

Positioning firms along the capabilities ladder

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Abstract

A major challenge for innovation scholars is the measurement of capabilities. We develop and apply a novel methodology for quantifying the capability development of firms, where capabilities are measured in terms of expenditures on certain activities. These activities can be sorted in a hierarchy of increasing difficulty, and firms can be sorted according to their positions on the capabilities ladder. Our nestedness algorithm, inspired by biology and network science, defines an activity as complex if it is performed by only a few firms at the upper rungs of the ladder. We analyze balance sheet and innovation data of almost 45'000 Indian firms for the time period 2000-2020, and observe significant nestedness. Lower rungs of the capabilities ladder correspond to basic managerial and production activities. Mid-level rungs correspond to internationalization and acquiring absorptive capacity. Higher level rungs are more related to M&A and innovation. ICT capabilities seem to have become more fundamental lower-level rungs on the capabilities ladder in recent years. We find that capability ranking can explain future growth patterns and survival probability of firms, summing up in one number their future potential trajectories.

Keywords: Capabilities, Competences, Complexity, Balance sheet data, Resources

JEL codes: L2, D2, O12

1 Introduction

Given the importance of capabilities for learning, knowledge transfer, and product and process innovation, capabilities have been a central concern of innovation scholars (Archibugi

and Coco, 2005; Hobday and Rush, 2007; Dosi et al., 2020). However, despite theoretical interest, empirical work in this area has been held back by measurement issues, and difficulties in operationalizing the capabilities construct at the firm-level (Costa et al., 2021). This was emphasized in a recent literature review on capabilities: “Organizational capability is a central construct in theories of competitive advantage, strategic choice, firm boundaries, learning and adaptation, and technological change. Yet, if organizational capabilities are to fulfill their potential to illuminate these phenomena, there is an urgent need to surmount the problems of identification and measurement that continue to impede empirical research.” (Grant and Verona, 2015, p.72).

This article therefore seeks to contribute to the measurement of capabilities. Research into capability measurement faces (at least) two major challenges, however. A first challenge relates to how capabilities are operationalized and linked to real-world phenomena. The lack of precision and specificity with which capabilities are identified in some studies is a problem for knowledge accumulation and subsequent theory-building (Grant and Verona, 2015, p.66). Failure to connect abstract constructs like “capabilities” and “resources” to real-world phenomena risks leading to tautological statements (Arend, 2006), for example if (unobserved) valuable capabilities are invoked to explain the performance of successful firms. We address this concern by complementing the existing literature with a new approach that uses objective data on firms’ reported expenditures.

A second challenge relates to how these capabilities can be arranged (ideally, in quantitative terms) into a hierarchy, such that a distinction can be made between advanced and lower-level capabilities. Positioning capabilities into a hierarchy or a ladder is useful for the purposes of making specific normative recommendations to firms regarding which steps to take next, i.e. the paths that should be taken by firms to upgrade their processes to progress to higher-value markets and activities. In this way, we seek to contribute to our understanding of capabilities and their measurement. Cirera and Maloney (2017) discuss the concept of a “capabilities escalator” according to which capabilities are in a tripartite hierarchy of basic production/management, technology adoption, and invention/innovation

capabilities. We draw on this intuition to attempt to develop a hierarchy of capabilities based on company expenditures in 47 different dimensions, sorting these capabilities into a hierarchical order by applying network science algorithms (Tacchella et al., 2012).

We therefore contribute to the literature by proposing a new method for sorting activities (and hence firms) into a hierarchy based on the complexity of activities, that we refer to as the ‘capabilities ladder’. Our measure of capabilities has a number of advantages. While some previous research has made valuable contributions to the measurement of capabilities using subjectively-reported indicators of capabilities (e.g. Bloom and Van Reenen, 2010; Danneels, 2016), nevertheless subjectively-reported indicators are costly and may include biases (Grant and Verona, 2015). Our approach to measuring capabilities refers to concrete observations of firm-level expenditures in various areas. While subjectively-reported data carries the risk of ‘cheap talk’, our indicators of activity require the actual commitment of resources. Although some previous research sought to analyze detailed data on capabilities from specific industries (e.g. Ethiraj et al (2005) and Chatterjee (2017) for the software services industry; Pandza (2011) for a pharmaceutical firm), our approach is general in the sense that it refers to firm activities that are observed across sectors. Our approach requires detailed balance sheet data for firms, but this type of information is usually readily available across sectors and countries, therefore making our approach amenable to replication and extension in a large range of contexts.

Our analysis shows that the lower rungs of the capabilities ladder correspond to basic managerial and production activities, such as borrowing money, owning land and building assets, and expenses due to outsourcing professional jobs. Mid-level rungs correspond to internationalization and acquiring absorptive capacity. Higher-level rungs in the capability ladder are less clearly ordered into a hierarchy. Overall, therefore, the positioning of firms on the capabilities ladder is more clearly defined at lower and mid-level rungs than at the top. Focusing on changes in the structure of the ladder over time, ICT capabilities have become more present at the fundamental lower-level rungs on the capabilities ladder in recent years. Our capabilities ranking is correlated with firm size for small firms but not for

large firms, indicating that firm growth is associated with capability development in small firms but not for larger firms.

The paper unfolds as follows. Section 2 presents our background regarding the conceptualization and measurement of capabilities. Section 3 presents our methodology. Section 4 presents our data on 44,971 Indian firms for the period 2000-2020. Section 5 contains our analysis and results, first sorting the expenditure items into a hierarchy according to our algorithm, and then investigating dynamics in the hierarchy of the ladder. Overall scores for capabilities are compared across broad industry groups and for firm-level variables (firm size and survival). Section 6 concludes.

2 Background

2.1 The measurement of capabilities

“The core problem of empirical research into organizational capability is that organizational capabilities are latent constructs that are inherently unobservable.” (Grant and Verona, 2015, p.61). The unobservable nature of capabilities is one of their core characteristics, because it is this tacit and ambiguous aspect of capabilities that allows firms to provide competitive advantage without being imitated by rivals (Hilliard and Goldstein, 2019). However, the unobservable nature of capabilities is a headache for empirical researchers. As a consequence, indirect approaches to measuring capabilities are required. A common approach in the previous literature involved the analysis of questionnaire or telephone survey responses from firms to obtain subjective assessments of their firms’ capabilities (e.g. Bartel et al., 2004; Bloom et al., 2013; Danneels, 2016; Costa et al., 2021). Surveys of firms can shed valuable light on phenomena that are not detectable using administrative sources only (e.g. Costa et al., 2021). Subjectively-reported indicators of capabilities have drawbacks however. Grant and Verona (2015) identify three sources of error in self-reported assessments of capabilities: deliberate misreporting, perceptual and cognitive distortions (leading to unintended biases in responses), and a lack of information on the part of the respondent.

These biases can be attenuated, for example by checking the background and expertise of individual respondents (Danneels, 2016), or by performing double-blind interviews (Bloom and Van Reenen, 2010) but this is time-consuming and costly. We do not seek to diminish the commendable achievements of previous research that obtains subjectively-reported measurements of capabilities, but we seek to complement the existing literature with a new technique for the development of capabilities based on factual observations in company balance sheets.

This paper therefore measures capabilities using objective data, although (given the unobserved nature of capabilities) this is done in an indirect way. Our approach draws on a generally-accepted definition of a capability as the ability to perform an activity or function using a set of tangible resources (Amit and Schoemaker, 1993; Helfat and Peteraf, 2003; Danneels, 2016). An important point is that a capability has material as well as cognitive components (Danneels, 2016). While the “ability to perform” is fundamentally unobservable, nevertheless this ability can only manifest itself through the deployment of material resources. For example, a marketing capability may require a customer database, which serves as a contextual requisite for the organizational routines supporting this marketing capability (Dosi et al., 2000). The number of general management and functional executives, to cite another example, was taken by Fortune and Mitchell (2012) to proxy for managerial and functional capabilities. As such, an organizational capability is only observed when it is performed through the application of a routine involving tangible resources (Grant and Verona, 2015).

An example of an (individual-level) capability is given in Grant and Verona (2015, p.61):¹ playing the violin. Such a capability is only observed when someone actually starts to play the violin, and the capability remains latent or dormant until a violin is physically involved. In our context, buying a violin would be taken as evidence of a capability for playing violin. Furthermore, we do not distinguish between the quantity and quality of violins being purchased, instead we analyze binary variables regarding objectively-reported

¹A violin analogy also appears in the discussion of capabilities in Costa et al. (2021, p.5).

expenditures in various areas to deduce the state of a firms' set of capabilities. Continuing with the analogy, we are not concerned with whether some violinists are 'better' than others, because our main concern is whether an agent is able to carry out a specific activity (such as playing the violin) purposefully, repeatedly, reliably, and in a minimally satisfactory manner (Helfat and Winter, 2011; Danneels, 2016). In this way, firms' expenditures in various areas can be considered to leave a paper trail of the performance of tasks that would only be undertaken if firms have capabilities in certain areas that are (given the current competitive environment) considered to be sufficiently developed that they are consistent with an overall profit-seeking strategy.

A similar approach has been taken in previous papers that took R&D expenditures as an indicator of (unobserved) technological capability (Helfat, 1997; Rothaermel and Hess, 2007). In these papers, the fact that firms consider it to be in their interests to invest in R&D is taken as a signal that these firms have sophisticated routines and management practices in place to undertake complex activities relating to R&D. Our paper extends this line of investigation, because the dimension of R&D investment is only one out of 47 areas of expenditure that are analyzed to assess a firm's position in capability space.

An influential stream of research in the measurement of capabilities has emerged from the World Management Survey (e.g. Bloom and Van Reenen, 2007, 2010; Bloom et al., 2012). Our approach is similar to theirs, in that we measure and quantitatively analyze capabilities in a variety of sectors and for a potentially large number of firms. A difference, however, is that our approach can be applied at low cost to a population of firms that report detailed balance sheet data. Furthermore, our focus is not on management capabilities but on capabilities across various functions, such as marketing, financial practices, human resource practices, IT strategy, internationalization and innovation. Importantly, these capabilities are reflected not in self-reported data but in how firms actually spend their money in various activities and areas. Another important difference is that analysis of the World Management Survey does not seek to arrange capabilities in a hierarchy (but instead calculate an aggregate sum as an indicator of management capabilities, implicitly

giving equal weight to each dimension of management capability). In contrast, our analysis yields a data-driven ordering of firms' activities and capabilities into a hierarchy, i.e. a map of which activities generally appear to be precursors or prerequisites for others. We then investigate how this data-driven ordering relates to actual firms' performance in terms of growth and survival.

2.2 Capabilities: inputs, intermediates, outputs, and processes

Evolutionary scholars generally consider that firms have heterogeneous capabilities which correspond to *different* ways of doing things (Nelson and Winter, 1982; Dosi, 2000). But how different? This subsection seeks to be more specific about the ways in which firms differ. We return to our analogy of capabilities for playing the violin, then look at the case of innovation capabilities such as R&D capabilities that has been studied in the capabilities literature (e.g. Helfat, 1997; Rothaermel and Hess, 2007).

Capabilities are organizational-level competences for knowing how to do certain types of activities (Dosi et al., 2008). As such, capabilities are formed of routines as well as other *inputs* that can be considered to be 'contextual requisites' for the capability (Dosi et al., 2008, p. 1167). In our example, R&D capability is not just the intangible routines and competences for managing an R&D project, but necessarily involves the actual commitment of R&D funds in order to come to life, therefore it can be proxied by R&D investments. Investment in a capability, at the simplest level, is binary, although more complex levels could also be envisaged (e.g. a continuous variable corresponding to the logarithm of amount invested).

Of course, "[t]aking a first cut at an activity does not constitute a capability" (Helfat and Peteraf, 2003, p. 999). Inputs correspond more closely to 'intentions' rather than actual capabilities *per se*, although it is considered here that an initial purposive allocation of resources into capability development is a generally useful proxy for actual capabilities, even if the proxy is not valid in some exceptional cases. Furthermore, attempts at pushing forward the firms' technologically-feasible production set by moving in new types of complex

Table 1: Conceptual distinctions between input, intermediate, output, and process aspects of capabilities.

	Violin-playing capability	R&D capability
INPUT: Investment in a capability	Buy/rent a violin	Invest in R&D
INTERMEDIATE: An input for further activities, although it already indicates partial accomplishment	Paying for expedited delivery of a certificate that confirms passing a violin exam	Paying application fees for a patent
OUTPUT: Overall success of the capability	Initial goals are met, e.g. audience is satisfied	Commercial success, satisfactory performance outcomes
PROCESS: Ways of enacting the capability	Various bowing techniques: détaché, martelé, spiccato, legato, tremolo, col legno, etc. With/without backing music. Type of violin: Pre-Baroque, Stradivarius, Classical, Stroh, Electric, Semi-Electric, 5-string, etc.	Various R&D management styles: e.g. institutional differences across countries prioritize monitoring vs incentives (Bloom and Van Reenen, 2010). Various IP strategies, project management approaches, risk preferences, problem solving approaches, decision rules, knowledge bases, collaboration partners, etc.

activities, even if these attempts turn out to be commercially unsuccessful, are a signal of ambition and have been observed to confer performance benefits (Braguinsky et al., 2021).

Other items maybe be considered to be intermediate. For the violin example, an intermediate capability for violin playing could be concretely measured in terms of payments specifically for dispatching a certificate after having passed a standardized exam such as ABRSM grade 8. Novice violinists would not be able to make such a payment. With regards to innovation capabilities, expenditures on patent applications can be considered as positioned partway between inputs and outputs (Griliches, 1990), because while spending on patent applications constitutes evidence that a firm believes that they have something worth patenting, nevertheless many patents are worthless and many patents require considerable expenditures on further development before being able to attain commercial success.

Likewise, new product introductions can be considered to be proxies for “market pioneering” capabilities (Franco et al., 2009) that we might call ‘intermediate’ in the sense that the market introduction of new products shows that the firm is at least capable of producing a new product, although there is not yet any evidence of its market success (the ‘output’).

The outputs of capabilities can be considered following Dosi et al. (2008, p. 1175): “the ultimate test of validity for any capability theory of industrial performances resides in its capability to account for inter-firm differences in profitability and growth patterns.” Outputs therefore correspond to ‘performance outcomes’, and furthermore they may be difficult to measure. An R&D department’s capabilities, for example, are difficult to evaluate independently of its links to, and the performance of, other departments in the firm. A firm is a combination of R&D capabilities, manufacturing capabilities, and marketing capabilities, and so on, and it may be difficult to know whether a firm’s overall success is due to its R&D capabilities or (instead) its marketing capabilities or hiring capabilities. Nevertheless, at a conceptual level, it is worth distinguishing the outputs of a capability from the inputs, intermediates, and processes of the capability.

The process of capabilities refers to how they are implemented (i.e. details on the multidimensional mapping function from inputs to outputs). When firms are said to have different “ways of doing things”, the reader’s mind may tend to turn to differences in processes. Processes of capabilities may correspond more closely to more traditional discussions in the literature regarding concepts such as routines and interdependent team-working practices (Nelson and Winter, 1982). There will be a lot of variety in processes (e.g. degree of mechanization, allocation of tasks, establishment and use of communication channels, procedures for documenting errors). Process aspects of capabilities are difficult to quantify for many reasons (e.g. because there are so many possible dimensions involved, and also because firms’ processes are difficult to observe). The overall ‘level’ of capabilities may differ between firms in the same industry (e.g. production capabilities for Château d’Yquem Premier Cru Supérieur vs Tavernello boxed wine). Furthermore, different ‘versions’ of a capability may combine different constellations of inputs to yield the same overall ‘level’ of

capability (Helfat and Peteraf, 2003, p. 1003). Process aspects of capabilities may be less important if we do not particularly seek to know ‘how the sausage is made’ as long as it is made in a minimally satisfactory manner (Helfat and Peteraf, 2003; Helfat and Winter, 2011; Danneels, 2016).

Table 2 distinguishes between the inputs, intermediates, outputs, and processes of capabilities.² In this paper, we measure capabilities by essentially focusing on inputs.³

A related dimension for conceptualizing capabilities is that capabilities here correspond to deliberate actions rather than automatic and habitual practices. There is a debate in the dynamic capabilities literature regarding whether the development of new capabilities emerges from either routine-based learning or purposive deliberate learning (Arndt et al., 2018; Barreto, 2010). Routine-based learning occurs when the semi-automatic repeated enactment of organizational routines, and their possible mutations in the context of a dynamic environment, leads in an unintended way to the emergence of new capabilities. Deliberate learning, in contrast, relies on strategic decision-making and planning activities that involve deliberate actions and may use codified knowledge sources (Zollo and Winter, 2002). In our research, capabilities are measured in such a way that they correspond to intentional and purposive decisions regarding the allocation of resources. It seems reasonable to assume that firms will not spend resources in specific areas without being aware of the bills and fees they are paying. This does not mean, of course, that routine-based learning never occurs; it merely means that a quantitative analysis of routine-based learning is beyond the scope of the current paper. Our analysis considers that intentional and deliberate investments in capabilities relate to more purposive and strategic aspects of capability development (Zollo and Winter, 2002), while humbly recognizing that intentions and conscious purposes may be distant from actual observed instances of capability, which may involve activities and outcomes that are automatic and habitual in nature (Dosi et al., 2008).

²Our distinction between inputs, intermediates, and outputs does not closely correspond to the distinction in Helfat and Peteraf (2003) between the founding, development, and maturity of capabilities, because all of our dimensions (inputs, intermediates, outputs, and also processes) apply at all stages of Helfat and Peteraf (2003)’s lifecycle (founding, development, maturity), while the reverse does not hold.

³Not all our measured activities are inputs, however. Patent expenditures, for example, would be intermediate activities rather than inputs (Griliches, 1990).

3 Methodology

The biology literature introduced the concept of “nestedness” to explain that in many systems the capabilities required to deal with specific advanced ecological niches were nested in those required for more basic ones. Similarly, in economic systems, those countries that were able to export advanced products were also exporting basic ones (Bustos et al., 2012). This intuition can be formalized through algorithms inspired by network science (Hidalgo and Hausmann, 2009; Tacchella et al., 2012) to provide a natural ranking of countries and products. Domínguez-García and Munoz (2015) shows that Tacchella et al. (2012)’s algorithm works best for recovering the rankings in nested biological systems.

Here, the same algorithm analyzes activities of around 45’000 Indian firms, to explore patterns in the following types of areas: Is a firm investing in R&D? Applying for patents? Using external know-how? Exporting? Each activity is the fingerprint of advanced production and technological capabilities, and the algorithm uses this data to simultaneously measure both the rankings of the most advanced activities, i.e. the activities that are not accessible to firms that are not high enough on the capability ladder, and the position of the firms in the ladder. This allows a quantitative definition of concepts that were previously either described qualitatively or measured by ad hoc case studies.

To illustrate: research has found that innovative firms are more dependent on external finance (Brown et al., 2017). How are these two capabilities (innovation and seeking external finance) arranged in the capabilities ladder? A simple approach would involve comparing the conditional probabilities of innovating if a firm has access to external finance, and vice versa. The algorithm we will use instead does not look at the two capabilities in a vacuum, but takes an eco-systemic approach by looking at all the activities of all firms to evaluate the relative positioning of the two activities. At the same time it defines the ladder – i.e. the ranking of capabilities – and the position on the ladder of the firms, by defining a firm as high up the ladder if it is able to perform complex activities, and defining a capability as complex if those firms that are at the lower rungs of the ladder are not observed to perform

it. The algorithm is validated against a null model in which firms’ activities are reshuffled between firms to show that nestedness is indeed a key force shaping firms’ behavior. More details on the algorithm are reported in Appendix B.

4 Data

Some influential empirical investigations of capabilities have previously focused on Indian firms (Ethiraj et al., 2005; Bloom et al., 2013). A drawback of these two previous studies, however, is that they focused on small sample sizes. We use PROWESS, from the Centre for Monitoring the Indian Economy (CMIE). Data comes from the annual reports of companies (both public-listed and unlisted), which include balance sheets and profit and loss accounts. PROWESS is the most comprehensive database available for Indian firms. The companies covered account for about 70% of industrial output, 75% of corporate taxes, and over 95% of excise taxes. We also merge with Patstat for patent data.

Our unbalanced panel includes 44,971 firms in the period 2000 to 2020, for a total of 441,207 observations. Table 2 shows some general characteristics of firms in our sample. Sales demonstrates considerable skew, and therefore we take the natural logarithm of sales as a measure of size, to avoid outliers in the regressions.

Table 2: Mean, Standard Deviation, and 5th and 95th percentiles for the main descriptive variables in our sample.

Variable	Mean	St.Dev.	5th percentile	95th percentile
Sales (million rupees)	3717	45646	0.8	10093.9
Age	18.6	16.8	1	51
Growth Rate	0.08	0.84	-0.94	1.08

A binary variable, in our baseline analysis, indicates whether or not the firm is investing in any particular area. (Robustness analysis in Appendix D confirms that our results are not sensitive to alternative thresholds for dichotomization.)⁴ The amount of spending

⁴While a binary variable is needed for the analysis, the literatures on both complex systems and management science teach us that to set *any* expense as the firm having that capability could be naïve: a certain amount of resources is needed to have an R&D department, and by considering any expense as the finger-

is therefore considered to be less important than whether or not a firm actually spends anything in this area (following e.g. Crépon et al., 1998; Bartz-Zuccala et al., 2018; Coad et al., 2020), because what matters is the binary variable of reaching a “rung” on the capabilities ladder, not the scale of activity on that particular rung. In this way, small firms that spend less on certain activities (e.g. R&D) receive the same ‘score’ regarding their capability in this area as large firms that spend larger amounts on the same activities, because both firms appear to possess the required capability.

We divide 47 firm activities (signalling underlying capabilities) into 7 groups: 1) Production Capabilities; 2) Technological Capabilities; 3) Innovation; 4) Basic Managerial & Organizational Capabilities; 5) Internationalization; 6) Environment and Social Amenities; 7) I.T. and Communication.⁵ Appendix A provides details on the activities. This binary dataset is the starting point of our analysis, represented in Figure 1 in matrix form for one year (2019): each row corresponds to a firm and each column corresponds to an activity. The different colors represent different groups of activities. At a first glance, we can observe that certain activities (eg. production colored by red, managerial activities colored by black) appear more often than others (eg. Technology adoption colored by green).

5 Results

5.1 The capability ladder

Given the matrix of activities as in Figure 1, our algorithm then checks for nestedness, i.e. whether activities can be ranked to highlight that firms doing complex activities are also likely to do simpler ones. (Nestedness and the ranking algorithm are presented in Appendices B and C.) Put differently, our iterative algorithm rearranges rows (i.e. sorting activities according to their difficulty) and rearranges columns (i.e. sorting firms according

print of firms’ capabilities could add more noise than signal. Appendix D checks that our main results hold for alternative thresholds.

⁵Previous research into capabilities has distinguish between client-specific capabilities and project management capabilities (Ethiraj et al., 2005), or between technological and R&D capabilities, and customer and marketing capabilities (Danneels, 2016).

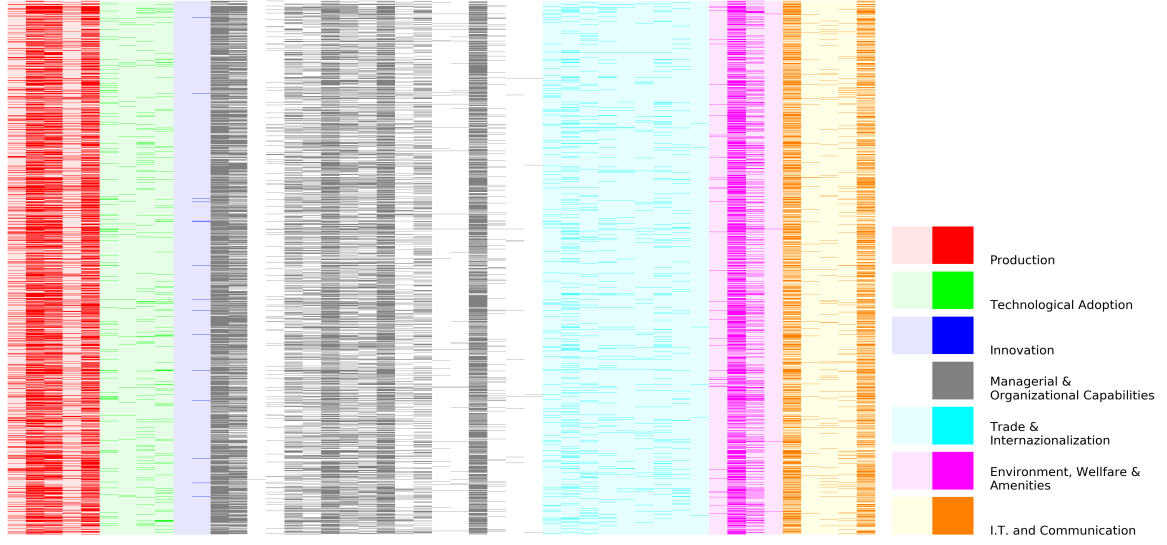


Figure 1: Matrix of activities by firm for year 2019. 28689 firms active in that year in our database are represented by rows and the 47 firms' activities are represented by columns. Colour online.

to their 'fitness') to move from the raw data in Figure 1 to the results matrix in Figure 2, which displays clear nested behaviour. Indeed, rows and columns can be rearranged to cluster the present and absent values much better than in a random matrix with similar characteristics. Hence, it is meaningful to sort activities into a hierarchy. If Figure 2 appeared as a solid block-diagonal triangle wedged in the upper left corner, this would mean that firms at a particular rung engage in all the activities at lower rungs. If, however, Figure 2 were a thin diagonal line, this would correspond to firms at a particular rung only engaging in a small number of activities at the rungs immediately preceding it. And of course, if Figure 2 were a solid square (with density = 100%, then all firms engage in all activities (at all rungs). Instead, the density of our matrix is 21.6% (i.e. firms perform on average 21.6% of the activities). Some firms at upper rungs engage simultaneously in many activities at lower rungs, but this is not always the case because there are many gaps in the upper triangle.

Figure 2 suggests that, as a first step, firms need basic managerial capabilities and

production capabilities. Internet access and basic communication needs arise at about the same time. At a second step, firms engage in internationalization and gaining absorptive capacity for future innovation. At a third step, firms have more idiosyncratic patterns of engaging in product innovation or patenting, merging, environmental policies, and so on.

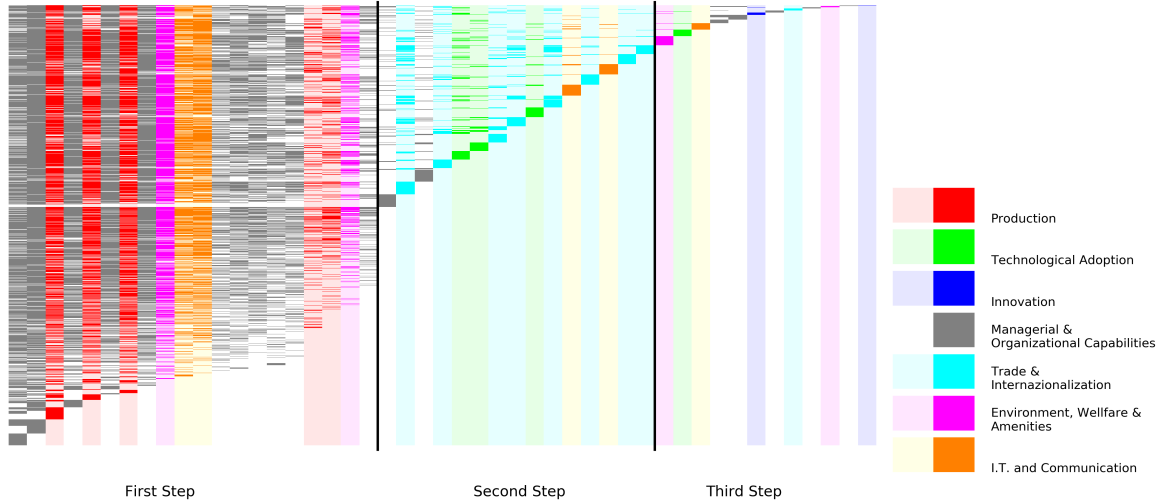


Figure 2: Matrix of activities by firm for year 2019. 28689 firms active in that year in our database are represented by rows and the 47 firms' activities are represented by columns. Same as Figure 1, but columns and rows are reordered to highlight nestedness. Colour online.

The optimal rearranging of columns and rows can be also considered as a natural ranking of activities and firms. In the next section we will look at the ranking of firms, and its significance in measuring firms' capabilities. Focusing now on the 47 activities, we see that the first three rungs of the ladder are the ability to borrow, to own land & building assets, and to outsource professional employment. The three most advanced are product development, patenting, and external specialist consultants.

Figure 3 shows the dynamics of the hierarchy of activities over the available time window (2001-2020). As expected, this hierarchy of activities is quite stable over this period. The main exceptions are ICT related capabilities and Environmental, Welfare & Amen-

ties. Indeed, while ICT capabilities were the fingerprint of an advanced organization in the early 2000s (that is, it was a complex activity performed only by complex organizations), they became a standardized and necessary step for climbing the capabilities ladder already around 2005. It is instead only in 2015 that Environmental, Welfare & Amenities capabilities became a (slightly) more basic rung of the ladder, as Indian firms have to first give precedence to environmental activities with respect for example to Internationalization. In appendix A we show the evolution of the single activities during the time period of our analysis.

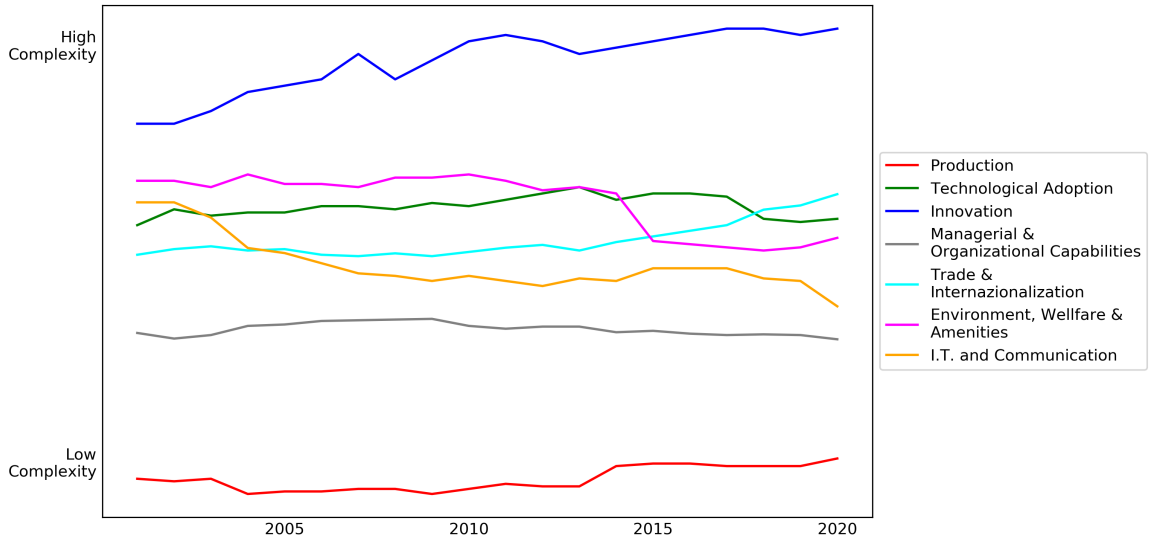


Figure 3: Dynamics of the hierarchy of activities over the period 2001-2020. Colour online.

What is the probability of moving up or down the ladder from one year to the next? A transition matrix (Table 3) allows a further description of the dynamics of capabilities by shedding light on the transition probabilities for firms. Three interesting observations appear. First, around 90-95% of the probability refers to firms that either stay on the same quintile or move to the neighbouring quintile: not surprisingly, firms' capabilities are quite stable over time. Second, there are no steps that appear to be much more difficult to overcome than others, instead quintiles are similar. Third, upgrades are slightly more likely

than downgrades in our data, which is also in line with expectations: firms tend to upgrade their capabilities over their lifetimes, and firms exits make the capability distribution stationary.

Quintile	1	2	3	4	5	Total
1	79.19	13.24	2.95	1.97	2.65	100.00
2	11.26	64.90	14.92	4.36	4.57	100.00
3	1.94	12.44	63.33	14.40	7.89	100.00
4	1.21	4.07	12.45	65.35	16.92	100.00
5	1.53	3.98	6.97	16.15	71.38	100.00

Table 3: Transition probability matrix for firms between quintiles of the capabilities ladder. Each cell represent the probability (as a percentage) of moving the next year in a specific quintile (columns) of the capabilities ladder depending on the starting quintile (rows).

5.2 Populating the ladder

In the previous section, we defined and described the ladder as it emerged from the algorithm. This process defined the landscape where firms coevolve.

We can now describe the firms present at different levels of the capabilities ladder. Indeed one could look at the rows of the matrix and look at the characteristics of the firms located at various rungs of the ladder. We first focus on the average firm’s capabilities by industry. A first relevant point is that, at each rung, there is a mix of firms from different sectors. However, this mix is not random: firms in the financial and real estate (K-L), trade (G-I), professional scientific and technical sectors (M), as well as energy (D-F) and other services (N-S) tend to be present along all the spectrum of capabilities, while ICT service sectors and manufacturing firms are mostly located in the two highest steps. This is shown by the average position of firms in the global ranking by industry, as plotted in Figure 4.

In Figure 4, the size of the circle is proportional to the number of firms, and clearly, one can observe that the industrial sectors are not equally populated, or homogeneous. One of the biggest (one third of the firms, 16564 firms out of 49439 in 2019) and most heterogeneous sectors is the manufacturing sector. We further disaggregate it using Pavitt’s taxonomy (Pavitt, 1984) to split the manufacturing firms into four main taxa, as reported in Figure 5.

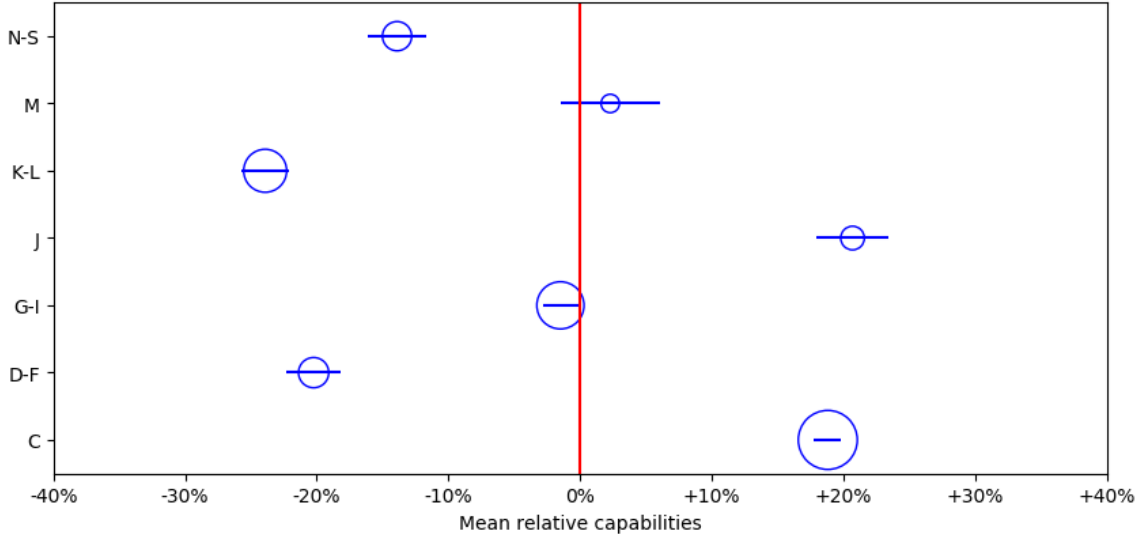


Figure 4: Relative average position in the capabilities ladder with respect to the average of all Indian firms of the firms of a specific industry. Year 2019. Error bars represents 2 standard errors – i.e. $\approx 95\%$ confidence interval. Size of the circle is proportional to the number of firms in the sector. Industries: C- Manufacturing; D-F: Energy, Water, Construction; G-I: Wholesale and retail trade, deposit and distribution, food and accommodation; J- Information and Communication; K-L- Financial and real estate; M- Professional, Scientific and Technical Activities; N-S: Other services (Administration, Health, Education, Other). Colour online.

We see that while firms in supplier dominated sectors do not have average capabilities higher than service-sector firms, taxa characterized by more reliance on technological capabilities (Specialized Suppliers and Science Based sectors) show a significantly higher position in the ranking, similar to ICT service firms.

5.3 Firm growth and capabilities

The firm growth process involves enlargement in quantitative terms (regarding indicators such as revenues, employees, assets, profits) as well as episodic reorganization and restructuring events (linked to the strategic development of capabilities) that are more qualitative in nature. Figure 6 shows that these two processes (firm size and capabilities) are indeed correlated. It shows a non-parametric Nadaraya-Watson kernel regression between firm size (proxied by log of sales revenue) and the order of the firm in the capabilities ranking.

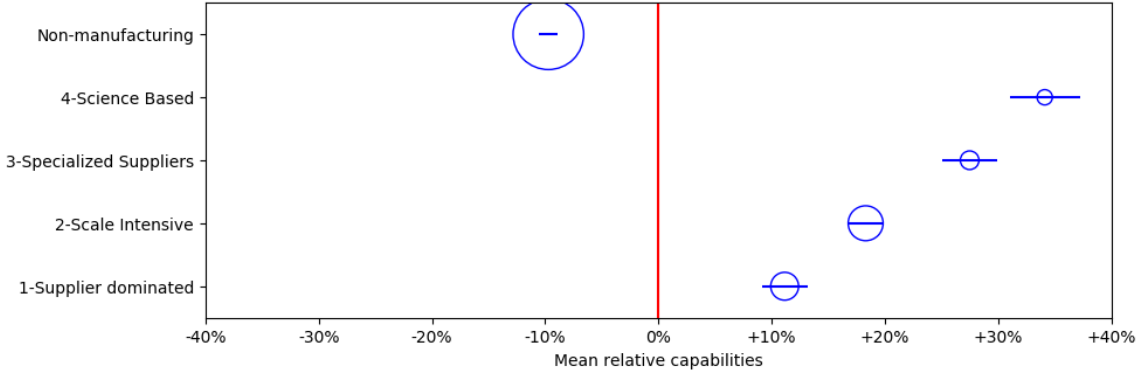


Figure 5: Relative average position in the capabilities ladder of manufacturing firms of a specific Pavitt taxum with respect to the average of all Indian firms. Year 2019. Error bars represents 2 standard errors – i.e. $\approx 95\%$ confidence interval. Size of the circle is proportional to the number of firms in the sector. Colour online.

Firms increase in size is limited by the firms' present capabilities. Interestingly, however, the positive correlation fades in the upper half of the distribution, roughly corresponding to firms that passed the first step highlighted in section 4.1. While a certain size is necessary to support advanced capabilities, the relationship disappears above $\log(\text{sales}) \approx 6$, equivalent to sales of about 40 crore Indian rupees, or approximately 5 million US\$. Overall, the relationship arises from two different dynamics: the growth dynamics and the survival probability.

To better understand the dynamics of firms size in relation to its capabilities, we now look at the growth and survival of firms depending on their capabilities and sales. In Figures 7 and 8 respectively, we look at the expected growth rates (relative to the growth rate of that size class) and survival probability of firms after 7 years⁶ depending on their initial size and capability class. Firms are divided by size class in four quartiles (approximately less than 5.6 crores rupees, between 5.6 and 23.7 crores rupees, between 23.7 and 81.8 crores rupees, and over 81.8 crores rupees), and in terms of the capability ladder we split the firms in the first step (the most populated step) into two subclasses I.A and I.B, to get a total of four capability classes. Once we observe the two processes separately, we gain a better

⁶The general pattern for different delta years is similar. The same figures for different delta years are provided upon request by the authors.

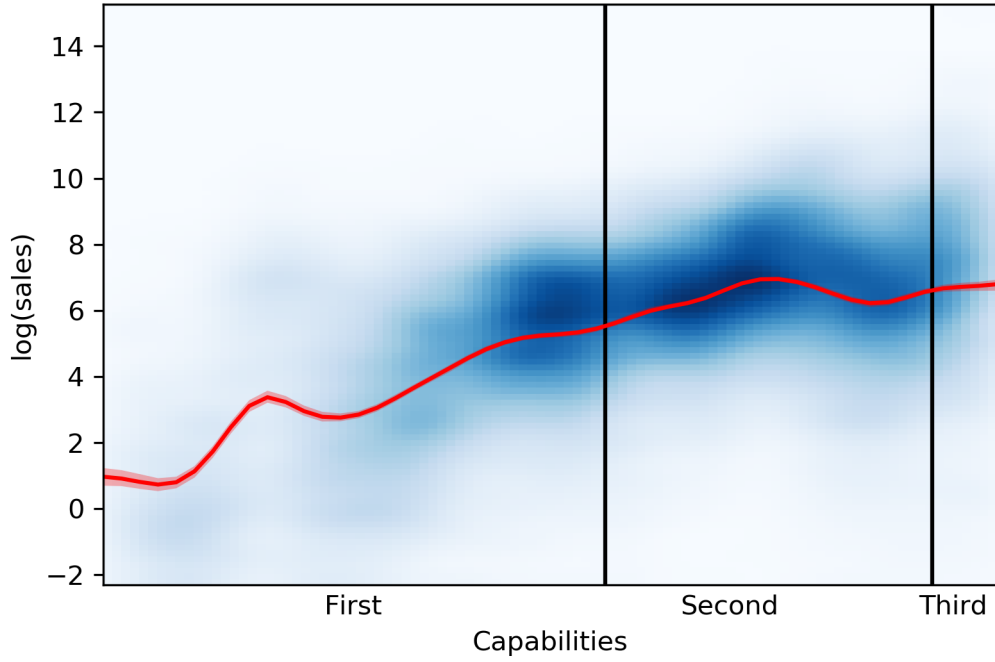


Figure 6: Color map representing firms' density with respect to size of the firms (in terms of the natural logarithm of sales) and its (inverse) position in the ranking, i.e. its capabilities, in 2019. The two vertical black lines separates the three steps. The red line is a non-parametric Nadaraya-Watson kernel regression. Colour online.

understanding of the dynamics leading to Figure 6. First, the datapoints in Figure 7 shows a general trend from bottom-left to top-right, indicating that, for firms in every size class but the smallest ones, higher capabilities are associated with significantly higher average growth: in a 7 years period the average growth rate between at the step I.A and a firm at the III step has a difference of more than 1.2 in log scale, i.e. the sales of a firm with capabilities in the highest group are expected to end up 3.3 times larger at the end of a 7 years period than the sales of a firm with the same initial sales but in the lowest group with respect to its capabilities. Second, by looking at the survival rate (Figure 8), capability development improves survival outcomes from completing the activities at the first step of the ladder, although subsequent development of capabilities has no clear survival benefits for firms. A possible explanation is that higher positions in the capability ladder correspond

to entering into more risky activities (exporting, patenting) and sustaining higher fixed costs.⁷ This is reminiscent of Arora and Nandkumar (2011), who observe that capable entrepreneurs with high opportunity costs will take more risks and place less value on the option of survival. Another possible explanation is that some of these cases of non-survival correspond to lucrative exits via acquisition or trade sale. While firms in ‘Size class 0’ have maximum survival probability at step I.B, climbing up the ladder of production and managerial capabilities without engaging in R&D and exporting activities, firms in higher size classes have their maximum survival probability while remaining at step II of the ladder, avoiding only the riskiest activities (patenting, introduction of new products, etc).

Assuming a linear behaviour for the relationship between growth and capabilities, we can add further controls to better understand the growth process by using parametric regressions. The relationship between firm size and capabilities is confirmed by looking at the future growth of the firms that are higher in capabilities than their size would indicate, i.e. firms that are below the red line in Figure 6. Table 4 shows the results of a Fixed Effects regression of firm growth for different sectors:

$$Growth_{i,t} = \alpha + \beta_1 Size_{i,t-1} + \beta_2 Age_{i,t-1} + \beta_3 Capabilities_{i,t-1} + v_i + \gamma_t + \epsilon_{i,t} \quad (1)$$

where firm growth is defined in terms of log-differences of sales, i.e. $Growth(i,t) = \log(sales(i,t)) - \log(sales(i,t-1))$ for firm i in year t . The controls include size (measured by log sales), log of age of the firm, year dummies (γ_t) and two-digit sector dummies (v_i). Interestingly, there is a clear threshold effect: the larger the firm, the higher on the ladder it should be placed to be able to grow.

Notice that this effect is specific for firm growth: an alternative performance variable

⁷This result contrasts with Bloom et al. (2019, Figure 2, Panel C, p.1659), who observe higher survival rates for firms with higher-scoring management capabilities. This is presumably because of the differences in the operationalizations of ‘capabilities’ across the two studies, given that the capabilities indicators in Bloom et al. (2019) correspond to relatively low-risk activities such as frequency of tracking performance indicators and procedures for setting production targets. This underscores the distinct and complementary contribution of our approach.

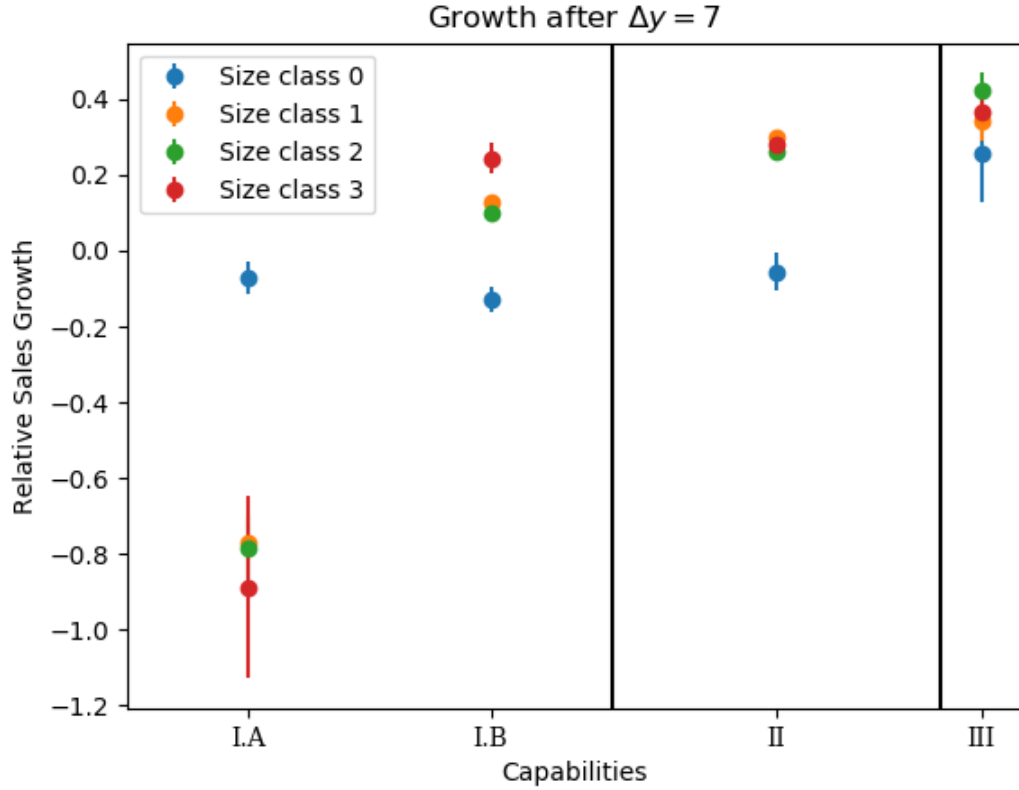


Figure 7: Average 7 years sales growth relative to the size class for different size and capability classes. Bars represent two standard errors, $\approx 95\%$ confidence interval. Colour online.

(i.e. profitability) is not affected by the spread of firms in different activities (see Appendix B). Indeed, a lean operation not involved in R&D or internationalization could well have a higher profitability than a large corporation could. An explanation could be that the gains from capability development are not clearly visible in the ‘bottom line’ of final profits, because they are shared with stakeholders such as skill-upgrading employees. Increasing the operational complexity of the firm only seems necessary for increasing the scale of operations, not for boosting profitability or enhancing survival.

In the previous exercise we analysed the relation between firms’ performance and capabilities, ignoring any co-evolutionary process. Indeed, to question the *dynamic process of capability accumulation* inside firms is beyond the scope of the present paper. Nonethe-

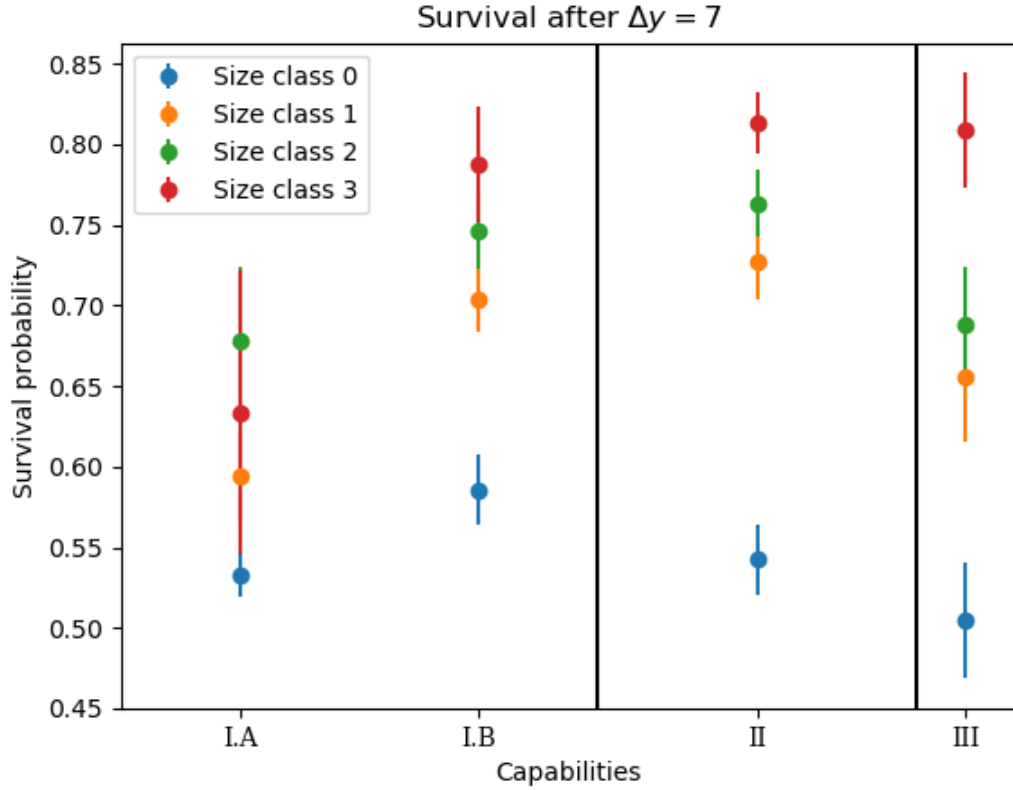


Figure 8: Survival probability after 7 years for different size and capability classes. Bars represents two standard errors, $\approx 95\%$ confidence interval. Colour online.

less, we want to justify our naming choice for the hierarchical capability structure we built: “capability ladder”, instead of “capability escalator”. In figure 9 we look at the relationship between age and capabilities. While there is an expected positive relation between capabilities and age, it is clearly much less striking than what we observed in figure 6: while firm capabilities strictly constrain firm size, there are firms of any age at any level of capabilities. This explains our preference for the term “ladder” to “escalator”: there is nothing automatic in the process of accumulating capabilities. Firms can remain simple units for decades, while other firms may be at the edge of the frontier just a few years after incorporation.

Table 4: Fixed Effect regression of firm growth with respect to lagged size, age and the position in the ladder of the firm (‘capabilities’) normalized from 0 (beginning of the ladder) to 1 (top of the ladder). Column 1 and 2 involve manufacturing firms (industry C), columns 3 and 4 involves ICT firms (industry J), while columns 5 and 6 involves all firms in the sample.

	(1)	(2)	(3)	(4)	(5)	(6)
Size	-0.3003*** (0.0079)	-0.3118*** (0.0081)	-0.3403*** (0.0054)	-0.3512*** (0.0057)	-0.3256*** (0.0045)	-0.3371*** (0.0047)
Age	-0.2046*** (0.0165)	-0.2060*** (0.0171)	-0.2050*** (0.0179)	-0.2074*** (0.0181)	-0.2312*** (0.0124)	-0.2329*** (0.0127)
Capabilities		0.1643*** (0.0195)		0.2792*** (0.0235)		0.2462*** (0.0162)
Observations	121703	118231	155869	150569	277572	268800
R^2	0.201	0.205	0.199	0.200	0.196	0.198
Firm clusters	13359	13173	22523	22100	35882	35273

Notes: Standard errors in parentheses.

Key to significance stars: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6 Concluding Discussion

We contribute to the innovation literature by introducing and applying a novel methodology for quantifying firms in terms of their capabilities, and putting these capabilities (and hence also the firms) in a hierarchy that we refer to as the capabilities ladder. These operational routines correspond to a variety of functional areas, such as marketing, financial practices, human resource practices, internationalization, and innovation. Our nestedness algorithm, inspired by biology and network science, defines a capability as complex if few firms at lower rungs of the ladder are observed to perform it. We analyse balance sheet and innovation data of almost 45’000 Indian firms 2000-2020, and observe significant nestedness, as compared to a random allocation of activities in firms. Lower rungs of the capabilities ladder correspond to basic managerial and production capabilities. Mid-level rungs correspond to internationalization and acquiring absorptive capacity. Higher-level rungs are less clearly ordered into a hierarchy. Higher-level rungs are more focused on one side with environmental and welfare, and the other side with innovation in terms of patenting and

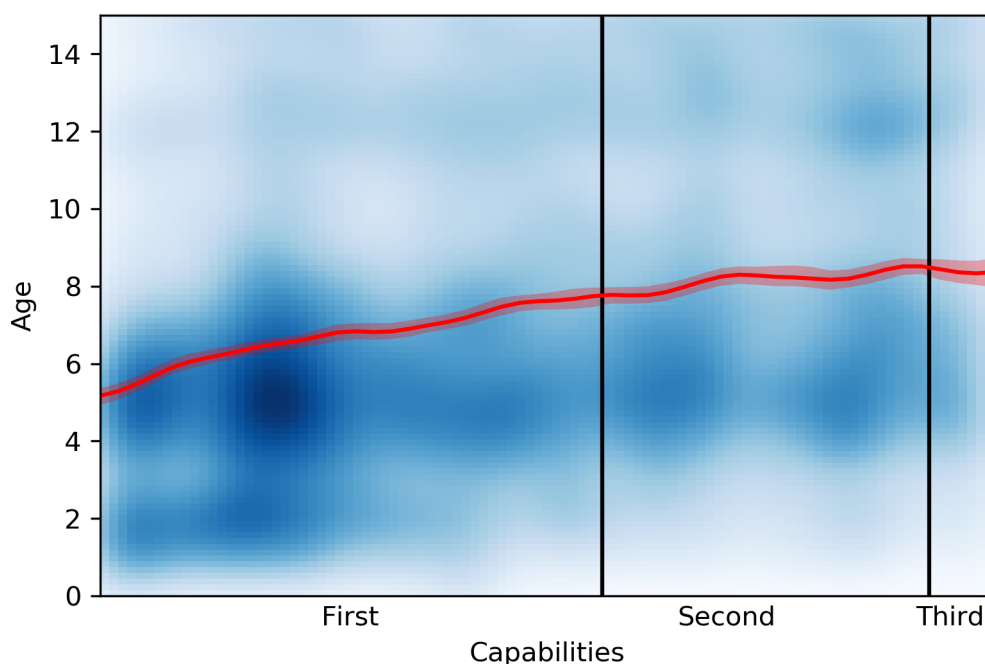


Figure 9: Color map representing firm’ density with respect to age of the firms (up to 15 years old firms) and its (inverse) position in the ranking, i.e. its capabilities, in 2019. The two vertical black lines separates the three steps. The red line is a non-parametric Nadaraya-Watson kernel regression. Colour online.

introducing new products. Further analysis showed some interesting changes in the ordering of the rungs over time. For example, ICT capabilities – once rare – have become more fundamental lower-level rungs on the capabilities ladder in recent years, as ICT capabilities have become more widely used and have permeated a wider range of processes. While the observation that ICT capabilities have become more commonplace in recent decades may seem obvious, it is here quantified precisely and we can see how ICT capabilities became fundamental steps in the early 2000s, while for example investments in the well-being of employees became a fundamental step only in the second half of the past decade.

Interestingly, we saw that firms with higher capabilities have higher growth rates, but when the firm is involved in too many advanced activities with respect to their size it has a lower survival probability. As a first step, firms need to have basic managerial capabilities

and production capabilities. Internet access and basic communication needs arise at about the same time. At a second step, firms engage in internationalization and gaining absorptive capacity for future innovation. Subsequent rungs of the capabilities ladder are less precisely arranged in a hierarchy (i.e. nestedness is weaker), as firms with adequate capabilities have more latitude to climb their own customized ladders. For lower capability firms, though, the capability ladder is set out quite clearly. These combined dynamics generate an equilibrium distribution where capabilities relate strongly with firm size for small firms with few capabilities, while for higher capability levels there is a different regime, likely depending on the firm sector, age, and some idiosyncratic firm's characteristics, breaking the observed relationship between size and capabilities. While this work assesses the strong relationship between the capability measure and firms' future performance (in terms of sales growth and survival), a further development of this line of research could take the shape of an advanced quantitative forecasting exercise to investigate how well the measure allows us to forecast firms' future performance, with the standard instruments of such evaluations. In practice this would be achieved by analyzing a subset of firms' data up to a certain year, and checking the accuracy of the predictions on that year's data regarding firms' survival and growth for the following years, compared with their real evolution. Similar methods have indeed been successful in forecasting the growth of countries (Tacchella et al., 2018). A second relevant further development is to look at the dynamics of capabilities accumulation in firms: how much are capabilities genetics in nature, and how much can the ladder be climbed? And, more importantly, what can a firm do to climb the ladder?

Some limitations of our work (and empirical work in this area more generally) can be mentioned. First, we use a dummy variable for capability, for reasons discussed in Section 2, which could be a limitation because this operationalization does not take into account how much a firm spends in a certain area, or how skilful the capability is (e.g. some violinists have better capabilities than others). Robustness analysis in Appendix D, however, confirms that our results are not sensitive to alternative thresholds for dichotomization. Second, and relatedly, we take an inputs-based indicator of capabilities, rather than an output-

based indicator. A problem could be that inefficient and optimistic firms may lack the capabilities to effectively create value from expenditures in these areas (e.g. to benefit from R&D investment). Third, our statistical analysis focuses on conditional associations rather than applying a causal econometric framework. While intertemporal associations are useful for purposes of predictions and forecasting, nevertheless future work applying causal techniques would offer a deeper understanding of capability development.

Some policy implications can tentatively be discussed, drawing on our analysis. First, a number of policy initiatives seek to provide support to firms facing particular challenges, such as taking first steps into export markets. Our results help to better understand the precursors and prerequisites for certain types of activities, which could make policy targeting more effective if firms become eligible for policy support conditional on their existing capabilities. For example, publicly-funded export assistance could be made conditional on having a website; or eligibility for R&D grants could be made conditional on patent applications or having certain technological search routines or skilled employees. There may be drawbacks to making policy support conditional on capabilities, however. Grazzi et al. (2021) argue that some firms might accelerate their movement up the capabilities ladder (e.g. prematurely enter export markets) in order to become eligible for export promotion policies, which leads to a misallocation of policy support towards ill-prepared firms. Another possible drawback of making policy support conditional on existing capabilities (according to our methodology) would be that firms could learn how to “game the system” and imitate high-capability firms by spending in areas where they have no capabilities, in an attempt to appear sophisticated.⁸

To summarize, therefore, we present a novel methodology for the measurement and sorting of capabilities within firms, and hope that our methodology and results will help to improve our ability to measure capabilities as well as helping to refine the theory of capabilities and capability development.

⁸This drawback could be attenuated if the threshold for dichotomization (capability or not) is not fixed at zero, but at a small yet non-negligible positive value.

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A Ranking of the capability variables in time

In this appendix, we list the individual firm activities used in the analysis (Table A.1) and we show their individual evolution in time in terms of complexity (Figure A.1).

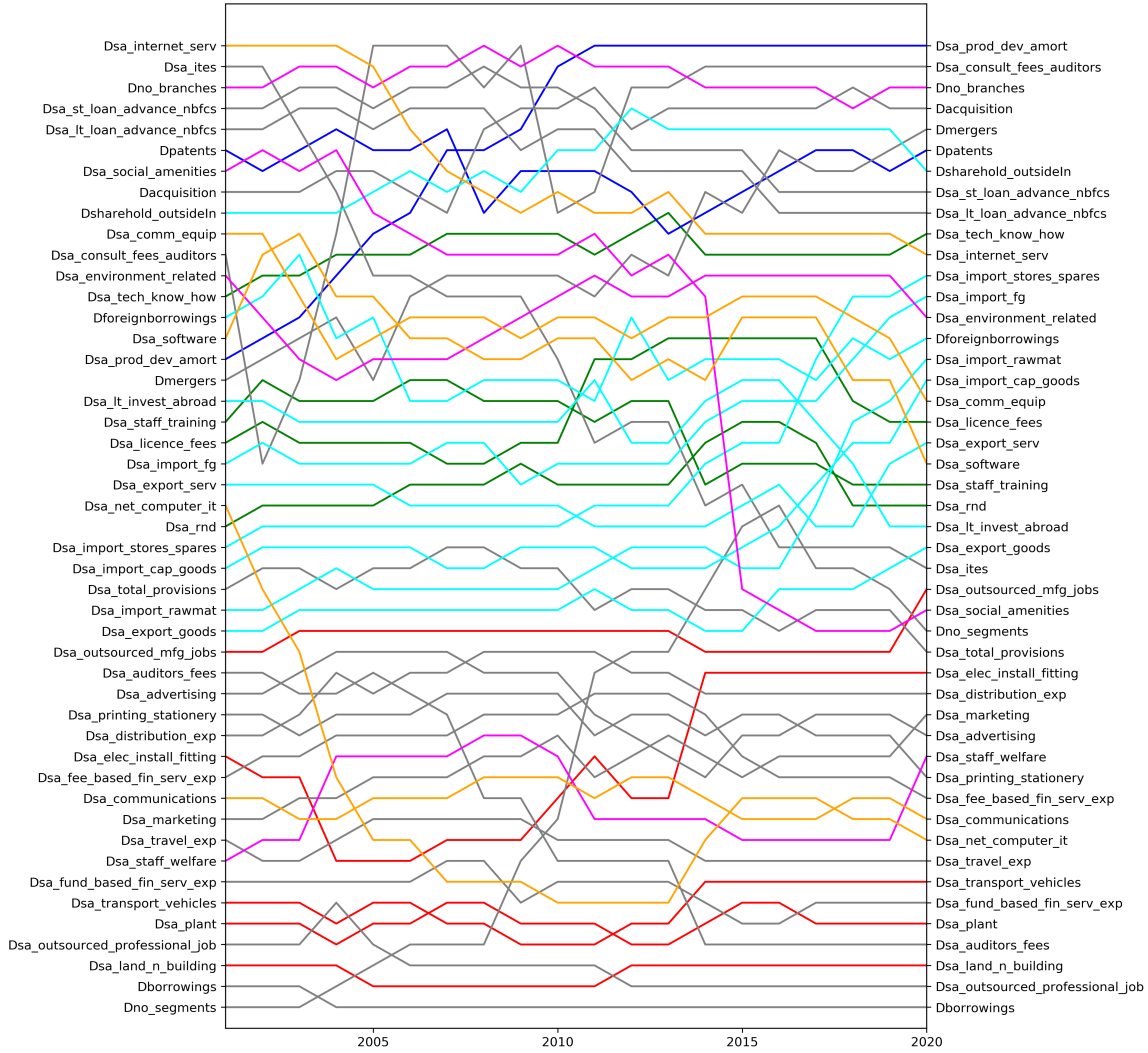


Figure A.1: Dynamics of the hierarchy of activities over the period 2001-2020. Colour online.

B The ranking algorithm

In this type of analysis, the basic input is the matrix $M_{f,c}$ for a given year, whose entries take the value 1 if the firm f is active in the activity revealing the capability c and 0 otherwise. For example, the input matrix $M_{f,c}$ in our case for year 2019 is shown in Figure 1. From this starting input we try to infer at the same time the complexity of the activities and the “fitness” of the firms, i.e. their ability to perform complex activities. To task we use the Tacchella et al. (2012) algorithm, as it has been shown to be the best algorithm to highlight nestedness in biological systems (Domínguez-García and Munoz, 2015).

In particular, to calculate the fitness of firms and the complexity of the activities we iterate upon convergence the following set of non linear coupled equations:

$$\left\{ \begin{array}{l} \tilde{F}_f^{(n)} = \sum_c M_{fc} Q_c^{(n-1)} \\ \tilde{Q}_c^{(n)} = \frac{1}{\sum_f M_{fc} \frac{1}{F_f^{(n-1)}}} \end{array} \right. \quad \left\{ \begin{array}{l} F_f^{(n)} = \frac{\tilde{F}_f^{(n)}}{\langle \tilde{F}_f^{(n)} \rangle} \\ Q_c^{(n)} = \frac{\tilde{Q}_c^{(n)}}{\langle \tilde{Q}_c^{(n)} \rangle} \end{array} \right. \quad (\text{B.1})$$

where n is the iteration index and the normalization of the intermediate tilded variables with the average ($\langle \rangle$) of $\tilde{F}^{(n)}$ and $\tilde{Q}^{(n)}$ is made as a second step to ensure that the final measures have average 1.

The top-left equation presents fitness (F_f) as a function of the set of activities c (proxies for capabilities) that a firm f has (M_{fc}) that is weighted by the complexity Q_c of these activities. In other words, firm-level fitness is calculated as the sum of activities undertaken by a firm weighted by complexity weights. This seems uncontroversial and in line with intuitions from the innovation literature. Firms engaging in just one simple activity would get a low score. Firms engaging in all possible activities would get the highest score. Firms engaging in a small number of the most “complex” activities (as reflected by the complexity weights Q_c) would get a relatively high score.

The bottom-left equation calculates the complexity at the level of activities (not at the level of firms). To a first approximation, the complexity of an activity is inversely proportional to the number of firms engaging in it. However, complexity depends not only on the raw number of firms, but on the fitness of these firms. The intuition is that complexity is strongly influenced by the lowest-fitness firm that is able to engage in this activity. If a high-fitness firm is able to undertake an activity, this is given low weight for calculating an activity's complexity, because it is expected that high-fitness firms can easily fulfil low-complexity tasks. If an activity is undertaken by all firms, then the average fitness of the firms undertaking this activity would be relatively low, it would get a low score for complexity (Q_c). If an activity is undertaken by a small number of high-fitness firms, it would get a high score for complexity.

The set of non linear equations cannot be solved algebraically, and they are therefore solved numerically by iterating the coupled equations until a fixed point is reached. This allow us to rank firms and activities in a unique way. These rankings, as shown in Figure 2, allow reorganizing the matrix to highlight its nestedness. Indeed it has been shown in Domínguez-García and Munoz (2015) that equations B.1 are the best equations to find the ranking representing the importance of species in nested systems: once the species are ordered according to equations B.1, the nestedness of the system is the highest with respect to ordering of rows and columns based on different centrality measures. Equations B.1 will also be the rankings we use in our computations when referring to the complexity of capabilities (Q_c) or firms (F_f).

C Measuring nestedness

A crucial part of this work is assessing the nestedness of the matrix, i.e. the fact that firms able to perform activities classified as complex, are also able to perform simpler activities more than what we would expect if firms were selecting activities randomly. While this looks intuitively obvious, we first need to clarify two points: how are we going to measure the nestedness, and what “randomly” means in this context. First, as a measure of nestedness we use ‘Nestedness as a measure of Overlap and Decreasing Fill’ (NODF), (Almeida-Neto et al., 2008), a measure of the actual overlap between firms’ activities. The measure gives a number between 0 (no overlap) and 1 (perfectly triangular matrix). According to this measure, our matrix for 2019 has a NODF of **0.742**. To be able to compare this value with what we would expect from a random matrix, we have to clarify how a random assignation of activities to firms would occur.

The easiest process we can imagine is a process where each firm-activity link has the same probability. As the density of our matrix is 0.216 — firms perform on average 21.6% of the activities — if this is our null model each firm will have a probability 0.216 of being active in any given activity. The distribution of NODF for matrices produced by this null model is represented in Figure C.1. Clearly, the empirical NODF is much higher than the NODF measured in the matrices produced by this null model.

Of course, this does not seem particularly surprising: we know that there are firms more diversified in different activities, and that this is not the outcome of a random process but of different firm capabilities. We can therefore change our null model, and assume now that each firm has the same expected diversification as in the empirical matrix, but with random selection regarding which specific activities it is doing. If a firm is empirically active in 50% of the activities, the corresponding random firm will have a 0.50 probability of being active in each activity. The distribution of NODF for matrices produced by this null model is represented in Figure C.2. Again, also this null model cannot produce matrices with a NODF as high as the empirical matrix.

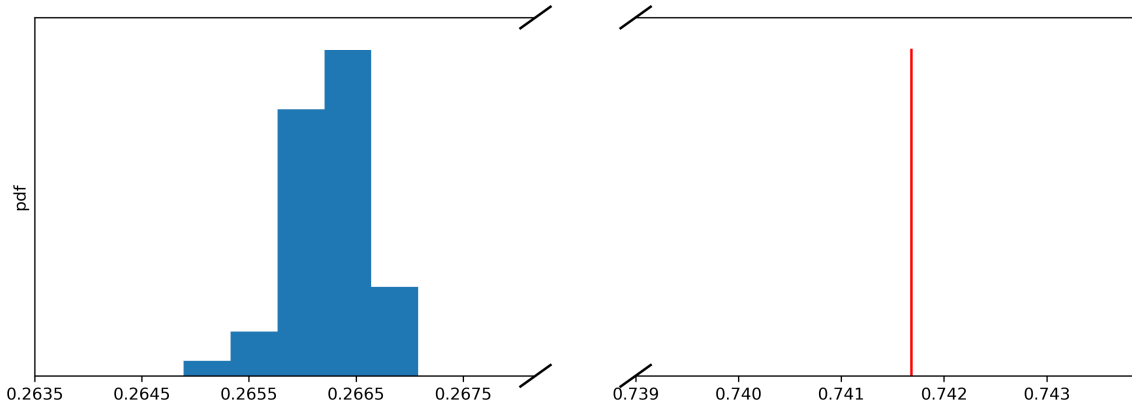


Figure C.1: Probability distribution of the NODF of matrices generated by a homogeneous null model (blue area), compared with the NODF of the empirical matrix (red line). Colour online.

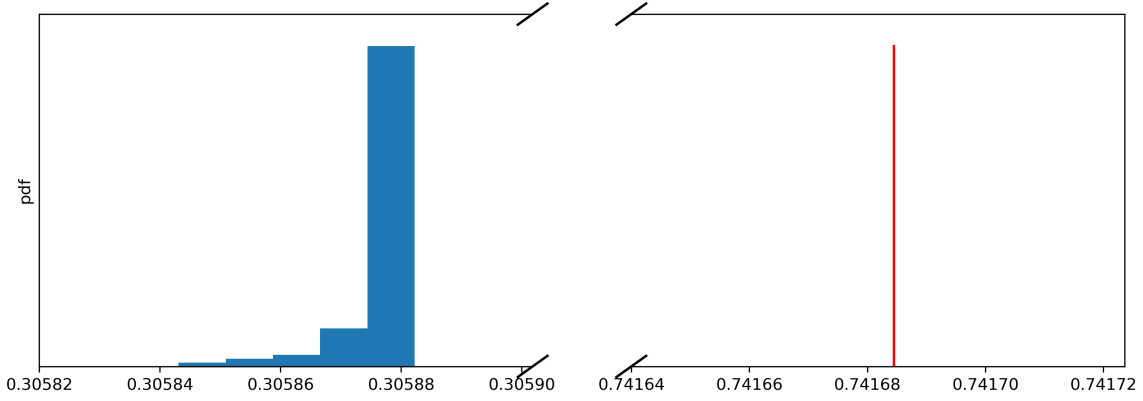


Figure C.2: Probability distribution of the NODF of matrices generated by a null model preserving heterogeneous expected firms diversification (blue area), compared with the NODF of the empirical matrix (red line). Colour online.

There is a further objection: we know that activities are not all the same and some activities are less ubiquitous than others. This is not the outcome of a random process but of higher capabilities required. We can propose therefore one more null model, and assume now that each activity has the same expected ubiquity as in the empirical matrix, but which specific firms are doing that activity is randomly selected. If an activity is performed by 30% of the firms, each firm will have 0.30 probability of being active in that activity. The distribution of NODF for matrices produced by this null model is represented in Figure C.3. Also this null model cannot produce matrices with a NODF as high as the empirical

matrix.

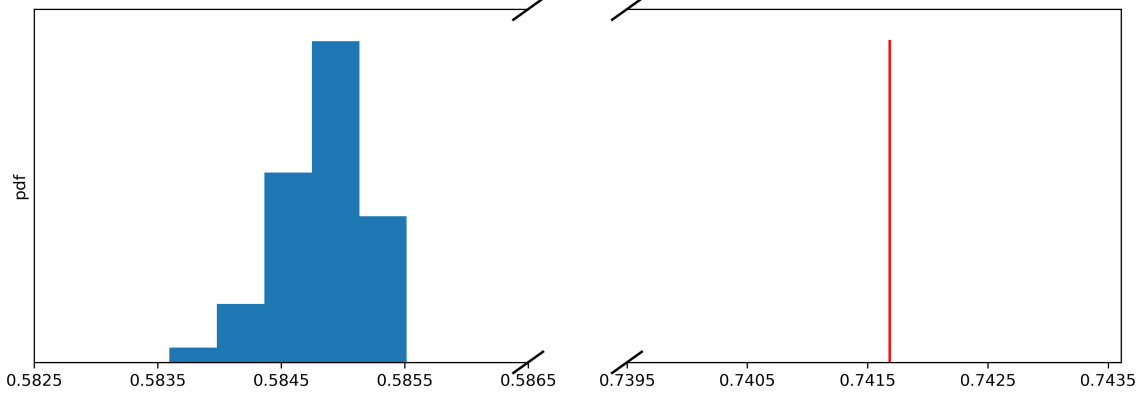


Figure C.3: Probability distribution of the NODF of matrices generated by a null model preserving heterogeneous expected activities ubiquities (blue area), compared with the NODF of the empirical matrix (red line). Colour online.

Finally, in the empirical matrix are present at the same time both the constraints tackled in the previous two paragraphs. Therefore, we want a null model representing random matrices such that both of the following are satisfied: each firm has its expected diversification and each activity has its expected ubiquity. To solve both constraints at the same time we need to solve a system of equations numerically with techniques inspired by the maximization of entropy (Saracco et al., 2015). The distribution of NODF for matrices produced by this last null model is represented in Figure C.4. Even this last null model cannot produce matrices with a NODF as high as the empirical matrix.

In table C.1 we show the statistics of the distribution of NODF for matrices generated with the four models, and the Z-score of the empirically observed values of NODF for the matrix assuming the four different null hypotheses. An interesting result is that, even if no null model approaches the empirical value (0.742), we can see how the heterogeneous ubiquity of activities is a crucial ingredient to generate a nested matrix, more than the diversification of firms.

Overall, the comparison between the nestedness of an empirical matrix with a random matrix is not a trivial task, as it is not clear which constraints are actually to be discounted and which are into the definition of nestedness itself (Bruno et al., 2020). In our case

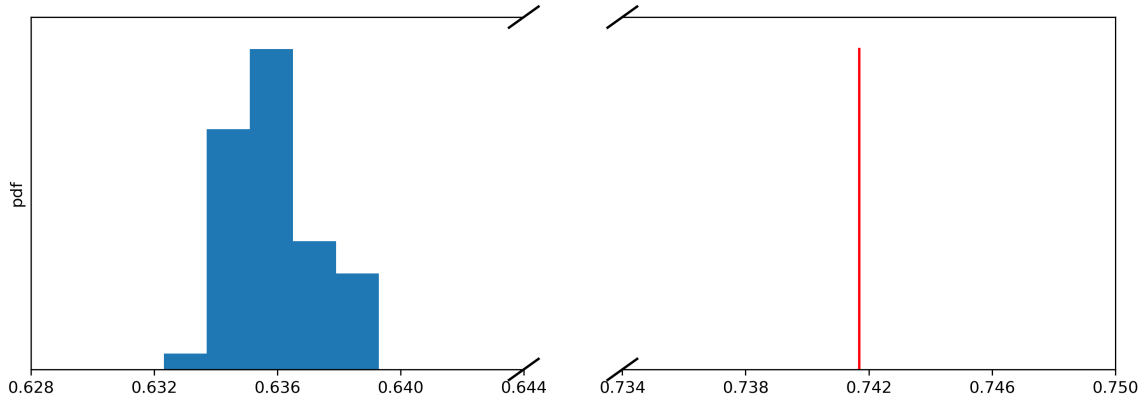


Figure C.4: Probability distribution of the NODF of matrices generated by a null model preserving heterogeneous expected activities ubiquities and expected firms diversifications (blue area), compared with the NODF of the empirical matrix (red line). Colour online.

however, the nestedness observed, measured as NODF, is above the random case even discounting every possible constraint. To perform advanced activities, a firm has to climb the ladder.

Notice that the large values of the Z-score in table C.1 should not surprise the reader: having many firms in our sample, even small signals are highly statistically significant. As a comparison, it is instructive to look at the case of survey data. Applying the same computations to data from the World Management Survey⁹ (employed by several studies, among others, Bloom et al. (2012)), we can define firm capabilities from managers' answers to the survey questions. For instance, to the question “Can you describe the production process for me?”, a manager could answer with different scores, where score 1 would imply the introduction of few modern manufacturing techniques in an ad-hoc manner, score 3 would imply introduction of modern manufacturing techniques in an informal or isolated manner and score 5 would imply that all major aspects of lean manufacturing have been introduced formally. The observed nestedness in the empirical matrix of capabilities extracted by this survey data, as measured by NODF, is 0.299. While it is *statistically* significantly different from the strict null model, with a Z-score of ≈ 10 from the null model average of 0.253, it is not *economically* significantly different. As NODF spans from 0 to 1, the signal with

⁹Please see <https://worldmanagementsurvey.org/>, last accessed 22/02/2022.

respect to random noise is just 4.5% more. More striking, even with the looser null model devoid of any constraint, a complete random rendition of a matrix of a certain density, the null model average is 0.218.

D Varying the threshold for dichotomization

Are even small amount of expenses signals of firms capabilities? According to our methodology so far, a firm that spends 1 rupee on R&D would be classified as having R&D capabilities. A reasonable objection to the idea of dichotomization is that it could mix signal and noise: as we consider a firm as having the proper capabilities for an activity if they have any expense in said activity, very small and inconsequential amounts of expenses gets conflated with important expenses. Furthermore, the threshold could be in absolute terms (assuming for example that expenses less than the wage of two researchers is not a signal of a working R&D department) or in relative terms (a big multisegment firm paying two researchers does not reflect the same focus as a small startup with the same expenses), or even have a different threshold for different sectors (to perform R&D activities in two sectors could have a very different cost).

Indeed in the exercise presented in this paper we define a firm-activity link to be “True” if there is any expense. This could be problematic, as any noise could obfuscate the signal. For example this is what happens when applying the same algorithms employed in this paper to countries and products, the original context in which these algorithms were devised: as small amounts of trade in a sector are often random and not representing capabilities, the signal is maximum when small amounts are cleaned off. This is typically done by considering a link as true when the country shows “Revealed Comparative Advantage” (Balassa, 1986).

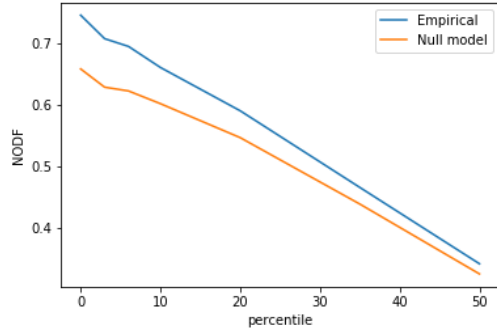
Therefore, in this appendix we look at the dichotomization process considering that small amounts of activities could be just noise. We will look at two different algorithms as possible candidates to clean the potential noise.

The first algorithm uses an absolute threshold for each activity. We first choose a

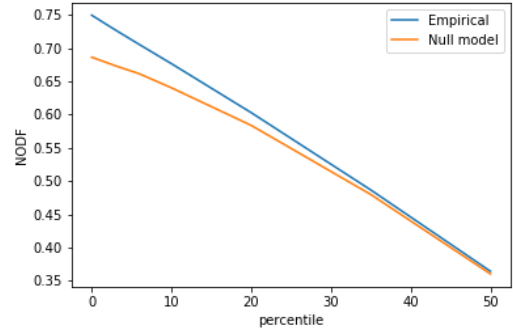
percentile (N), and later for each firm’s activity we compute the N-th percentile of the expenses (among the non-zeros value). We assign a “True” value to the binary matrix for a firm-activity link if the firm’s expenses in that activity are greater or equal than the N-th percentile for that variable, instead of just greater than 0. If N is equal to 0, the exercise is the same as the one proposed in the article: all the expense thresholds are equal to minimum for that variable, and we have therefore a “True” value in the link between a firm and an activity if the expenses of the firm in that activity are different from zero. When N increases, we stop considering “True” the bottom percentiles of the expenses, so that small amounts of expenses in one activity are not considered as revealing firm’s capabilities in that field. This algorithm goes toward the first kind of objection, the idea that a small enough R&D department is not an R&D department.

The second algorithm we tried to use to clean our matrix is using a relative measure. The procedure is the same as the previous algorithm, with a threshold set for each activity depending on a specific percentile. However, we now use a relative matrix as the starting data: instead of activities expenses, we look at activities expenses divided by total firms’ sales. In this way, when we remove the bottom percentile, we are removing firms not highly involved in a specific activity with respect to their size. For example, according to this algorithm, a big multisector firm with two researchers would not be considered as involved with R&D, while a small startup with the same setup could be considered a firm performing R&D. Of course, also in this case, when the percentile N is equal to zero we have the same exercise of the baseline proposed in the article.

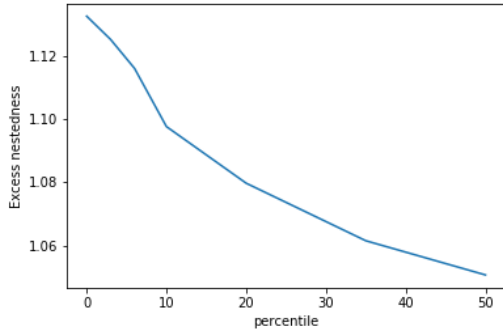
To evaluate the best cleaning strategy, we look at the excess nestedness, i.e. if the system looks less random when we clean the small values: this is what is expected if there was no information in small values. The results are shown in figure D.5. For each case, as in the previous appendix we compute the empirical nestedness as NODF and we also run a Bilateral configuration model to produce null models for the random case. We measure excess nestedness as the ratio between the empirical NODF and the average NODF for the null models. For both algorithms, it looks like even small amounts of expenses in one



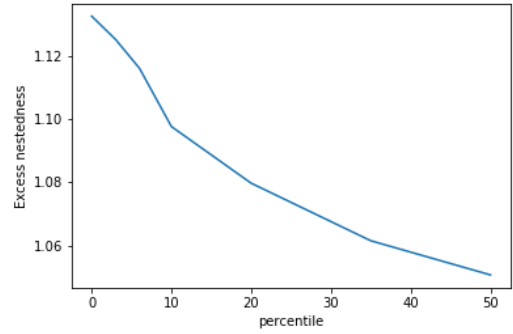
(a)



(b)



(c)



(d)

Figure D.5: Nestedness (NODF) (a and b) and excess nestedness, computed as empirical NODF divided by the mean NODF obtained with a Bilateral configuration model, (c and d) setting a different threshold depending on the absolute value (a and c) or relative value (b and d) of expenses.

category are more likely to represent a small signal than noise. The higher the threshold the less signal remains. Not surprising, when we move to a threshold of 50%, we lose any excess nestedness: if to be considered active in a field you have to have more than the median value of expenses, firms will be considered specializing in different activities, instead of diversifying and increasing their capabilities portfolio.

Table A.1: Definition of variables

Variable name	Set	Definition
Dpatents	Innovation	Patents
Dsa_prod_dev_amort	Innovation	Product Development Expenses
Dsa_consult_fees_auditors	Managerial & Organizational	Expenses: Consultancy fees to auditors
Dno_branches	Environment, Welfare & Amenities	No of branches
Dno_segments	Managerial & Organizational	No of segments or business units
Dsa_lt_loan_advance_nbfcs	Managerial & Organizational	Long term loans and advances
Dsa_st_loan_advance_nbfcs	Managerial & Organizational	Short term loans and advances
Dsa_tech_knowhow	Technological Adoption	Technical knowhow fees paid to external parties
Dsa_internet_serv	I.T. and Communication	Expenses on internet services
Dmergers	Managerial & Organizational	Merged with another company
Dsa_environment_related	Environment, Welfare & Amenities	Environment and pollution control related expenses
Dsa_leased_in_ast	Managerial & Organizational	Leased in assets
Dsa_license_fees	Technological Adoption	License fees (for use of intellectual property) paid
Dsa_comm_equip	I.T. and Communication	Assets – communication equipment
Dshareholder_outsideIn	Internationalization	Shareholders outside India
Dsa.ITES	Managerial & Organizational	Expenses – Outsourced IT enabled services and other professional jobs
Dsa_staff_training	Technological Adoption	Staff Training Expenses
Dsa_import_fg	Internationalization	Import of finished goods
Dsa_rnd	Technological Adoption	R&D expenses
Dsa_lt_invest_abroad	Internationalization	Long-term investment abroad
Dsa_export_serv	Internationalization	Export of Services
Dforeignborrowings	Internationalization	Foreign currency borrowings
Dacquisition	Managerial & Organizational	Acquirer
Dsa_import_stores_spares	Internationalization	Import of stores and spares
Dsa_import_cap_goods	Internationalization	Import of capital goods
Dsa_import_rawmat	Internationalization	Import of raw materials
Dsa_export_goods	Internationalization	Export of goods
Dsa_outsourced_mfg_jobs	Production Capabilities	Expenses: Outsourced manufacturing jobs
Dsa_total_provisions	Managerial & Organizational	Provisions for i) bad and doubtful advances, ii) debts & debtors, diminution in investments and iii) unspecified contingencies
Dsa_distribution_exp	Managerial & Organizational	Distribution expenses
Dsa_elec_install_fitting	Production Capabilities	Assets – Electrical installations
Dsa_software	I.T. and Communication	Assets - Software
Dsa_marketing	Managerial & Organizational	Expenses on market research, branding, product designing for targeted markets
Dsa_printing_stationery	Managerial & Organizational	Printing and Stationery Expenses
Dsa_staff_welfare	Environment, Welfare & Amenities	Expenses on staff welfare
Dsa_advertising	Managerial & Organizational	Advertising expenses (Media campaign etc)
Dsa_communications	I.T. and Communication	Communication expenses (telephone, postage etc)
Dsa_net_computer_it	I.T. and Communication	Assets - Computers and IT systems
Dsa_fee_based_fin_serv_exp	Managerial & Organizational	Fee based financial services expenses (Bank charges etc)
Dsa_travel_exp	Managerial & Organizational	Travel expenses
Dsa_transport_vehicles	Production Capabilities	Assets – transport vehicles
Dsa_plant	Production Capabilities	Assets – plant and machinery
Dsa_fund_based_fin_serv_exp	Managerial & Organizational	Fund based financial services expenses (Interest paid on loans)
Dsa_auditor_fees	Managerial & Organizational	Fees paid to auditor associated with the company (internal)
Dsa_outsourced_professional_job	Managerial & Organizational	Expenses: Outsourced professional jobs
Dsa_land_building	Production Capabilities	Assets – land and building
Dborrowings	Managerial & Organizational	Borrowings

Null model	Mean	St.Dev.	Zscore
Homogeneous probability - C.1	0.266	3.7810^{-4}	1260.83
Heterogeneous firms diversification - C.2	0.306	6.4510^{-6}	67612.9
Heterogeneous activities ubiquity - C.3	0.585	3.4610^{-4}	453.6
Bilateral configuration model - C.4	0.636	1.3610^{-3}	78.1

Table C.1: Mean and Standard deviation of the NODF for matrices generated with different null model, and T-statistics of the empirical value (0.710). All the corresponding p-values are below machine precision.

E Relative Profitability (ONLINE SUPPLEMENTARY MATERIALS)

Profitability can be taken as an alternative dependent variable (besides sales growth and survival) for investigating the link between capabilities and firm performance. This appendix shows the results of running a regression looking at the relative profitability of the firm compared to other firms in its 4-digits sector. Time-invariant firm specific effects, as well as some basic controls (lagged values of the logarithms of firm size and firm age) are controlled for. The main takeaway is that capabilities are far from being statistically significantly associated with relative profitability.

	(1)	(2)
Size	1.7688 (1.8228)	1.4923 (1.9284)
Age	-2.1014 (2.1622)	-2.0956 (2.2747)
Capabilities		8.5995 (6.6688)
Observations	277559	268800
Firm clusters	35881	35273

Table E.1: Capabilities and firm profitability: Fixed effects estimation

F Geographical characterization of firms (ONLINE SUPPLEMENTARY MATERIALS)

We can look at the position of firms in the ladder from a development angle, by looking at the average capabilities of firms in different Indian states, analyzing the vast heterogeneity in terms of industrial capabilities of Indian states. Notice that these results are suggestive, but they do not allow for a clear causal interpretation. On the one hand, here we do not take into account the potentially confounding role of variables such as urban density, sectoral specialization, firm size, regional infrastructure, and so on. On the other hand, the average capability of the firms in the state should not to be seen as a measure of excellence: a state with many young and active start-ups would have low average firm capabilities. With these caveats, in Figure F.1 we show the average capabilities per state. Haryana and Kerala firms have on average the most developed capabilities, while West Bengal and NCT of Delhi have the least developed capabilities. In Figure F.2 we show, for the four states with the most firms in our sample, the distribution of firms at different steps of the ladder.

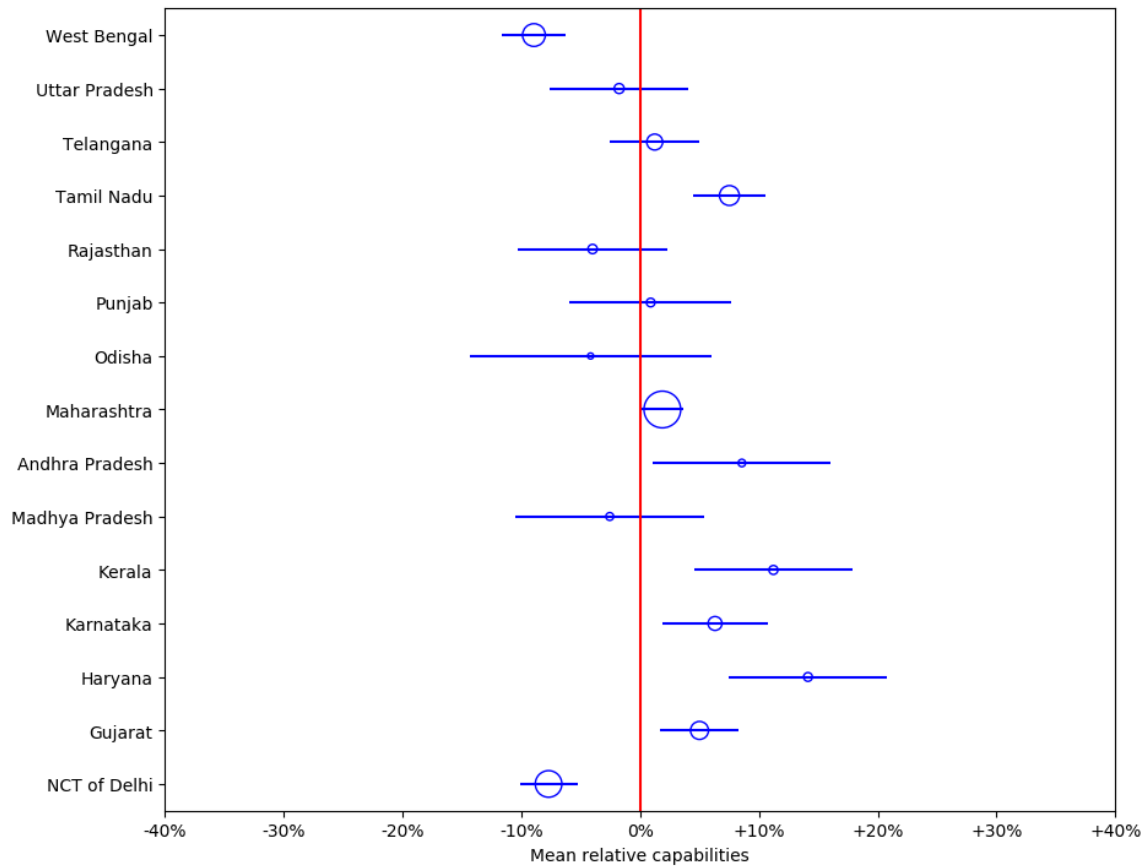


Figure F.1: Relative average position in the capabilities ladder of firms in different Indian states with respect to the average of all Indian firms, Year 2019. Error bars represents 2 standard errors – i.e. $\approx 95\%$ confidence interval. Size of the circle is proportional to the number of firms in the sector. Colour online.

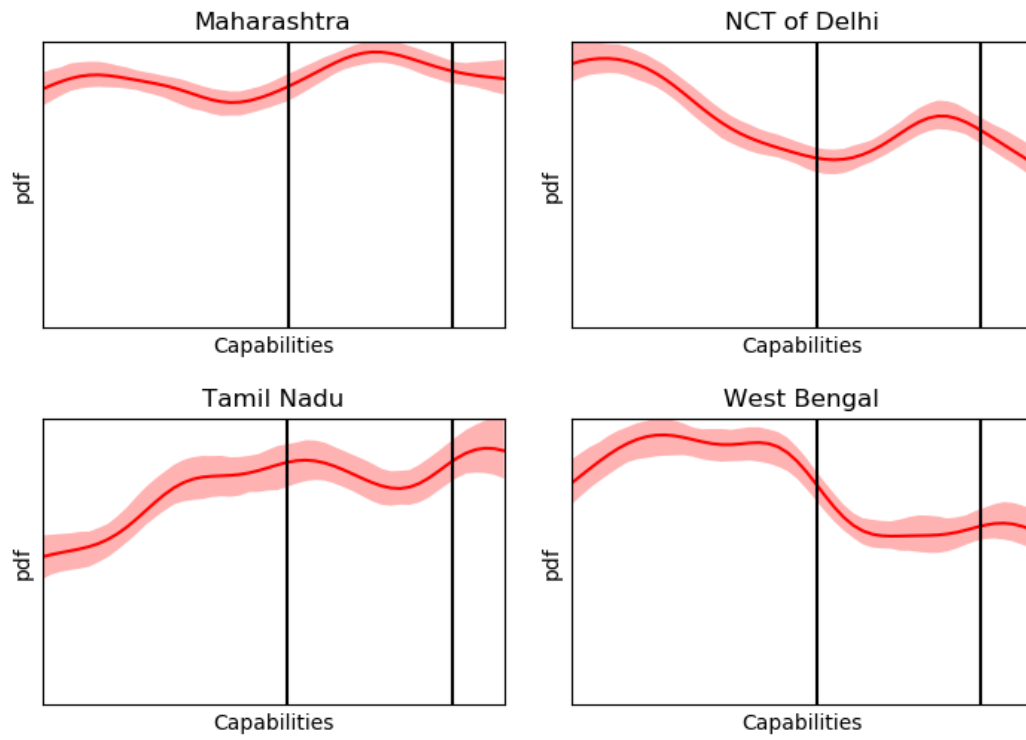


Figure F.2: Probability distribution of firms of the state by capability (inverse) ranking among Indian firms, for the four states with the most firms in our database. The two vertical black lines divide the three steps. Colour online.