppliers and governance regimes in traditional micro-level datasets, there is widespread evidence that suppliers tend to underperform compared to producers of final goods. Such effects display, however, a large degree of heterogeneity depending on the very characteristics of the suppliers (Accetturo & Giunta, 2017; Agostino et al, 2019; Agostino et al, 2015; Agostino et al, 2016; Giunta et al, 2012; Kimura, 2002; Veugelers et al, 2013). In fact, performance disadvantages were found to be reduced or completely dissolved for more-capable firms that engage in innovation and exporting. Agostino et al. (2020) and Brancati et al. (2017) point at the role of *relational* GVCs as superior conduits for supplier learning, while Pietrobelli & Saliola (2007)

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[4] The Global Value Chains Initiative (https://globalvaluechains.org/) compiles an extensive list of case studies related to GVCs.

show that higher involvement between buyers and suppliers in design and R&D is associated with a better performance of suppliers in Thailand.

These latter studies are of particular interest because they provide a taxonomy of governance explicitly using firm-level surveys. Agostino et al. (2020) and Brancati et al. (2017) focus on Italian two-way traders and exporters of intermediates to classify GVC participants, further relying on participation in networks and involvement in product design to disentangle different governance regimes. Pietrobelli & Saliola (2007), in turn, develop a methodology that, like the one we will present in the next section, is also applicable to suppliers in local markets. They rely on a rich set of variables on interfirm relationships to classify governance modes according to the type of buyer (multinational, domestic, or exporter) and the level of its involvement in aspects such as the specification of the products sold by suppliers, the presence of technical standards, joint R&D, and technical assistance. Although our dataset does not provide the same information about specific relationships, we rely on products made according to buyer specifications as an indicator of engagement between buyers and suppliers, while simultaneously accounting for the role of supplier capability to retrieve a taxonomy of governance regimes.

Our paper is also informed by the literature on FDI spillovers, which presents several points of contact with studies on value chains when exploring learning by suppliers. Backward spillovers – i.e., spillovers that flow from foreign-owned buying firms to suppliers along the value chain – are recognized to generate positive and significant effects on productivity (see Hvranek and Irsova, 2011 for a meta-analysis of this literature). At the same time, several factors are seen to play a critical role in shaping the underlying effects in a highly non-linear way. Broad evidence suggests the importance of firms' absorptive capacities (i.e., internal resources and capabilities providing firms with the ability to learn and use external knowledge; Crespo et al., 2009; Fu et al, 2011) and technology gaps (i.e., the uneven technological mastery levels between producers and receivers of spillovers; Blalock & Gertler, 2009; Fu & Zhang, 2011; Girma, 2005; Girma & Ğrg, 2007). Our paper builds on these insights to explicitly study heterogeneities in value-chain governance regimes, and confirms that both factors influence suppliers' learning and innovation.

## 3. DATA AND MAIN VARIABLES

Before moving to the discussion of the empirical strategy, this section presents the data sources and the main variables employed in our analysis. Most of our data comes from the MET (*Monitoraggio, Economia e Territorio*) database on Italian firms. The survey contains information on research activities and innovation outcomes, including investment in R&D projects and details on the development of product and process innovations. The MET survey also asks firms about export activities, distribution of the workforce by task, and several commercial dimensions, such as the types of products sold (final goods, intermediates, and services) and earnings originated from sales-to-order activities (i.e., subcontracting). These unique characteristics differentiate it significantly from common innovation surveys and provide us with an opportunity to construct a novel approach for classifying governance modes. We make use of four waves of the survey – 2009, 2011, 2013, and 2015 – and match them with official balance-sheet information provided by CRIF-Cribis D&B (details on the sampling scheme of the MET survey are provided in Section A1 of the Online Appendix).[5] We focus on the subset of manufacturing sectors, for which the GVC theoretical framework was originally created and is still mainly applied for.[6] The final estimation sample ranges from approximately

[5] Despite two additional waves are available (2017 and 2019) we restrict our analysis to a reduced time span due to data availability about the task distribution of the workforce (which we employ in the construction of our governance modes and whose question was removed from the survey in 2017).

[6] There have been applications of the GVC governance theory to value chains in services sectors (see, for example, for IT-related analyses Keijser et al., 2021 and Lema, 2012). However, these attempts are still relatively scarce, and it remains unclear to what extent and to which areas of services the theory of value-chain governance can be applied without significant adaptations.

8,000 to about 28,000 observations, depending on the model specification. Table A in Appendix synthesizes the main variables used throughout the paper, while Table 1 presents some descriptive statistics and compares the overall sample with the merged set of observations we use for most analyses. Because we impose constraints on the availability of balance-sheet data (not available for unincorporated firms, *società di persone*), our restricted sample contains firms that are on average larger, older, and more internationalized. Although our approach controls for unobserved and observed firm heterogeneity, including size, this comparison suggests that our results are more representative of the relatively larger companies in the overall Italian population.[7]

*Table 1 – Descriptive statistics*

| | Total Sample | | | | Restricted Sample | | | |
|---|---|---|---|---|---|---|---|---|
| | N | Avg | Stdev | p50 | N | Avg | Stdev | p50 |
| PRI | 27,906 | 0.047 | 0.095 | 0.00 | 24,579 | 0.048 | 0.095 | 0.00 |
| Stor | 51,060 | 0.319 | 0.463 | 0.00 | 24,579 | 0.34 | 0.438 | 0.00 |
| Sup | 50,691 | 0.21 | 0.367 | 0.00 | 24,579 | 0.205 | 0.372 | 0.00 |
| Dep | 32,840 | 0.14 | 0.27 | 0.00 | 14,895 | 0.13 | 0.24 | 0.00 |
| MB_High | 32,835 | 0.08 | 0.27 | 0.00 | 14,895 | 0.08 | 0.26 | 0.00 |
| Prod | 51,060 | 0.3 | 0.46 | 0.00 | 24,579 | 0.3 | 0.46 | 0.00 |
| Proc | 51,060 | 0.24 | 0.43 | 0.00 | 24,579 | 0.23 | 0.42 | 0.00 |
| Rad | 51,055 | 0.28 | 0.45 | 0.00 | 24,579 | 0.28 | 0.45 | 0.00 |
| Imit | 51,055 | 0.26 | 0.44 | 0.00 | 24,579 | 0.25 | 0.44 | 0.00 |
| Ln Innov Rev | 44,821 | 3.71 | 6.33 | 0.00 | 23,375 | 3.71 | 6.46 | 0.00 |
| Exporter | 51,060 | 0.49 | 0.5 | 0.00 | 24,579 | 0.58 | 0.49 | 1.00 |
| Ln Export | 44,947 | 7.18 | 7.23 | 9.29 | 23,449 | 8.67 | 7.28 | 12.52 |
| Size | 51,060 | 2.97 | 1.31 | 2.83 | 24,579 | 3.49 | 1.14 | 3.30 |
| Age | 50,675 | 3 | 0.7 | 3.09 | 24,579 | 3.11 | 0.65 | 3.22 |
| Vertical integration | 43,900 | 0.3 | 0.26 | 0.29 | 23,282 | 0.3 | 0.22 | 0.29 |
| Group | 51,060 | 0.17 | 0.38 | 0.00 | 24,579 | 0.21 | 0.41 | 0.00 |

*Notes*: This table synthesizes the main descriptive statistics of our dataset. We present the number of observations (N), averages (Avg), standard deviations (Stdev), and medians (p50) for the entire set of companies available in the MET survey (left panel) and for the restricted sample used throughout this paper (right panel).

[7] Notice that this constraint does not induce sizable distortions for our research questions as excluded firms, typically micro-sized, are the least likely to participate in a GVC. Moreover, to the extent that smaller companies have the largest potential gains from value-chain participation, if a bias exists this is allegedly an attenuation bias for our results on the positive impulse of GVCs on firms' innovativeness. Nevertheless, we explicitly control for firms' size and fixed effects (purging any characteristic that is stable over time) which should account for most of this bias. Finally, there is no clear indication that such a sample selection shapes our findings on the heterogeneity of firms' innovativeness and performance to the specific characteristics of the governance mode.

*Stor* and *PRI* refer, respectively, to the share of sales-to-order in the total earnings of the firm and to the percentage of employees devoted to planning, research, and innovation activities (as opposed to workers employed in production, management and commercial functions). We postpone a detailed discussion of these measures in Section 4, where we advance our methodology for identifying governance regimes. The MET survey also allows for a straightforward identification of suppliers, as it asks firms about the share of revenues from the sales of semi-finished (intermediate) goods to other firms (*Sup*). Importantly, this measure allows us not only to identify the effect of being a supplier or not, but also to quantify how intensively firms engage in value chains as suppliers (as some of these firms may also sell final goods outside the value chain).

The central focus of our empirical analysis is on *innovation*. This emphasis is justified by the GVC literature regarding it as an indispensable step towards upgrading for suppliers. In fact, the innovation process is seen to be determined to a great extent by value-chain governance (Gereffi, 2019) and its outcome to be highly sensitive to the incentives and restrictions posed by the very form of participation in a GVC. In the MET survey, innovation is defined as the development of a new product, process, or the improvement of an existing one by the firm. This is akin to the concept used in the Community Innovation Surveys (CIS) and in similar questionnaires. We use product (*Prod*) and process (*Proc*) innovations as our main indicators, but we also distinguish between innovations that are new to the market (*Rad*) and new to the firm (*Imit*), which we refer to as radical and imitative innovations, respectively. In additional specifications we broaden our analysis to test for the influence of governance upon some of the possible effects of innovations. First of all, we exploit the share of sales from product innovations to analyze the performance associated to the innovation process (*Ln Innov Rev* in our notation). Moreover, we further look at export activities, that are typically significantly affected by innovations (Becker & Egger, 2013b; Caldera, 2010; Dosi et al., 2015; Brancati et al., 2021; among many others). We employ both the extensive (a dummy for exporting firms, *Exporter*) and intensive margins of export (log of exported value, *Ln Exports*) as alternative dependent variables to explore this dimension.

Finally, in most regressions we include structural controls for the log and squared log of firm age and number of employees,[8] as well as for the lagged log of vertical integration (value-added-to-revenues ratio) and for the participation of the company in a corporate group, which are frequently seen as important strategic and financial facilitators of innovation (Adelman, 1955; Armour & Teece, 1980).

In the following section, we present our classification for value-chain governance regimes. Our procedure translates the detailed and highly descriptive ideas of the GVC literature presented above into a simplified methodology applicable to a firm-level survey, with the purpose of testing the influence of governance regimes upon innovation by suppliers. Because it is impossible to exactly pin down these governance regimes on a large scale (rather than in detailed case studies) we rely on a more general approach focusing on some important features of the original theory that connect our analysis to this literature.

## 4. CAPABILITY, COORDINATION, AND GOVERNANCE REGIMES IN VALUE CHAINS

The theory of governance in GVCs, briefly summarized in Section 2, recognizes three main determinants of value-chain governance regimes: (i) the complexity of transactions, (ii) the extent to which complexity can be mitigated by codifiability and (iii) the capability of suppliers.

[8] Whereby the squared terms account for diminishing returns in firms' experience and size, respectively (Huergo & Jaumandreu, 2004; Raymond et al., 2015).

The combination of such attributes results in governance types that can be mapped out into degrees of explicit coordination and power asymmetry that are strictly increasing across modular, relational, and captive value chains (Gereffi et al., 2005). At the opposite extremes of this classification, market and hierarchical GVCs present, respectively, the lowest and highest levels of coordination and power asymmetry.

Despite the relevance of such classification for firms' activity and learning opportunities within a value chain, data availability on inter-firm relationships represents a critical limitation for the construction of an empirical counterpart. Relevant information is needed on many dimensions, including the characteristics of a firm's buyers or suppliers, their position in the value chain (suppliers or producers of final goods), their technological capabilities and the two transactional determinants of governance (complexity and codifiability of transactions). This level of granularity is hardly available in most surveys. The MET dataset makes a relevant step forward in this direction, although capturing the complexity and codifiability of transactions is still not directly possible. To overcome this drawback, we propose a classification of governance regimes that focuses on proxies for two dimensions characterizing the taxonomy: suppliers' technological capabilities and the degree of coordination and power asymmetry in the value chain. Due to its direct relationship with value chain governance modes, the latter provides a strong indication of the prevailing governance regime for suppliers. The former, in turn, offers a second piece of information that allows us to create a closer correspondence with the governance regimes proposed by Gereffi et al (2005), especially when the levels of coordination and power asymmetry in different categories are thought to be close in the GVC framework.

To proxy for capabilities, we take advantage of the share of employees devoted to planning, research, and innovation activities (*PRI*). This variable captures a broad set of skills within the firm related to the generation and management of technological change, which is an ideal indicator for our purpose. Notice that our measure does not only include R&D personnel, but also accounts for other knowledge-related functions that go over and above research activities. While this allows in general for a clearer characterization of firms' skills, it is of double importance in sectors that are not R&D-intensive, whereby simple measures of R&D are knowingly regarded as poor proxies for firm capabilities.

As an additional dimension, we employ the share of sales-to-order in the total revenues of the firm (*Stor*) as a proxy for the degree of coordination and power asymmetry in the value chain. Commercial relationships of this kind are described in the survey as "the production and sale of products made-to-order under specifications provided by the buyer", which entail a significant level of explicit coordination and signal a clear departure from simple arms-length transactions based only on prices and quantities. The higher levels of coordination and information exchange in these transactions, in turn, can create channels for suppliers to learn from their clients. However, power asymmetries between the parties may also limit the scope of action of these firms, whereby a strong control by the buyer (e.g., through strict contractual arrangements defining sanctions in case of a breach) may impose constraints on a supplier's incentives to innovate and upgrade (Alcacer & Oxley, 2013).

In our dataset, we find indication that higher levels of *Stor* are indeed associated with increasing degrees of coordination and power asymmetry in value chains. The MET survey provides information that relates even more directly to this aspect, i.e., the share of the most important buyer in total sales-to-order revenues (*Stor_MB*), which is a straightforward indicator of the level of commercial dependence of the supplier on its main made-to-order buyer. In the context of customized transactions, sales that are more concentrated to one buyer will tend to be related to higher levels explicit coordination, higher investments that are specific to the relationship, and larger switching costs. Crucially, the correlation between this variable and the share of sales to order in total revenues (*Stor*) is strong and positive (0.62), which ultimately results in a compounded effect upon the overall dependence of suppliers on a single buyer in terms of their *total* sales, as *Stor* and *Stor_MB* will tend to increase simultaneously.[9] Unfortunately, information about the main buyer (*Stor_MB*) is only available for the last two waves of the MET survey (2013 and 2015), which would greatly reduce our sample size as well as our ability to control for unobserved firm characteristics. For this reason, our main specification relies on a more general measure of subcontracting (*Stor*) allowing to track governance regimes over a longer time span. Nevertheless, we still employ *Stor_MB* in our robustness checks (Section 5.2) to reassure the reader about the consistency of our results.[10]

## 4.1 CLASSIFICATION OF GOVERNANCE REGIMES

Table 2 reports our taxonomy for governance regimes. We rely on *Stor* to position firms along the 'degrees of explicit coordination and power asymmetry' and combine it with the capability level proxied by *PRI* to pin down a broad correspondence with the original classification in Gereffi et al. (2005). While our effort makes an important contribution in the definition of an empirical counterpart that can be employed on an economy-wide scale (rather than a few case studies), it is worth reminding that we do not regard our taxonomy to perfectly classify governance regimes. Rather, we provide a detailed approximation by building on important insights from the original theory so to relate our analysis to the theoretical framework of the GVC approach.

[9] The interaction between *Stor* and *Stor_MB* identifies the share of the most important sale to order buyer in a firm's *total* sales. We employ this measure ("dependence", in our notation) in Section 5.2, where we present our robustness tests.

[10] Firms engaging in sales-to-order activities are also 56%-more likely to participate in networks, defined as "significant and ongoing relationships with other companies, entities, or institutions", especially networks for commercial purposes. Many of these networks are likely to involve closely-coordinated relationships.

*Table 2 – Classification of governance regimes*

| | | PRI: Technological Capability | | | Most likely correspondence w/ Gereffi et al (2005) |
|---|---|---|---|---|---|
| | | Low<br>PRI = 0 | Medium<br>0 < PRI ≤ 0.09 | High<br>PRI > 0.09 | |
| Stor:<br>Explicit Coordination and Power Asymmetry | Independent<br>Stor = 0 | 1<br>LC-IS | 2<br>MC-IS | 3<br>HC-IS | Market |
| | Flexible<br>0 < Stor ≤ 0.97 | 4<br>LC-FSS | 5<br>MC-FSS | 6<br>HC-FSS | Modular |
| | Specialized<br>Stor > 0.97 | 7<br>LC-SSS | 8<br>MC-SSS | 9<br>HC-SSS | Captive / Relational |

*Notes:* This table reports the construction of our taxonomy for GVC governance modes. Labels show the acronym for each group: LC, MC, and HC stand for low, medium, and high capabilities, whereas IS, FSS, and SSS stand for independent suppliers, flexible STOR Suppliers, and specialized STOR suppliers. Cutoff levels are shown under the corresponding measure employed.

In this context, Table 2 summarizes the nine categories obtained by intersecting low, medium, and high levels of our two proxies. Because of the high skewness of *PRI* and *Stor* (nil for 60% and 55% of the sample, respectively) we cannot rely on simple terciles for our classification. We start by defining *Stor* = 0 and *PRI* = 0 as the low regime for both variables, and split remaining observations in approximately equal numbers between the medium and high regimes.[11] Despite intuitive, our choice of cutoffs can be considered, to some extent, *ad hoc*. As we discuss in Section 5, we assuage concerns on the arbitrariness of our choice by testing alternative thresholds and employing threshold-regression techniques to select cutoffs in a data-driven fashion. Interestingly, our choice is very close to the thresholds that emerge from such empirical approach. We provide further details on this issue in Section A3 of the Online Appendix.

[11] Because of specificities in the respective distributions, we end up using as a second cutoff the 74th percentile for *Stor* (since 25% of the observations are concentrated at the upper bound; i.e., *Stor* = 1) and the 79th percentile for *PRI* (which provides a more equal distribution than the $80^{th}$ percentile, whose value spans up to the $84^{th}$ percentile). Details on the distribution of *Stor* and *PRI* are provided in Appendix III.

Notice that the total of nine categories outnumbers to the original taxonomy of Gereffi et al. (2005). However, this allows for exploring higher degrees of heterogeneity along both dimensions, which brings some important insights that we will explore in Section 6. We later reduce the *PRI* classes to two subgroups, resulting in six simplified governance modes with a closer correspondence with the GVC theory. A reader may also note that most of the correspondence with Gereffi et al (2005) in Table 2 appears to be determined by the degree of *Stor*. However, as we discuss in the coming paragraphs, the level of *PRI* is critical in establishing the extent to which these regimes converge/diverge from the original categorization of the GVC theory.

Before moving to an outline of our empirical methodology, it is worth briefly discussing the expected characteristics of each group. First of all, we classify categories 1-3 as Low-Capability Independent Suppliers (LC-IS), Medium-Capability Independent Suppliers (MC-IS) and High-Capability Independent Suppliers (HC-IS). Firms within these groups are suppliers of intermediates that do not rely on sales-to-order operations to sell their products (i.e., their goods are not made-to-order under buyer specifications) and operate under conditions that are similar to the market-based governance regime in the original classification of Gereffi (they are also less likely to engage in networks with other firms, as emphasized in Footnote 9). As such, their transactions are mostly governed by price mechanisms, with a reduced exchange of knowledge and extra informational inputs from their buyers. Since these firms do not appear to rely on buyer-supplier relationships to a meaningful extent, we expect the presence of sufficient internal capabilities to be especially important for their innovation performance.

Notice that low-capability firms in Category 1 (LC-IS) – as well as the ones in 4 (LC-FSS), to be discussed next – involve regimes that do not correspond to the governance categories predicted by the GVC theory. This is because, while such situations are quite frequent (Gereffi et al., 2005, p. 87; p. 101), suppliers with low capability in a context of reduced explicit coordination (likely involving low levels of complexity and high codifiability in transactions) would tend to be excluded from value chains, especially international ones. This is either due to their lower efficiency or to a higher propension for local relationships involving transactions with low technical requirements. Within this framework, we do not expect significant innovation premia from supplying intermediates, either because of the difficulty in generating and absorbing knowledge of such firms, or due to the low learning opportunities offered by value chains in this context.

In a symmetric way, we classify categories 4-6 as Low-, Medium-, and High-Capability Flexible sales-to-order (hereinafter, STOR) Suppliers (LC-FSS, MC-FSS, and HC-FSS, respectively). These companies rely on intermediate levels of sales-to-order, which means that they operate flexibly, supplying products manufactured both in autonomy and according to the clients' specifications as made-to-order goods. Their dependence on specific buyers is not high: we will see on Table 3 below that, on average, sales-to-order from the main buyer (*Stor_MB*) is around 20%, which indicates that only around 9% of their *total* revenue arises from the main subcontractor.[12] This indicates that despite engaging in sales-to-order relationships, they are likely to retain a high level of autonomy over their production decisions. They can therefore supply several clients while relying on coordination mechanisms that go beyond pure price setting and involve richer knowledge flows compared to pure market-based transactions. While low-capability firms (LC-FSS) are unlikely to benefit from such relationships, this mode of governance corresponds quite closely to modular value chains in the original classification of Gereffi et al. (2005) for firms with medium and high capabilities (MC-FSS and HC-FSS). Clearly, this argument also depends on the actual complexity of transactions or the existence

[12] This number is obtained from the group average of variable *Dependence* resulting from the interaction between *Stor_MB* and *Stor*. For this group of suppliers, the average of *Stor* is around 44% (see Table 4).

of codes and standards that could signal a high level of codifiability, about which we have no information in the dataset. Nonetheless, these firms share a high level of modularity in their operations in the sense that suppliers and customers can likely be linked and delinked easily from the value chain, while still dealing with large volumes of non-price information flowing across firms due to the necessity of specifying the characteristics of products and processes. This mode of governance, therefore, stands between arms-length and relational value chains in terms of explicit coordination and power asymmetry between buyers and supplier.

Finally, we classify firms in categories 7-9 as Low-, Medium-, and High-Capability Specialized STOR Suppliers (LC-SSS, MC-SSS, and HC-SSS, respectively). In such regimes firms operate almost exclusively as sales-to-order suppliers, which therefore indicates high levels of explicit coordination. Importantly, these suppliers are much more reliant on a few buyers, with a dependence on the main subcontractor (*Stor_MB*) of about 40%.[13] This condition provides firms with the opportunity to develop high-quality linkages with their buyers, especially in the case of highly-capable suppliers that can exploit complementary capabilities to develop innovations. At the same time, such a high dependence can represent a limiting factor if the suppliers' capabilities are low and the level of power asymmetry becomes too high. Thus, on the one hand, firms in the LC-SSS group have low skills and are likely operating in regimes like *captive* or semi-hierarchical value chains, facing strong limitations to their innovation process. On the other, MC-SSS and HC-SSS are more likely to operate under *relational* governance, creating bonds of mutual dependence with buyers within complex transactions encompassing two-way flows of knowledge in the value chain.

[13] A similar level of total revenue is obtained from the main sales-to-order buyer (*Dep* = 40%) since *Stor* is close to 100% for this group of firms.

## 5. EMPIRICAL METHODOLOGY

Our empirical analysis takes advantage of the taxonomy outlined in Section 4 to explore the effect of governance regimes onto firms' innovativeness. The baseline specification is a standard reduced-form model for the introduction of innovations, augmented with a vector of dummies for our GVC governance modes. Because firms participate in value chains to a different extent, we allow the effect of governance regimes to be mediated by the degree of involvement in a GVC, as captured by the share of sales coming from intermediate goods.[14] Our baseline model reads as follows:

$$Inov_i = \alpha_0 + \boldsymbol{\delta G_i} \times Sup_i + \alpha_1 \mathrm{PRI}_i + \alpha_2 Stor_{\mathrm{i}} + \boldsymbol{\beta}\mathbf{Z_i} + \alpha_i + \nu_t + \mu_i \qquad (1)$$

wherein $Inov_t$ is the outcome of the innovation process (in most cases a binary variable), $\mathbf{G_i}$ is the vector of nine dummy variables reflecting our classification of governance regimes, and $Sup_i$ is the share of firms' turnover realized from sales of intermediate/semi-finished products to other firms, allegedly capturing the reliance on vale chains. We also allow for a direct impact of $PRI_i$ (share of employees in design, research, and innovation) and $Stor_i$ (share of turnover from sales-to-order activities) so as to control for effects that are merely linked to such characteristics and are not related to value chain participation. Finally, $\mathbf{Z_i}$ is the vector of time-varying firm-level structural controls (degree of vertical integration, dummy for corporate group belonging, log of firms' age and size, both in levels and squared to allow for diminishing returns), while $\alpha_i$ and $\nu_t$ are, respectively, firm and time fixed effects which perfectly account for persistent unobserved heterogeneity (all firm-specific factors that do not vary over time)

[14] Clearly, firms producing final goods may be involved in value chains as well: for instance, as buyers or even as suppliers of final goods to other firms (e.g., to wholesalers or as OEMs to other industrial firms). Such companies might also develop supply relationships with other firms by selling custom-made capital goods. However, these possibilities have quite different implications in terms of governance and, since we have no further information in our dataset, we cannot make any informed speculation about governance for them.

and cyclical components or common shocks (so to purge the model from the effect of the business cycle onto innovations and GVC participation).

Our research question is mainly informed by the significance and the potential heterogeneities associated with the elements in $\boldsymbol{\delta}$. Notice that, since $Sup_i$ is a continuous interacted variable between 0 and 1, each estimate in vector $\boldsymbol{\delta}$ reflects the mediating role of governance groups upon the relationship between supplier's share of intermediate sales and their innovation performance. Although this approach is in line with our theoretical framework and hypotheses, we also show that results are consistent if one assumes the effect of governance regimes to not depend on the intensity of engagement in sales of intermediates (i.e., excluding the interaction with $Sup_i$ in Section 6.4).

Since $Inov_i$ is, in most cases, a dummy dependent variable, the natural model for Equation 1 calls for a non-linear estimator of binary choices. Nonetheless, the need to control for unobserved characteristics requires firm-level fixed effects, which for such models are generally not consistent (i.e., incidental parameters problem). We adopt a double approach and estimate Equation 1 employing both linear-probability fixed-effects models (FE-OLS; i.e., within estimator) and random-effects probit models (RE-Probit) with Mundlak correction.

The Mundlak approach consists of estimating a random-effects model augmented with the time-averages of the right-hand side variables in the equation. This allows to control for the correlation between the individual effects and the regressors, thus relaxing the unrealistic orthogonality conditions of standard random effects (Wooldridge, 2010). When presenting results for such estimators, we only report average marginal effects for simplicity of interpretation. Overall, both approaches provide results that are largely consistent.

A final issue that is worth discussing is related to the possible endogeneity arising from the simultaneity between our dependent variable and the set of regressors. In absence of appropriate instruments, one way to deal with this problem is to lag the right-hand side of the model, which imposes a time hierarchy and takes care of the simultaneity bias. In our case, however, imposing lags in the fixed effects model is not feasible because it would require an excessive reduction in the sample size due to the need of balanced observations in three consecutive waves. Nonetheless, our results remain broadly in line when we employ pooled models to allow for lagged regressors (as shown in Section 6.4).

# 6. RESULTS

## 6.1. MAIN RESULTS

Some descriptive results are presented in Table 3, whereby we synthesize the conditional distribution of several measures along our taxonomy for GVC governance regimes. First of all, Independent Suppliers (groups 1, 2, and 3) appear to be the most common typology as well as the subset grouping the largest companies in terms of employees. Importantly, such firms also tend to display the highest levels of innovativeness, together with Flexible STOR Suppliers (groups 4, 5, and 6), while Specialized STOR Suppliers (groups 7, 8, and 9) seem to be characterized by a substantially lower innovation propensity.

Such a heterogeneity is likely driven by the different environment in which firms operate. While the heterogeneity in *PRI* and *Stor* across our taxonomy is achieved by construction, column 6 clearly shows the strong correlation with *Stor_MB,* whereby higher share of turnover from of made-to-order relationships are also associated with (steeply) increasing dependence on their main buyer. This evidence further reassures about the capability of our classification to capture heterogeneous levels of explicit coordination and dependence. In our empirical exercise we explore whether behind such a heterogeneity there are some nexuses linking GVC governance regimes to the innovation performance of the firms involved.

*Table 3 – Governance regimes and conditional distributions among suppliers*

| Category | Obs (%) | PRI (%) | Sup (%) | Stor (%) | Stor_MB (%) | Prod (%) | Proc (%) | Size |
|---|---|---|---|---|---|---|---|---|
| 1 LC-IS | 25.63 | 0.00 | 70.58 | 0.00 | 0.00 | 0.18 | 0.17 | 3.45 |
| 2 MC-IS | 8.80 | 4.34 | 57.98 | 0.00 | 0.00 | 0.58 | 0.43 | 4.27 |
| 3 HC-IS | 10.12 | 17.67 | 57.26 | 0.00 | 0.00 | 0.50 | 0.40 | 3.91 |
| 4 LC-FSS | 11.28 | 0.00 | 65.79 | 44.63 | 20.75 | 0.21 | 0.23 | 3.20 |
| 5 MC-FSS | 5.75 | 4.58 | 52.51 | 43.12 | 18.55 | 0.55 | 0.45 | 3.76 |
| 6 HC-FSS | 6.54 | 17.61 | 52.45 | 45.20 | 21.45 | 0.53 | 0.43 | 3.49 |
| 7 LC-SSS | 21.18 | 0.00 | 85.63 | 99.99 | 40.35 | 0.14 | 0.17 | 3.19 |
| 8 MC-SSS | 5.27 | 4.43 | 83.47 | 99.95 | 36.01 | 0.36 | 0.41 | 3.67 |
| 9 HC-SSS | 5.45 | 17.24 | 79.35 | 99.97 | 39.52 | 0.39 | 0.37 | 3.40 |
| Overall Avg | - | 4.76 | 69.70 | 42.35 | 17.33 | 0.30 | 0.28 | 3.52 |
| Total Obs | - | 7253 | 7,253 | 7,253 | 4,972 | 7,253 | 7,253 | 7,253 |

*Notes:* This table reports the distribution of suppliers across governance regimes (in column 1) and the conditional averages for each group along the main variables employed in the analysis (columns 2-to-8). The two bottom rows display the total number of observations available for each measure in the sample and the overall averages. All variables are defined in Appendix (Table A).

Table 4 presents our baseline results from random effects Mundlak probit models (average marginal effects are reported).[15] In columns 1 and 2, we focus on the introduction of new products, that can shed light on important features of the influence of value-chain governance upon innovation for suppliers. First of all, the direct effect of *PRI* is very strong and significant, confirming a priori expectations on the role of firms' capability in absorbing and elaborating knowledge. Conversely, the effect of *Stor* is largely negative, thus pointing at overall greater difficulties in the innovation process in case of high dependence on made-to-order relationshpis. On the top of these direct effects, significant heterogeneities emerge across the different governance regimes.[16]

[15] Linear probability models have very similar results in terms of size and significance of the coefficients (see Table 9 of Appendix I).

[16] Notice that additional controls are largely insignificant because most of their effects are captured by the time-demeaning process of the Mundlak correction (i.e., the time variation is not enough to achieve significance).

Firstly, Flexible STOR Suppliers (embedded in governance regimes with intermediate levels of explicit coordination and power asymmetry) show a positive and significant effect of supplying intermediates on their innovation performance, but only if technological capabilities are at medium levels (MC-FSS). Within this group, a one-percentage-point increase in *Sup* leads to a jump in the average marginal probability of innovating that is about 0.15%-higher than firms that do not sell intermediates. Such an effect can be small for firms with low levels of *Sup*, but can result in a dramatic increase in the likelihood of innovation when intermediates represent the main type of goods produced (15%-higher probability of innovation if *Sup* is equal to 100%).

*Table 4 – Governance Regimes and Innovation*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Model | RE-Probit | RE-Probit | RE-Probit | RE-Probit | RE-Probit | RE-Probit |
| Dependent Variable | Prod | Prod | Proc | Proc | Rad | Imit |
| PRI | 0.467*** | 0.447*** | 0.281*** | 0.269*** | 0.345*** | 0.329*** |
| | (0.059) | (0.054) | (0.052) | (0.048) | (0.056) | (0.056) |
| Stor | -0.035*** | -0.032*** | -0.010 | -0.010 | -0.019 | -0.032*** |
| | (0.012) | (0.011) | (0.011) | (0.011) | (0.012) | (0.012) |
| 1 LC-IS | -0.070*** | -0.072*** | -0.044** | -0.042** | -0.064*** | -0.051** |
| | (0.021) | (0.020) | (0.021) | (0.019) | (0.022) | (0.022) |
| 2 MC-IS | 0.048 | 0.047 | 0.074** | 0.059** | 0.031 | 0.067** |
| | (0.033) | (0.030) | (0.032) | (0.029) | (0.034) | (0.033) |
| 3 HC-IS | -0.010 | -0.006 | 0.017 | 0.024 | 0.050 | -0.064* |
| | (0.033) | (0.031) | (0.031) | (0.030) | (0.035) | (0.034) |
| 4 LC-FSS | 0.023 | 0.028 | 0.052 | 0.061** | -0.020 | 0.041 |
| | (0.035) | (0.032) | (0.033) | (0.030) | (0.033) | (0.036) |
| 5 MC-FSS | 0.147*** | 0.137*** | 0.149*** | 0.142*** | 0.140*** | 0.154*** |
| | (0.043) | (0.039) | (0.045) | (0.042) | (0.047) | (0.048) |
| 6 HC-FSS | 0.044 | 0.074 | 0.130*** | 0.143*** | 0.075 | 0.170*** |
| | (0.052) | (0.047) | (0.044) | (0.042) | (0.047) | (0.047) |
| 7 LC-SSS | -0.026 | -0.024 | -0.007 | -0.001 | -0.040* | 0.006 |
| | (0.026) | (0.023) | (0.022) | (0.020) | (0.024) | (0.024) |
| 8 MC-SSS | 0.024 | 0.022 | 0.107*** | 0.095*** | 0.013 | 0.106*** |
| | (0.035) | (0.033) | (0.037) | (0.034) | (0.037) | (0.041) |
| 9 HC-SSS | 0.034 | 0.030 | 0.018 | 0.012 | 0.014 | 0.034 |
| | (0.034) | (0.032) | (0.034) | (0.032) | (0.035) | (0.034) |
| Vertical integration | 0.029 | | 0.014 | | 0.015 | -0.003 |
| | (0.030) | | (0.026) | | (0.029) | (0.026) |
| Age | -0.122 | | -0.033 | | 0.036 | -0.028 |
| | (0.093) | | (0.091) | | (0.099) | (0.092) |
| Age^2 | -0.001 | | -0.009 | | -0.034 | -0.015 |
| | (0.021) | | (0.020) | | (0.022) | (0.021) |
| Size | 0.035 | | 0.036 | | 0.022 | 0.039 |
| | (0.036) | | (0.038) | | (0.039) | (0.038) |
| Size^2 | -0.000 | | -0.001 | | 0.001 | -0.001 |
| | (0.005) | | (0.006) | | (0.006) | (0.006) |
| Group | 0.027* | | 0.015 | | 0.025 | 0.022 |
| | (0.015) | | (0.015) | | (0.016) | (0.016) |
| Observations | 24,579 | 27,697 | 24,579 | 27,697 | 24,579 | 24,579 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Mundlak Correction | Yes | Yes | Yes | Yes | Yes | Yes |
| Region FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Sector FE | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes*: marginal effects from RE-probit models with Mundlak correction. The dependent variable varies across columns and is listed in the third row (*Prod* in columns 1-2, *Proc* in columns 3-4, *Rad* in column 5, and *Imit* in column 6). All models include year, sector (2-digit), and province (NUTS3-geographical level) fixed effects. All variables are defined in Appendix (Table A). Robust standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

The associated impact is by far the largest effect among all groups,[17] indicating that governance modes that are similar to modular value chains present the most favorable environment for suppliers to innovate. This is likely to be driven by the high level of information exchange in the context of less asymmetric value-chain relationships with capable suppliers. Notice that firms' capability levels have a critical role for FSS, although not in a linear fashion. Low-Capability Flexible STOR Suppliers (LC-FSS) do not appear to have any innovation premium as their intensity of intermediate goods sales increases. Interestingly, the estimate for firms with high levels of capability (HC-FSS) is also largely insignificant (albeit positive). A similar pattern is also found for other governance regimes, as we will discuss later in this section.

Secondly, we confirm that market-based relationships combined with low supplier capabilities (LC-IS) present the least favorable environment for innovations. Amongst these firms, a one-percentage-point increase in *Sup* implies a marginal *reduction* in the probability of innovating of about 0.07% compared to firms that do not sell intermediates. Such suppliers have low internal capabilities to absorb and create knowledge, which coupled with weak external sources of learning result in significantly lower propensity to introduce innovations. Notably, higher capability levels appear to offset this negative effect, as emphasized by the insignificance of MC-IS and HC-IS.

At the same time, firms in the group of Low-Capability Specialized STOR Suppliers (LC-SSS), which we can associate to captive value chains, do not present significant effects regarding the effect of *Sup* upon innovation. This pattern, together with the ones in the following columns, emphasizes how the potential benefits of explicit coordination and exchanges of tacit knowledge within captive relationships can be severely hindered by the lack of complementary capabilities needed to absorb such knowledge and make productive use of it.

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[17] Except for HC-FSS, we confirm that the coefficients for this category in columns (1) and (2) are significantly different from all others at the 10% level.

The picture for the remaining groups is more ambiguous. Contrary to the results in columns 1 and 2, the evidence for process innovations (columns 3 and 4) seems to suggest that medium capability firms benefit from supplying intermediates in relational and market-based value chains (MC-SSS and MC-IS, respectively). In column 3, a one-percentage-point increase in *Sup* is associated with a rise in the probability to develop a new process of 0.107% for SSC-MC suppliers and of 0.074% for MC-IS suppliers. Taken together, our results suggest that the innovation benefits arising from such value chains tend to be more limited in terms of both intensity of the impact and its scope, as only process innovations associate significantly with supplying intermediates for these groups. Moreover, there seems to be a slight advantage for relational compared to market-based governance, although this difference is not statistically significant.

Once again, highly capable firms do not appear to benefit from acting as suppliers even when operating in environments where medium capabilities have, instead, positive and significant effects. This result is not obvious, but also not entirely surprising. The learning possibilities connected to supplying intermediates depend on the firm's capabilities – which explains the negative or non-significant effects found for firms without *PRI* personnel – but also on the potential for knowledge transfer of the relationship with the buyer, which relates to the technology gap between the parties involved. Suppliers with capabilities that are too high will likely acquire little knowledge from their clients while relying more on internal or other external sources of learning. In other words, the positive effect of suppliers' absorptive capacity can be offset by the increasing technological gap with their buyers, thus resulting into non-linearities in the efficacy of spillovers (i.e., an inverse-U relationship between *PRI* and firms' innovativeness). This argumentation is consistent, for example, with Girma (2005), who employs threshold-regression techniques and finds higher spillovers at medium levels of absorptive capacities. For such firms, capabilities are sufficiently high to allow for learning, and at the same time not so large to imply negative or small technology gaps that may limit the transfer of new knowledge. A somewhat related effect is documented in GVC studies reporting knowledge hold-ups, whereby firms intentionally refrain from sharing core knowledge with highly-capable subcontractors if they fear the use of this knowledge in external transactions (i.e., with third parties) may be beneficial for their competitors (Alcacer & Oxley, 2013; Lee, Szapiro, & Mao, 2018). In Section 6.3, we indirectly test this hypothesis by including, for each governance group, interaction terms between the share of sales to the main client (*Stor_MB*) and the intensity of intermediate supply (*Sup*). As we will argument below, high-capability firms are the only ones significantly harmed by main buyer concentration, which is compatible with the effects of technology gaps.

Finally, columns 5 and 6 explore firms' degree of innovativeness by distinguishing between radical (new-to-the-market) and imitative (new-to-the-firm) innovations. Broadly speaking, the patterns emerged so far are largely confirmed. Independent firms with low capabilities (LC-IS) show negative effects regarding their probability to innovate, whilst capable suppliers in modular value chains (MC-FSS and HC-FSS) present positive and significant effects in their likelihood to introduce imitative innovations. Importantly, and in accordance with our previous argumentation, only medium levels of capability are associated with significant positive effects on innovations that are also new to the market. As for the other regimes, captive value chains are associated with negative effects on radical innovations, while, as expected, imitative ones appear to be easier to obtain in comparison.

### 6.2. INNOVATION RESULTS: EXPORTS AND SALES

Previous analyses indicate that supplying intermediates can have an effect on firms' innovativeness, whose sign and magnitude depends on the nature of the governance in the value chain. In this subsection, we look at sales of innovative products and exports to analyze the impact on some of the possible outcomes of a successful innovation. As for export activity, it is worth noticing that the governance mode of a value chain may have an effect that is not only operating though firms' degree of innovativeness (which is clearly an important determinant of export market entry, as in Becker & Egger, 2013a; Caldera, 2010; among many others), but can also result from the reduction in the cost of entry foreign markets induced by interfirm relationships within the value chains (Giovannetti et al., 2015; Greenaway & Kneller, 2004, 2008; Kneller & Pisu, 2007). This may be the case, for instance, when multinationals promote their most capable local suppliers to global ones, as suggested Choquette & Meinen (2014) or Moran (2005).

Columns 1 and 2 of Table 5 present our results on the extensive margins of export (a mere dummy for export market participation). Interestingly, Medium-Capability Specialized STOR Suppliers (MC-SSS) is the only consistently positive and significant estimate: a one-percentage-point increase in the share of sales in intermediates is associated with a 0.08%-higher likelihood of exporting (reaching 8% for firms that only sell semifinished products). As for the other governance modes, High-Capability Flexible STOR Suppliers (MC-SSS) is mildly positive, while other estimates are not found to be largely insignificant. In column 2 we explicitly control for a binary variable (*International network/group*) taking unitary value for firms belonging to international corporate groups or declaring to have connections with other international firms and entities. Such a measure is meant to capture the informational component of the entry cost, whereby a foreign parent company or commercial partner may directly reduce firms' costs of acquiring information on the international destination market, thus fostering export activity. While this variable proves to be extremely significant (t-stat of around six), our main results are virtually unchanged, likely suggesting that what we are capturing is indeed linked to a more direct effect of governance.

*Table 5 – Governance regimes, export, and sales*

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Model | OLS-FE | OLS-FE | OLS-FE | OLS-FE | OLS-FE |
| Dependent Variable | Exporter | Exporter | Ln Export | Ln Export | Ln Innov Rev |
| PRI | 0.225*** | 0.216*** | 3.523*** | 3.368*** | 7.319*** |
| | (0.049) | (0.049) | (0.759) | (0.752) | (1.030) |
| Stor | -0.022** | -0.024** | -0.292* | -0.318** | -0.538*** |
| | (0.010) | (0.010) | (0.154) | (0.154) | (0.178) |
| 1 LC-IS | -0.010 | -0.010 | -0.498* | -0.487* | -1.071*** |
| | (0.017) | (0.017) | (0.270) | (0.270) | (0.280) |
| 2 MC-IS | 0.031 | 0.031 | 0.439 | 0.464 | 0.489 |
| | (0.023) | (0.024) | (0.313) | (0.314) | (0.625) |
| 3 HC-IS | 0.035 | 0.035 | 0.419 | 0.415 | -0.221 |
| | (0.025) | (0.025) | (0.404) | (0.403) | (0.603) |
| 4 LC-FSS | -0.012 | -0.011 | -0.273 | -0.261 | -0.232 |
| | (0.028) | (0.028) | (0.409) | (0.406) | (0.425) |
| 5 MC-FSS | 0.048 | 0.046 | 1.082* | 1.021 | 1.497** |
| | (0.038) | (0.038) | (0.635) | (0.629) | (0.722) |
| 6 HC-FSS | 0.060* | 0.061* | 0.393 | 0.413 | 0.818 |
| | (0.035) | (0.035) | (0.583) | (0.579) | (1.043) |
| 7 LC-SSS | 0.006 | 0.006 | -0.060 | -0.061 | -0.241 |
| | (0.018) | (0.018) | (0.281) | (0.279) | (0.270) |
| 8 MC-SSS | 0.066** | 0.065** | 0.991** | 0.961** | 0.667 |
| | (0.033) | (0.00033) | (0.489) | (0.485) | (0.536) |
| 9 HC-SSS | -0.006 | -0.004 | -0.248 | -0.222 | 0.143 |
| | (0.029) | (0.030) | (0.464) | (0.466) | (0.601) |
| International network/group | | 0.059*** | | 1.076*** | |
| | | (0.010) | | (0.164) | |
| Observations | 27,697 | 26,168 | 24,542 | 23,189 | 23,375 |
| Adj. R-squared | 0.026 | 0.029 | 0.025 | 0.029 | 0.051 |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |

*Notes*: within estimator (linear probability model) with firm and year fixed effects. The dependent variable varies across columns and is listed in the third row (*Exporter* in columns 1-2, *Ln Export* in columns 3-4, and *Ln Innov Rev* in column 5). In columns 2 and 4 we control for a dummy taking value one if the firm is part of an international corporate group or declares to have international relationships with other firms or entities. Additional controls (not reported) follow the specification in Table 4. All variables are defined in Appendix (Table A). Robust standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Columns 3 and 4 explore the effect on the extensive margins of export by looking at (log) export revenues. Results point not only at positive and significant effects for MC-SSS suppliers, but also for Medium Capability Flexible STOR Suppliers (MC-FSS). On the other hand, Low Capability Independent Suppliers (LC-IS) now present negative coefficients, albeit not always significant. Finally, in column 5 we employ the (log) sales from innovative products (*Ln Innov Rev*) as an alternative dependent variable. Our findings are largely in line with the patterns emerged for extensive margins of innovation in Table 4, indicating that supplying intermediates not only has a stronger correlation with the probability of introducing innovations for for Medium Capability Flexible STOR Suppliers (MC-FSS), but also with the successful marketing of such products.

### 6.3. ROBUSTNESS I: DEPENDENCE, TECHNOLOGY GAPS, AND ALTERNATIVE THRESHOLDS

In this subsection, we present the first set of exercises aimed at assuaging possible concerns about the robustness of our results. First, we retrieve a more straightforward proxy for firms' overall commercial dependence on their most important client. We do so by interacting *Stor* with the share of the main buyer in total sales-to-order revenues (*Stor_MB*). The resulting variable (*Dep* in our notation) is likely to be a better proxy for explicit coordination and power asymmetry in the value chain, although having the limitation of being available only in the waves of 2013 and 2015 of the MET survey (as argued above). Controlling for firm unobservable characteristics is much harder with only two waves of the sample left; nonetheless, we expect our main results to be consistent when adopting this approach.

*Table 6 – Dependence on the main buyer and alternative thresholds.*

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Model | FE-OLS | FE-OLS | FE-OLS | FE-OLS | FE-OLS | FE-OLS | FE-OLS | FE-OLS |
| Dependent Variable | Prod | Proc | Rad | Imit | Prod | Proc | Prod | Proc |
| 1 LC-IS | -0.131*** | -0.107*** | -0.166*** | -0.126*** | -0.117*** | -0.124*** | -0.067*** | -0.042** |
| | (0.040) | (0.040) | (0.041) | (0.040) | (0.043) | (0.046) | (0.018) | (0.019) |
| 2 MC-IS | 0.096 | 0.048 | 0.052 | 0.095 | 0.038 | 0.081 | 0.051 | 0.083** |
| | (0.067) | (0.068) | (0.070) | (0.066) | (0.065) | (0.067) | (0.033) | (0.033) |
| 3 HC-IS | -0.067 | 0.127 | 0.099 | -0.100 | -0.014 | 0.036 | -0.064 | -0.007 |
| | (0.075) | (0.083) | (0.077) | (0.076) | (0.118) | (0.120) | (0.050) | (0.049) |
| 4 LC-FSS | -0.026 | -0.115* | -0.069 | -0.088 | 0.073 | -0.002 | 0.017 | 0.053 |
| | (0.060) | (0.059) | (0.062) | (0.064) | (0.069) | (0.078) | (0.032) | (0.035) |
| 5 MC-FSS | 0.201*** | 0.127 | 0.041 | 0.194** | 0.090** | 0.217** | 0.142*** | 0.209*** |
| | (0.076) | (0.093) | (0.092) | (0.090) | (0.084) | (0.092) | (0.047) | (0.048) |
| 6 HC-FSS | 0.045 | 0.174** | 0.115 | 0.125 | 0.056 | 0.257* | 0.036 | 0.099 |
| | (0.084) | (0.085) | (0.081) | (0.080) | (0.137) | (0.144) | (0.087) | (0.086) |
| 7 LC-SSS | 0.090* | 0.100** | 0.048 | 0.071 | -0.034 | -0.026 | -0.017 | -0.008 |
| | (0.049) | (0.048) | (0.049) | (0.044) | (0.050) | (0.045) | (0.020) | (0.020) |
| 8 MC-SSS | -0.021 | 0.131 | -0.022 | 0.050 | 0.088 | 0.156** | 0.066** | 0.091** |
| | (0.064) | (0.085) | (0.069) | (0.076) | (0.055) | (0.071) | (0.030) | (0.037) |
| 9 HC-SSS | 0.054 | 0.116 | 0.023 | 0.075 | -0.007 | 0.073 | -0.117** | 0.002 |
| | (0.074) | (0.085) | (0.083) | (0.073) | (0.120) | (0.114) | (0.051) | (0.062) |
| 4 LC-FSSxMB_High | | | | | -0.119 | 0.049 | | |
| | | | | | (0.148) | (0.133) | | |
| 5 MC-FSSxMB_High | | | | | 0.067 | 0.285 | | |
| | | | | | (0.225) | (0.206) | | |
| 6 HC-FSSxMB_High | | | | | -0.535* | -0.966*** | | |
| | | | | | (0.315) | (0.302) | | |
| 7 LC-SSSxMB_High | | | | | 0.075 | 0.108 | | |
| | | | | | (0.083) | (0.081) | | |
| 8 MC-SSSxMB_High | | | | | -0.106 | -0.158 | | |
| | | | | | (0.099) | (0.111) | | |
| 9 HC-SSSxMB_High | | | | | -0.277* | -0.127 | | |
| | | | | | (0.168) | (0.199) | | |
| Observations | 16,664 | 16,664 | 16,664 | 16,664 | 16,664 | 16,664 | 24,579 | 24,579 |
| Adj. R-squared | 0.089 | 0.057 | 0.051 | 0.054 | 0.091 | 0.061 | 0.064 | 0.045 |
| Firm-level controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes*: within estimator (linear probability model) with firm and year fixed effects. The dependent variable varies across columns and is listed in the third row (*Prod* in columns 1, 5, and 7; *Proc* in columns 2, 6, and 8; *Rad* in column 3; *Imit* in column 4). We control for *PRI* in columns 1-to-8, *Dep* in columns 1-to-4, and *Stor* in columns 5-to-8. In columns 1-to-4, the thresholds used for *Dep* are 0 and 0.13, while for *PRI* are 0.04 and 0.10. In columns 7 and 8 we employ the thresholds obtained from threshold-regression techniques outlined in Section A3 of the Online Appendix. Additional controls follow the specification in Table 4. All variables are defined in Appendix (Table A). Robust standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Alternatively, we allow for non-linearities by interacting $Stor$ with a binary variable for firms that are heavily dependent on their main buyer: we define $MB\_high$ so to take unitary value if $Stor\_MB$ is larger than 50%, which is equivalent to the 90th percentile of its distrubition. This exercise allows for the identification of heterogeneities within each governance group for firms facing extreme dependence on their main buyer. In line with our previous argumentations, we expect more-capable firms to be especially harmed by such a heavy dependence due to the influence of technology gaps hindering the learning potential of the relationship. Conversely, lower-capability firms should exhibit some benefits from the relational proximity allowed by the higher coordination levels with their buyers.

In columns 1-to-4 we present the main results employing a more-direct proxy for dependence ($Dep$). The essential difference compared to Table 4 regards the group LC-SSS (captive suppliers), which is found to have a positive and significant impact on product and process innovations. As for the other effects, our findings appear to be largely consistent. Firstly, firms in groups MC-FSS and HC-FSS have, in all cases, better innovation performances, although MC-FSS is not significant for process innovations in this specification. Secondly, LC-IS firms present strongly negative correlations in all columns. Results for radical and imitative innovations are also in line with those of Table 4. Once again, governance regimes with medium coordination and power asymmetry, combined with intermediate or high capability levels, appear to favor the innovation performance of suppliers. In contrast, low-capability suppliers in market-based value chains tend to become less innovative with increasing intensities of intermediates supply.

In columns 5 and 6 we interact supplier intensity for each governance group with $MB\_high_{it}$.[18] Interestingly, high-capability STOR suppliers, both flexible (HC-FSS) and specialized (HC-

[18] Notice that interactions for Independent Suppliers cannot be estimated since such firms have, by definition, nil sales-to-order and therefore no dependence on any buyer.

SSS), present strong negative estimates that are significant in most cases. HC-SSS firms with a dependence on their main sales-to-order buyer above 50% face a 0.28%-lower probability to introduce product innovations for each one-percentage-point increase in the share of sales from intermediates (as compared to firms in the same group but with lower levels of dependence). The same effect is estimated at -0.54% for MC-FSS suppliers' probability to innovate in product and -0.98% to innovate in processes. The remaining interactions are not significant, indicating that medium- and low-capability firms are not affected to the same extent by increasing levels of power asymmetry in the value chain.[19] Overall, this set of results confirms that extreme dependence on buyers tend to be especially harmful to highly capable firms, which is consistent with the influence of technology gaps on learning for these relationships.

Finally, in the last two columns, we test for alternative thresholds by employing a data-driven approach to recover the cutoffs employed in our governance classification. The use of threshold-regression models (detailed in Section A3 of the Online Appendix) assuages concerns on the arbitrariness of our choice (the only difference is in the cutoff between medium and high capability firms, which is higher here, at the 88$^{th}$ percentile) and provide results that are largely consistent with the ones discussed; the only noticeable difference being the negative effects for HC-SSS firms in column 7.

## 6.4. ROBUSTNESS II: SIMULTANEITY, SIMPLIFIED GOVERNANCE, AND ALTERNATIVE GOVERNANCE VARIABLES

In this subsection we present our final set of robustness tests aimed at dealing with identification issues and at simplifying our taxonomy of GVC governance modes. First, we

[19] If we reduce the *MB_high* cutoff from 50% to 35%; i.e., classifying lower buyer concentration levels as high, we find qualitatively similar, although weaker coefficients.

account for simultaneity bias by employing lagged regressors on the right-hand side of Equation 1. While this does not allow for the inclusion of firm fixed effects (as discussed in Section 5), we performed a pooled estimation augmented with a rich set of specific fixed effects controlling for the belonging 2-digit sector and NUTS2-region (together with time fixed effects already in the specification). Our results are virtually insensitive to the change in the estimating approach, with the only noticeable difference being a stronger effect for Medium-Capability Independent Suppliers (MC-IS). Such results are hardly affected by changes in set of controls (for instance augmenting the model with lagged labor productivity or region-time and sector-time fixed effects controlling for time-varying correlated shocks).

Next, we employ a simplified governance classification by merging medium- and high-capability categories within each group, which results in a total of six new classes of governance. Clearly, results are very similar to the ones discussed above, but they have the advantage to provide a slightly clearer correspondence with the governance modes of Gereffi et al. (2005). Overall, we confirm the better performance of modular suppliers (MC-FSS/HC) as well as the sizable underperformance of low-capability independent suppliers (LC-IS). Relational and market-based suppliers (MC-SSS/HC and MC-IS/HC) present positive effects in a few cases, with a slight edge for relational value chains, whereas captive suppliers (LC-SSS) present non-significant or negative effects.

As final exercises, we either replace *Stor* with a binary variable for suppliers or present results for the subsample of suppliers only (i.e., excluding observations where *Sup* = 0 and exploring the direct effect of governance). Once again, our results are highly consistent, despite heterogeneities in the coefficients are somewhat reduced (especially between modular suppliers and the other well-performing categories). In line with our main finding, the estimates for modular suppliers remain consistently above the ones for the other categories. All of these results can be found in Section A2 of the Online Appendix.

## 7. DISCUSSION AND CONCLUSION

Extant literature has largely advocated the critical role of governance regimes in affecting suppliers' innovation and upgrading in GVCs. Value-chain leaders and buyers are seen to promote learning, innovation, and upgrading along a GVC, with beneficial effects on the performance of upstream firms. Nonetheless, several studies have also emphasized how leaders frequently prefer to confine their suppliers to simpler activities characterized by lower value-added, while retaining for themselves the more strategic and profitable positions in the value chain. In such a context, the capabilities of suppliers and their margins of diversification are crucial, as they severely affect the strategies and actions of the leaders – e.g. more capable suppliers tend to be tasked with higher-value activities – as well as the possibilities to break through to superior tasks in the same, or possibly in another, value chain.

These important insights mostly originate from a vast literature of GVC cases studies, which have not yet been largely integrated into the framework of the empirical firm-level economic literature. In this paper, we contribute to this strand of research by making use of unique variables available in the MET survey that allow us to proxy for governance modes; namely, firms' broad technological capabilities and sales-to-order revenues. We then derive a comprehensive taxonomy to uncover new findings regarding the influence of value-chain governance upon suppliers' innovation performance.

Our results suggest that supplying intermediates is associated more strongly with innovativeness when the governance of the value chain is similar to a modular governance. Under such conditions, suppliers with medium or high capabilities deal with large inflows of non-price information from clients through sales-to-order transactions, while at the same time retaining a significant level of autonomy relative to their buyers. These results for modular value chains go partially against the usual findings of the GVC literature, which tend to indicate relational forms as the most favorable environment for suppliers to learn and innovate. We indeed observe positive and significant correlations between supplying intermediates and innovation in relational value chains, but these effects are more limited and stand below the ones described for modular suppliers. Moreover, suppliers with enough capabilities tend to perform similarly in market-based value chains, which indicates the benefits of explicit coordination are non-linear, diminishing at very high levels of coordination. This dynamics can become especially prominent in the presence of a small technology gap relative to buyers, limiting learning and the innovation potential.

Consistently with the predictions of the GVC theory, market-based relationships are found to be problematic for the innovativeness of firms with low capabilities, whereby scarce internal sources of learning are combined with poor external sources. For this group, we document consistently negative correlations between supplying intermediates and firms' innovation results. At the same time, firms classified as captive suppliers present almost always insignificant coefficients, suggesting that they obtain no innovation benefit from value-chain participation, despite not performing as badly as firms in market-based relationships with equally low technological capabilities.

Finally, we show that, while the direct effect of firms' internal capacity compounds the important positive influence of governance on suppliers' innovation, the largest and most consistent results are for suppliers with medium levels rather than very high levels of capabilities. We regard this as an indication of the role of technology gaps in value-chain relationships. This is an aspect frequently ignored by the GVC literature: highly capable firms often do not benefit from supplying intermediates, indicating that opportunities for learning faced by these firms are significantly smaller. This is further confirmed by robustness results showing that highly capable firms are the ones suffering the most from high levels of dependence on their suppliers.

Our results bear some relevant policy insights. We lend support to value chain policies that attempt to promote engagement, coordination, and knowledge transfer between firms, including policies focused on promoting spillovers from foreign direct investments. This potential, however, does not appear to be fully realized when firms do not preserve a level of strategic independence and the capacity to relate independently with many clients. In this context, expanding and diversifying the markets for these firms appears to be a promising area for policy action, that should foster not only the technological but also the commercial capabilities of local suppliers. Nonetheless, our results concur with most of the GVC literature in pointing at the importance of technological capabilities in the creation of opportunities for suppliers. Finally, although our study did not look at national and regional characteristics and at the innovation systems in place, these features are known to play an important role in the facilitation of knowledge exchanges between companies and in supporting the development of capabilities. Therefore, they are also likely to influence the relationship between the governance of the value chain and suppliers' innovation and learning.

Lastly, it is worth warning again the reader that our framework is unable to clearly identify causality nexuses and, as such, results should be taken with a grain of salt. Nevertheless, we trust this work may help advancing a promising area for future empirical GVC studies based on firm-level datasets.

## APPENDIX: VARIABLE DEFINITION

*Table A – Definition of the main variables*

| Name | Definition | Type |
|---|---|---|
| Sup | Share of sales from intermediates in total revenues | Bounded: (0-1) |
| Stor | Share of sales-to-order in total revenues | Bounded: (0-1) |
| Stor_MB | Share of sales-to-order from the main buyer | Bounded: (0-1) |
| MB_high | High dependence on the main buyer (Stor_MB>50%) | Binary |
| PRI | Share of employees devoted to planning, research, and innovation | Bounded: (0-1) |
| Prod | Introduction of product innovation | Binary |
| Proc | Introduction of process innovation | Binary |
| Rad | Introduction of radical innovation (new to the market) | Binary |
| Imit | Introduction of imitative innovation (new to the firm) | Binary |
| Ln Innov Rev | Log of 1 + revenues from product innovations | Continuous |
| Export | Exporting company | Binary |
| Ln Export | Log of 1 + exported sales | Continuous |
| Age | Log of 1+ age | Continuous |
| Size | Log of 1+ employees | Continuous |
| Vertical Intergration | Log of value-added-to-sales ratio | Continuous |
| Group | Corporate group belonging | Binary |

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# The Influence of Value-Chain Governance on Innovation Performance: A Study of Italian Suppliers

## Online Appendix

### A1. SAMPLING OF THE MET SURVEY

The MET survey is the widest private survey administrated in a single European country and it is specifically conceived to study Italian firms' characteristics and strategies, with particular attention to their innovation behavior, internationalization processes, and performance.

The original sample comprises five waves -- 2008, 2009, 2011, 2013, and 2015-- and roughly 24,000 firm-level observations in each cross-section. The sample follows a disproportionate Bayesian scheme and its large sample size allows for a representativeness along three different dimensions: four size classes, 12 2-digit sectors, and 20 geographical regions (at the NUTS2 level).

The population of interest of the MET survey refers to enterprises belonging to all the size classes (1-9 employees, 10-49, 50-249, 250 and above) operating within the manufacturing (construction excluded) and production services sectors.[20]

Starting from the 2009-wave, the disproportionate sampling scheme employs Bayesian techniques so to increase the precision of the estimates regarding R&D, innovation, and internationalization strategies, which are the core of the survey. Exploiting information from the previous waves, these techniques draw on a tree-based classification model to detect those

[20] The sampling design follows 12 aggregated 2-digit sectors: Food, Textile, Furniture, Printing and Publishing, Chemical, Machinery, Transportation, Engineering, Electric, and Mineral, for the manufacturing sector, and two production service sectors for distributive trades, transportation, and storage services, or information, communication services, administrative and support service activities.

strata (intersection of 20 regions, 12 2-digit sectors, and four size classes) with the larger diffusion of such relevant activities. This procedure allows for a better understanding of the phenomena under study.

## A2. ADDITIONAL ANALYSES

*Table A1 – Governance regimes and innovation: linear probability models*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Model | FE-OLS | FE-OLS | FE-OLS | FE-OLS | FE-OLS | FE-OLS |
| Dependent Variable | Prod | Prod | Proc | Proc | Rad | Imit |
| PRI | 0.560*** | 0.545*** | 0.338*** | 0.331*** | 0.418*** | 0.400*** |
| | (0.066) | (0.062) | (0.060) | (0.056) | (0.065) | (0.066) |
| Stor | -0.037*** | -0.037*** | -0.011 | -0.014 | -0.018 | -0.032*** |
| | (0.012) | (0.011) | (0.011) | (0.010) | (0.012) | (0.011) |
| 1 LC-IS | -0.067*** | -0.067*** | -0.041** | -0.038** | -0.060*** | -0.047** |
| | (0.018) | (0.017) | (0.019) | (0.018) | (0.020) | (0.019) |
| 2 MC-IS | 0.059 | 0.061* | 0.093** | 0.078** | 0.039 | 0.086** |
| | (0.039) | (0.035) | (0.041) | (0.037) | (0.040) | (0.042) |
| 3 HC-IS | -0.016 | -0.012 | 0.021 | 0.030 | 0.053 | -0.077* |
| | (0.039) | (0.037) | (0.038) | (0.037) | (0.040) | (0.041) |
| 4 LC-FSS | 0.015 | 0.022 | 0.050 | 0.061* | -0.023 | 0.036 |
| | (0.032) | (0.029) | (0.035) | (0.031) | (0.031) | (0.035) |
| 5 MC-FSS | 0.169*** | 0.162*** | 0.189*** | 0.182*** | 0.165*** | 0.186*** |
| | (0.050) | (0.045) | (0.059) | (0.055) | (0.058) | (0.059) |
| 6 HC-FSS | 0.062 | 0.104* | 0.178*** | 0.202*** | 0.093 | 0.214*** |
| | (0.065) | (0.060) | (0.057) | (0.054) | (0.058) | (0.057) |
| 7 LC-SSS | -0.019 | -0.013 | -0.008 | 0.000 | -0.035* | 0.004 |
| | (0.020) | (0.018) | (0.020) | (0.018) | (0.021) | (0.020) |
| 8 MC-SSS | 0.026 | 0.031 | 0.135*** | 0.128*** | 0.017 | 0.122** |
| | (0.037) | (0.035) | (0.046) | (0.043) | (0.041) | (0.049) |
| 9 HC-SSS | 0.021 | 0.021 | 0.016 | 0.013 | 0.006 | 0.022 |
| | (0.037) | (0.035) | (0.042) | (0.039) | (0.039) | (0.039) |
| Observations | 24,579 | 27,697 | 24,579 | 27,697 | 24,579 | 24,579 |
| R-squared | 0.063 | 0.061 | 0.045 | 0.041 | 0.034 | 0.045 |
| Firm-level controls | Yes | No | Yes | No | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes*: within estimator (linear probability model) with firm and year fixed effects. The dependent variable varies across columns and is listed in the third row (*Prod* in columns 1-2, *Proc* in columns 3-4, *Rad* in column 5, and *Imit* in column 6). Additional controls (not reported) follow the specification in Table 4. All variables are defined in Appendix (Table A). Robust standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

*Table A2 – Accounting for simultaneity bias*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Model | OLS | OLS | OLS | OLS | OLS | OLS |
| Dependent Variable | Prod | Prod | Proc | Proc | Rad | Imit |
| PRI | 0.435*** | 0.493*** | 0.257*** | 0.316*** | 0.398*** | 0.346*** |
| | (0.052) | (0.052) | (0.049) | (0.049) | (0.052) | (0.050) |
| Stor | -0.050*** | -0.059*** | -0.019* | -0.025** | -0.037*** | -0.023** |
| | (0.012) | (0.011) | (0.011) | (0.010) | (0.011) | (0.011) |
| 1 LC-IS | -0.105*** | -0.100*** | -0.043** | -0.039** | -0.059*** | -0.056*** |
| | (0.020) | (0.019) | (0.019) | (0.019) | (0.020) | (0.020) |
| 2 MC-IS | 0.125*** | 0.141*** | 0.141*** | 0.165*** | 0.043 | 0.123*** |
| | (0.041) | (0.038) | (0.043) | (0.039) | (0.041) | (0.042) |
| 3 HC-IS | -0.012 | 0.002 | 0.012 | 0.039 | -0.048 | 0.044 |
| | (0.036) | (0.036) | (0.037) | (0.036) | (0.036) | (0.037) |
| 4 LC-FSS | -0.056* | -0.078** | 0.032 | 0.002 | -0.042 | 0.008 |
| | (0.032) | (0.030) | (0.032) | (0.030) | (0.031) | (0.032) |
| 5 MC-FSS | 0.159*** | 0.175*** | 0.141*** | 0.175*** | 0.097* | 0.164*** |
| | (0.050) | (0.051) | (0.050) | (0.050) | (0.051) | (0.050) |
| 6 HC-FSS | 0.086 | 0.062 | 0.171*** | 0.154*** | 0.056 | 0.067 |
| | (0.054) | (0.051) | (0.051) | (0.048) | (0.055) | (0.052) |
| 7 LC-SSS | -0.085*** | -0.095*** | 0.019 | 0.003 | -0.023 | -0.026 |
| | (0.020) | (0.020) | (0.020) | (0.019) | (0.021) | (0.020) |
| 8 MC-SSS | 0.036 | 0.037 | 0.092** | 0.090** | 0.013 | 0.110*** |
| | (0.042) | (0.041) | (0.040) | (0.038) | (0.042) | (0.041) |
| 9 HC-SSS | -0.031 | -0.046 | 0.032 | 0.046 | 0.015 | -0.020 |
| | (0.043) | (0.043) | (0.042) | (0.041) | (0.044) | (0.041) |
| Observations | 11,358 | 12,480 | 11,358 | 12,480 | 11,358 | 11,358 |
| R-squared | 0.138 | 0.121 | 0.116 | 0.095 | 0.105 | 0.112 |
| Firm-level controls | Yes | No | Yes | No | Yes | Yes |
| Region FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Sector FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes*: pooled linear probability model with year fixed effects. The dependent variable varies across columns and is listed in the third row (*Prod* in columns 1-2, *Proc* in columns 3-4, *Rad* in column 5, and *Imit* in column 6). All regressors are lagged once to account for simultaneity bias. Additional controls (not reported) follow the specification in Table 4 (but are also lagged). All variables are defined in Appendix (Table A). Robust standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

*Table A3 – Simplified governance regimes*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Model | FE-OLS | FE-OLS | FE-OLS | FE-OLS | FE-OLS | FE-OLS |
| Dependent Variable | Prod | Prod | Proc | Proc | Rad | Imit |
| PRI | 0.541*** | 0.530*** | 0.314*** | 0.314*** | 0.413*** | 0.370*** |
| | (0.065) | (0.060) | (0.060) | (0.055) | (0.064) | (0.065) |
| Stor | -0.037*** | -0.038*** | -0.011 | -0.014 | -0.018 | -0.032*** |
| | (0.012) | (0.011) | (0.011) | (0.010) | (0.012) | (0.011) |
| 1 LC-IS | -0.069*** | -0.069*** | -0.043** | -0.040** | -0.060*** | -0.050*** |
| | (0.018) | (0.017) | (0.019) | (0.018) | (0.020) | (0.019) |
| 2 MC-IS/HC | 0.022 | 0.026 | 0.059** | 0.056** | 0.046 | 0.007 |
| | (0.027) | (0.025) | (0.029) | (0.027) | (0.029) | (0.030) |
| 4 LC-FSS | 0.013 | 0.021 | 0.049 | 0.061** | -0.024 | 0.036 |
| | (0.032) | (0.029) | (0.034) | (0.031) | (0.031) | (0.035) |
| 5 MC-FSS/HC | 0.116*** | 0.132*** | 0.183*** | 0.192*** | 0.129*** | 0.199*** |
| | (0.042) | (0.038) | (0.042) | (0.040) | (0.043) | (0.041) |
| 7 LC-SSS | -0.020 | -0.014 | -0.010 | -0.001 | -0.035* | 0.002 |
| | (0.020) | (0.018) | (0.020) | (0.018) | (0.021) | (0.020) |
| 8 MC-SSS/HC | 0.026 | 0.027 | 0.073** | 0.069** | 0.012 | 0.070** |
| | (0.028) | (0.026) | (0.032) | (0.030) | (0.030) | (0.033) |
| Observations | 24,579 | 27,697 | 24,579 | 27,697 | 24,579 | 24,579 |
| R-squared | 0.063 | 0.058 | 0.044 | 0.041 | 0.034 | 0.043 |
| Number of groups | 16,195 | 17,924 | 16,195 | 17,924 | 16,195 | 16,195 |
| Firm-level controls | Yes | No | Yes | No | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes:* within estimator (linear probability model) with firm and year fixed effects. This table reports results based on a simplification of our nine governance regimes that is closer to the one in Gereffi et al. (2005), as discussed in Section 6.4. The dependent variable varies across columns and is listed in the third row (*Prod* in columns 1-2, *Proc* in columns 3-4, *Rad* in column 5, and *Imit* in column 6). Additional controls (not reported) follow the specification in Table 4. All variables are defined in Appendix (Table A). Robust standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

*Table A4 – Employing a dummy for suppliers*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Model | RE-Probit | RE-Probit | RE-Probit | RE-Probit | RE-Probit | RE-Probit |
| Dependent Variable | Prod | Prod | Proc | Proc | Rad | Imit |
| PRI | 0.540*** | 0.521*** | 0.312*** | 0.307*** | 0.409*** | 0.373*** |
| | -0.065 | (0.061) | (0.059) | (0.055) | (0.064) | (0.065) |
| Stor | -0.029** | -0.030*** | -0.006 | -0.008 | -0.013 | -0.025** |
| | (0.012) | (0.011) | (0.011) | (0.010) | (0.012) | (0.012) |
| 1 LC-IS | -0.054*** | -0.056*** | -0.024 | -0.022 | -0.044*** | -0.031** |
| | (0.015) | (0.013) | (0.015) | (0.013) | (0.016) | (0.015) |
| 2 MC-IS | 0.103*** | 0.107*** | 0.088*** | 0.085*** | 0.060** | 0.125*** |
| | (0.028) | (0.026) | (0.028) | (0.026) | (0.028) | (0.030) |
| 3 HC-IS | 0.003 | 0.007 | 0.053* | 0.060** | 0.024 | 0.009 |
| | (0.027) | (0.026) | (0.028) | (0.027) | (0.030) | (0.030) |
| 4 LC-FSS | -0.000 | 0.010 | 0.034 | 0.038* | -0.014 | 0.030 |
| | (0.023) | (0.021) | (0.025) | (0.023) | (0.023) | (0.025) |
| 5 MC-FSS | 0.131*** | 0.140*** | 0.190*** | 0.178*** | 0.121*** | 0.184*** |
| | (0.035) | (0.033) | (0.037) | (0.035) | (0.040) | (0.038) |
| 6 HC-FSS | 0.041 | 0.064* | 0.095*** | 0.111*** | 0.056 | 0.116*** |
| | (0.039) | (0.037) | (0.035) | (0.033) | (0.035) | (0.037) |
| 7 LC-SSS | -0.024 | -0.018 | -0.007 | 0.000 | -0.040** | 0.011 |
| | (0.018) | (0.016) | (0.017) | (0.015) | (0.019) | (0.018) |
| 8 MC-SSS | -0.005 | 0.009 | 0.102** | 0.095** | 0.004 | 0.092** |
| | (0.034) | (0.031) | (0.040) | (0.037) | (0.037) | (0.041) |
| 9 HC-SSS | 0.016 | 0.018 | 0.040 | 0.033 | 0.014 | 0.039 |
| | (0.032) | (0.031) | (0.037) | (0.034) | (0.035) | (0.034) |
| Observations | 24,767 | 27,906 | 24,767 | 27,906 | 24,767 | 24,767 |
| R-squared | 0.064 | 0.061 | 0.046 | 0.041 | 0.034 | 0.046 |
| Firm-level controls | Yes | No | Yes | No | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes*: marginal effects from RE-probit models with Mundlak correction. The dependent variable varies across columns and is listed in the third row (*Prod* in columns 1-2, *Proc* in columns 3-4, *Rad* in column 5, and *Imit* in column 6). This table replicates Table 4, using a dummy for suppliers as an interacting variable with the governance regimes (rather than *Sup*). Additional controls (not reported) follow the specification in Table 4. All variables are defined in Appendix (Table A). Robust standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

*Table A5 – Main results for suppliers only*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Model | RE-Probit | RE-Probit | RE-Probit | RE-Probit | RE-Probit | RE-Probit |
| Dependent Variable | Prod | Prod | Proc | Proc | Rad | Imit |
| PRI | -0.156 | -0.217 | -0.16 | -0.194 | -0.284 | 0.136 |
| | (0.278) | (0.246) | (0.270) | (0.237) | (0.279) | (0.285) |
| Stor | -0.019 | -0.028 | 0.069 | 0.073 | 0.09 | -0.111 |
| | (0.100) | (0.094) | (0.101) | (0.094) | (0.096) | (0.097) |
| 2 MC-IS | 0.200*** | 0.200*** | 0.123** | 0.106** | 0.122** | 0.165*** |
| | (0.050) | (0.045) | (0.053) | (0.049) | (0.053) | (0.052) |
| 3 HC-IS | 0.138 | 0.146** | 0.142* | 0.145** | 0.213*** | 0.024 |
| | (0.074) | (0.066) | (0.074) | (0.068) | (0.075) | (0.079) |
| 4 LC-FSS | 0.055 | 0.058 | 0.033 | 0.032 | -0.022 | 0.106 |
| | (0.062) | (0.058) | (0.069) | (0.063) | (0.066) | (0.065) |
| 5 MC-FSS | 0.229*** | 0.232*** | 0.235*** | 0.215*** | 0.227*** | 0.238*** |
| | (0.072) | (0.065) | (0.074) | (0.068) | (0.072) | (0.075) |
| 6 HC-FSS | 0.206** | 0.227*** | 0.170** | 0.192** | 0.190** | 0.221** |
| | (0.083) | (0.078) | (0.084) | (0.078) | (0.083) | (0.091) |
| 7 LC-SSS | 0.009 | 0.014 | -0.080 | -0.083 | -0.137 | 0.117 |
| | (0.104) | (0.097) | (0.107) | (0.098) | (0.102) | (0.102) |
| 8 MC-SSS | 0.064 | 0.083 | 0.079 | 0.067 | -0.041 | 0.207* |
| | (0.111) | (0.104) | (0.121) | (0.112) | (0.113) | (0.118) |
| 9 HC-SSS | 0.143 | 0.160 | 0.029 | 0.012 | 0.054 | 0.177 |
| | (0.114) | (0.107) | (0.124) | (0.114) | (0.117) | (0.123) |
| Observations | 7,253 | 8,102 | 7,253 | 8,102 | 7,253 | 7,253 |
| R-squared | 0.085 | 0.071 | 0.082 | 0.072 | 0.065 | 0.086 |
| Firm-level controls | Yes | No | Yes | No | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes*: marginal effects from RE-probit models with Mundlak correction. This table replicates results in Table 4 by focusing on the subset of suppliers only. The dependent variable varies across columns and is listed in the third row (*Prod* in columns 1-2, *Proc* in columns 3-4, *Rad* in column 5, and *Imit* in column 6). This table replicates Additional controls (not reported) follow the specification in Table 4. All variables are defined in Appendix (Table A). Robust standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

*Figure A1 – Distribution of PRI*

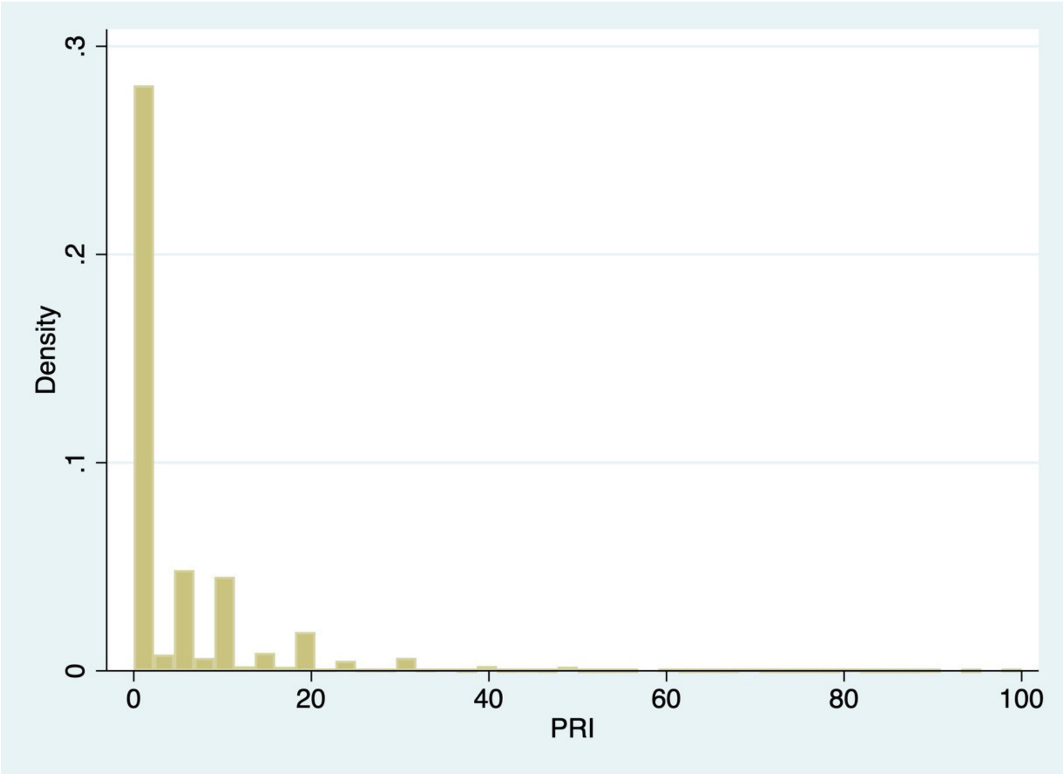
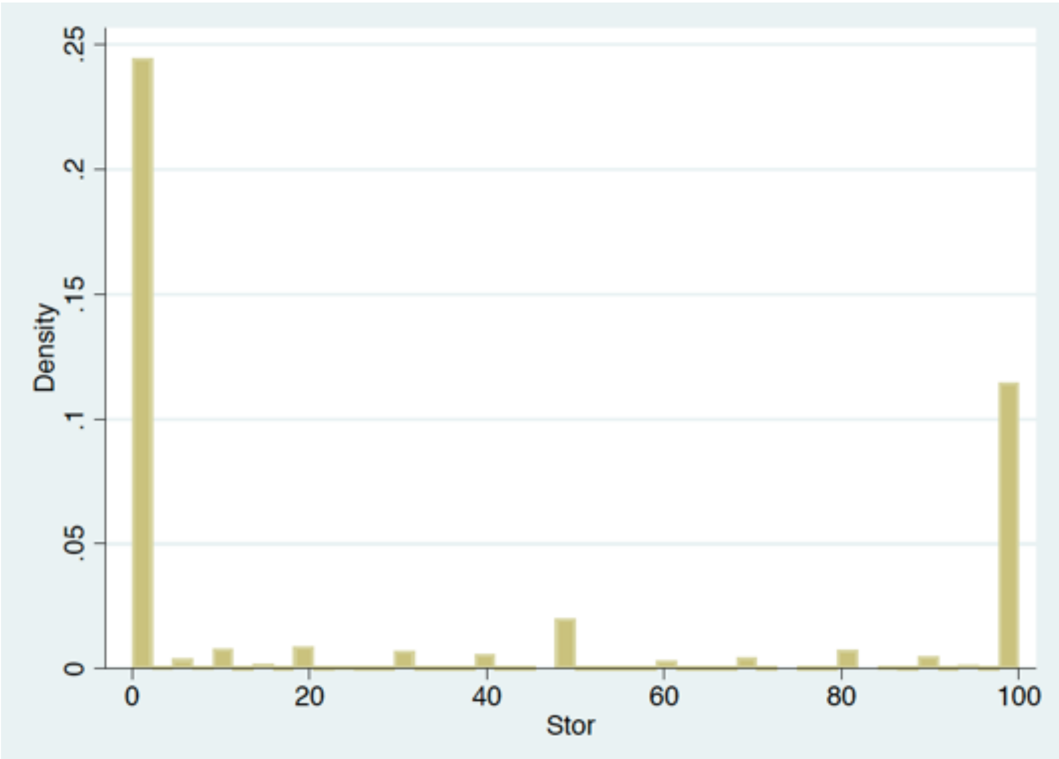



*Figure A2 – Distribution of Stor*



## A3. THRESHOLD PROCEDURE

In this section, we briefly explain our procedure to estimate the cutoffs that identify governance regimes by using a threshold regression method. We closely follow the procedures described by Hansen (1999) and start by estimating the model with a single threshold as follows:

$$Innov_i = \delta_1\, Sup_i\, I(X_i \leq \lambda_1) + \delta_2\, Sup_i\, I(X_i > \lambda_1) + \alpha_1 PRI_i + \alpha_2 \mathrm{Stor_i} + \; + \boldsymbol{\beta}\mathbf{Z_i} + \\ + \alpha_i + \nu_t + \mu_i \qquad \text{(A.1)}$$

wherein $Innov_i$ is a binary innovation variable, either product or process innovation, $Sup_i$ is the variable for which we allow non-linear effects, $X_i$ is the threshold variable that determines governance regimes (either $PRI_i$ or $Stor_i$), $Stor_i$ is the share of firms' turnover from sales to order, $PRI_i$ is the share of employment in planning, research, and innovation, $I$ is a binary variable taking value of one if the condition between parentheses is satisfied for that observation, $\mathbf{Z_i}$ is the vector of controls, while $\alpha_i$ and $\nu_t$ are firm and time fixed effects. The effect of $Sub_i$ on $Innov_i$ is given by coefficients $\delta_1$ when $X_i$ is not above the first threshold $\lambda_1$. When $X_i$ is above $\lambda_1$, this effect is given by the coefficient $\delta_2$.

We estimate $\lambda_1$ by least squares, which involves: (i) estimating equation (A.1) for distinct values of $\lambda_1$; and (ii) obtaining an estimate of $\hat{\lambda}_1$by selecting the value of $\lambda_1$ that minimizes the sum of squared errors obtained from the regressions in step (i). We limit our search to values of $Sup_i$ below 100%, and define a minimum range of 10% for each regime, i.e. each estimated regime must include at least 10% of observations within the estimation interval. Once we obtain $\hat{\lambda}_1$, estimation of $\hat{\lambda}_2$, the second threshold, is obtained by the same procedure, i.e. choosing the values of $\lambda_1$ and $\lambda_2$ that minimize the sum of squared errors of the following equation:

$$Innov_i = \delta_1\, Sup_i\, I(X_i \leq \lambda_1) + \delta_2\, Sup_i\, I(\lambda_1 < X_i \leq \lambda_2) + \delta_3\, Sup_i\, I(X_i > \lambda_2) + \alpha_1 PRI_i + \\ \alpha_2 \mathrm{Stor_i} + \boldsymbol{\beta}\mathbf{Z_i} + \alpha_i + \nu_t + \mu_{it} \qquad \text{(A.2)}$$

Since this is computationally demanding, we follow a sequential procedure, i.e. we fix $\hat{\lambda}_1$ while searching for $\hat{\lambda}_2$ according to steps (i) and (ii) above. Adopting this approach, $\hat{\lambda}_2$ is efficient but $\hat{\lambda}_1$ is not. We therefore follow Hansen (1999) and take a third step, namely: (iii) fix $\hat{\lambda}_2$ to search once again for the first threshold, which we call $\hat{\lambda}_1{}^r$.

At each step we estimate the significance of the threshold we obtain. To do this, it is necessary to follow a bootstrap procedure since under the null hypothesis – $H_0: \delta_1 = \delta_2$ for (A.1) or $H_0: \delta_2 = \delta_3$ for (A.2) – the threshold is not identified and the test has a non-standard distribution. We follow once again the approach of Hansen (1999) and bootstrap to simulate the distribution of the likelihood ratio ($F_1$) test and obtain a p-value for the test. The likelihood ratio test is given by the following equation:

$$F_1 = n(t-1)\frac{S_0 - S_1}{S_1}$$

Where $S_0$ and $S_1$ are the residual sum of squares under the null and alternative hypotheses, respectively. The bootstrap is created by drawing from the distribution of the residuals of the estimated threshold model and repeating 100 times. The p-value is the number of times the simulated $F_1$ is above the actual one and we adopt a 5% level of significance for rejecting the null.

These procedures are done separately and independently for the two threshold variables ($PRI_i$ and $Stor_i$). Results are presented in Table A6. In columns 1-to-3 we report the results using product innovation ($Prod$) as the dependent variable and in columns 4-to-6 the results for process innovation ($Proc$). Columns 1 and 4 report models without thresholds for comparison, while the remaining columns show results for the estimation of equation (A.1). In columns 2 and 4, we observe that the model finds in both cases (for both *Prod* and *Proc* as dependent variables) two thresholds, both significant at 5% and at the same percentiles of *Stor*. In the case of *PRI*, columns 3 and 6 show diverging thresholds for the second higher cutoff, at p84 and p89, both above the level we use in the main text. We depict results for p84 in the main text, although results using p89 as a second thresholds for *PRI* are also compatible (not depicted).

*Table A6 – Threshold-regression techniques*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Model | FE-OLS | FE-OLS | FE-OLS | FE-OLS | FE-OLS | FE-OLS |
| Dependent Variable | Prod | Prod | Prod | Proc | Proc | Proc |
| Threshold Variable | - | Stor | PRI | - | Stor | PRI |
| Thresholds | None | 2 | 2 | None | 2 | 2 |
| PRI | 0.592*** | 0.585*** | 0.589*** | 0.381*** | 0.373*** | 0.353*** |
| | (0.063) | (0.063) | (0.067) | (0.058) | -0.058 | (0.061) |
| Stor | -0.028*** | -0.037*** | -0.030*** | -0.003 | -0.01 | -0.005 |
| | (0.011) | (0.012) | (0.011) | (0.010) | -0.011 | (0.010) |
| Sup | -0.008 | | | 0.022* | | |
| | (0.012) | | | (0.012) | | |
| Stor/PRI Low Regime | | -0.036** | -0.035** | | -0.006 | -0.014 |
| | | (0.016) | (0.014) | | -0.017 | (0.014) |
| Stor/PRI Medium Regime | | 0.058** | 0.074*** | | 0.107*** | 0.112*** |
| | | (0.027) | (0.022) | | -0.027 | (0.024) |
| Stor/PRI High Regime | | -0.003 | -0.063* | | 0.02 | 0.003 |
| | | (0.017) | (0.037) | | -0.018 | (0.038) |
| First Threshold Value | - | 0 | 0 | - | 0 | 0 |
| First Threshold Percentile | - | 55 | 60 | - | 55 | 60 |
| First Threshold P-value | - | 0.01 | 0 | - | 0 | 0 |
| Second Threshold Value | - | 0.97 | 0.10 | - | 0.97 | 14 |
| Second Threshold Percentile | - | 74 | 84 | - | 74 | 89 |
| Second Threshold P-value | - | 0.04 | 0 | - | 0.01 | 0 |
| Observations | 24,579 | 24,579 | 24,579 | 24,579 | 24,579 | 24,579 |
| Adj. R-squared | 0.061 | 0.061 | 0.061 | 0.039 | 0.041 | 0.043 |
| Firm-level controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes:* within estimator (linear probability model) with firm and year fixed effects. Column 1 reports the baseline regression of *Prod* on *PRI* and *Stor* (in addition to *Sup* and the other controls of Table 4). Column 2 and 3 present results of the threshold-regression techniques (outlined in Section A3) defining three regimes for *Stor* and *PRI*, respectively, as well as their associated effect on the dependent variable. Values and percentiles of the optimal cutoffs (two for each measure) are also reported. Columns 4, 5, and 6 report the symmetric analyses when using *Proc* as an alternative dependent variable. All measures are defined in Appendix (Table A). Robust standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.