ICAE Working Paper Series - No. 105 - March 2020

Theory and Empirics of Capability Accumulation: Implications for Macroeconomic Modelling

Matthias Aistleitner, Claudius Gräbner and Anna Hornykewycz

Revised Version, June 2020

JOHANNES KEPLER UNIVERSITÄT LINZ

ICAE INSTITUTE FOR COMPREHENSIVE ANALYSIS OF THE ECONOMY

Institute for Comprehensive Analysis of the Economy
Johannes Kepler University Linz
Altenbergerstraße 69, 4040 Linz
icae@jku.at
www.jku.at/icae

THEORY AND EMPIRICS OF CAPABILITY ACCUMULATION: IMPLICATIONS FOR MACROECONOMIC MODELLING*

WORKING PAPER

Matthias Aistleitner

Institute for the Comprehensive Analysis of the Economy
Johannes Kepler University Linz
matthias.aistleitner@jku.at

Claudius Gräbner†

Institute for Socio-Economics
University of Duisburg-Essen
&
Institute for the Comprehensive Analysis of the Economy
Johannes Kepler University Linz
claudius@claudius-graebner.com

Anna Hornykewycz

Institute for the Comprehensive Analysis of the Economy
Johannes Kepler University Linz
anna.hornykewycz@jku.at

June 11, 2020

ABSTRACT

The accumulation of new technological capabilities is of high empirical relevance, both for the development of countries and the business success of firms. This paper aims to delineate strategies for the consideration of processes of *capability accumulation* in comprehensive macroeconomic models. It comprises an interdisciplinary review of the literature specialized on capability accumulation by analyzing both empirical as well as theoretical literature on the firm and aggregated level. In doing so, it summarizes evidence on various determinants and mechanisms of capability accumulation and aligns them with the current representation of capability accumulation in macroeconomic models. Based on these results, it offers some suggestions on how macroeconomists may integrate these determinants derived from the specialized literature into their models.

Keywords Capability accumulation · complexity · economic development · innovation · technological change · agent-based modeling · endogeneous growth · knowledge accumulation and learning

*The authors gratefully acknowledge support of the Economic and Social Research Council (UK) under grant reference number ES/R00787X/1. We also acknowledge the role of the National Institute of Economic and Social Research (NIESR) in hosting the Rebuilding Macroeconomics Network.

†Corresponding author.

1 Introduction

The relevance of *technological capabilities* for growth and development on the national and regional level, as well as for the business success on the firm level has been documented by numerous empirical investigations (e.g. Baumol, 2002; Hidalgo and Hausmann, 2009; Romer, 1990). In the macroeconomic literature, it is argued "that countries tend to approach the level of income associated with the capability set available in them" (p. 10570 Hidalgo and Hausmann, 2009), while on the firm level, "[. . .] technological capabilities are central to [a firm's] identity, its strategies, and its potential for success" (Aharonson and Schilling, 2016, p. 81).

Researchers working on macroeconomic questions, therefore, face both a challenge and an opportunity: on the one hand, the literature shows that capability accumulation (hereafter CA) is an important determinant for macroeconomic dynamics, therefore offering a possibility for more accurate models of growth and development and a constructive interdisciplinary collaboration with researchers working on CA from a sociological, management studies or innovation studies perspective. On the other hand, transferring the fine-grained results on CA into a comprehensive macroeconomic model is difficult and often conflicts with the challenge of keeping the complexity of these models manageable. This challenge is exacerbated by the fact that, notwithstanding a substantial body of research, there is no consensus about the mechanisms underlying CA: while there are numerous empirical results on CA, a lot of authors remain silent on the "variety of mechanisms by which economies and organizations learn" (Hidalgo *et al.*, 2018, p. 452)".

The prime objective of the present paper is to facilitate an interdisciplinary collaboration and to address the challenge of considering CA within comprehensive macroeconomic models by (1) providing an overview over current strategies to integrate CA into macroeconomic models, (2) reviewing the empirical literature on CA on the micro- and macroeconomic level and (3) discussing specialized models dedicated to the investigation of CA processes and, thereby, delineating promising channels for integrating results from the specialized literature into comprehensive macroeconomic models. This would not only allow for the construction of more realistic macroeconomic models, but also to study how mechanisms of CA interact with other macroeconomic processes. This way, such undertaking could also feed back successfully into the research on CA as such.

Unfortunately, there is no unanimous and generally accepted definition of CA. This paper focuses on how agents – comprising both firms and countries – accumulate capabilities, and where capabilities are understood broadly as "the knowledge that goes into the making of products" (The Growth Lab at Harvard University, 2019). It is worth noting that numerous similar – and partly synonymous – terms are used in the literature. First, the topic of CA is related to the topics of *collective learning* and *knowledge accumulation*, which are particularly common in the organization science literature. CA as understood in this paper can be interpreted as a special form of learning, i.e. learning new or better ways to conduct certain economic activities. To avoid the more general and less precise notion of 'learning' we use the term 'capability accumulation', well aware that the latter is a subset of the former.

Second, there is a close connection to the terms *innovation* and *technological change*, most commonly used in management studies and economics, respectively. *Innovation* has been defined - *inter alia* - as "ways to exploit the latent potential of ideas" (Francis and Bessant, 2005, p. 171) or, more elaborately, "the recognition of opportunities for profitable change and the pursuit of those opportunities all the way through to their adoption in practice" (Baumol, 2002, p. 10). Thus, the term *innovation* tends to embrace all measures that transform an idea into a new approach to doing things and, therefore, seems to include – but is not limited to – technological capabilities. For our review, we considered papers studying *innovation* by deciding on a case-by-case basis whether the term is defined and used in a way that comprises our definition of *capabilities*. We took the same approach when it came to the term *technological change*, which is particularly common in economics. In a seminal paper, Romer (1990) defines technological change as "improvement in the instructions for mixing together raw materials" (p. 72). Technology is, thus, understood as the set of knowledge, actions and instruments available that can be used to transform input into output. The term is most often used with regard to the production process and the creation of new products. In contrast to *innovation*, which is mainly used in the context of firm and sector analysis, *technological change* is used both on the micro- and

macroeconomic level and, thereby, in a broader sense. Again, we decided on a case-by-case basis whether authors use the term *technological change* in a way that is consistent with our definition.

As indicated above, the aim of this paper is to facilitate the integration of insights on CA into more comprehensive models of macroeconomic development. To this end, we proceed as follows: section 2 provides a description of the *status quo*, i.e. an overview on how CA is currently considered in macroeconomic models. Then, central results on CA of the more specialized literature are summarized in section 3. Section 4 contains a discussion of how these results can be better integrated into macroeconomic models. Finally, section 5 offers a summary and conclusion.

2 CA in macroeconomic models

The challenge for macroeconomists is to take into account CA as an empirically highly relevant economic process, while at the same time keeping the overall complexity of the model manageable. This comes with trade-offs: a more complete depiction of the CA process makes it *ceteris paribus* more difficult to also include an adequate description of, for example, the central bank, the government or household behavior.[3] This section reviews how this challenge is currently addressed in different modeling frameworks. To keep the overview concise it focusrd on two representative modeling frameworks: *endogenous growth models*, which in many ways also provides the building blocks for CGE and DSGE models, and *agent-based macroeconomic models*. Together they account for a considerable share of macroeconomic models concerned with topics related to CA.

Endogenous growth models (EGMs) are among the most common approaches to study macroeconomic dynamics and development. Many central ideas related to the macroeconomic study of CA, such as the idea of *directed technological change* (e.g. Acemoglu, 2002a) or *innovation networks* (e.g. Acemoglu *et al.*, 2016a) either originated, or at least were discussed extensively, within this framework. The historical motivation to develop these models was the desire to study the role of CA for economic development *endogenously*, rather than treating it as an exogenous factor as common in the previously prominent neoclassical growth models (e.g. Solow, 1956; for an early overview see Löschel, 2002). Consequently, in EGMs CA is the outcome of the investment activities of (profit maximizing) agents, as well as the assumed market environment (for an extensive overview see, e.g., Acemoglu, 2009). A concise summary is given in table 1.

EGMs highlight different mechanisms according to which CA takes place and operates, most of which are related to the R&D decisions of firms.[4] A number of standard treatments have emerged: in one of the first contributions to the EGM literature, Rivera-Batiz and Romer (1991) subsume CA under a very general definition of *technology* which, aside from technological capabilities, comprises machinery, process knowledge and the quality of physical inputs. Here, CA takes place as an immediate consequence of firms investing into R&D or machines and reduces the marginal cost of production for the firm – the process of production becomes more efficient and CA is conceptualized as a kind of *process innovation*. A similar treatment dates back to Romer (1990), for whom the carriers of capabilities are skilled workers who benefit from the knowledge accumulated by older generations. In effect, CA, which again gets triggered by R&D investment, involves the process of inter-generational *knowledge spillovers*, and takes place in a cumulative way, where current generations build upon, and expand the stock of technological capabilities accumulated by previous generations. Weitzman (1998) introduces a variant of this setup by treating labor as a fixed factor in the production function, but to endogeneize the level of knowledge (i.e. $Y = F(K, A)$). Knowledge expands as a consequence of R&D investments and the re-combination of the existing set of ideas, thereby providing a different, yet complementary view on how CA improves productivity.

[3] Models that do not face this trace-off since they are dedicated to the modeling of CA processes as such are dealt with in section 3.3 below.

[4] Here we focus on the *mechanisms* underlying CA. Therefore, important contributions that characterize the empirical implications of these mechanisms, such as the skill biasedness of technological change, are not discussed explicitly. They can be thought of as consequences of the mechanisms mentioned here.

Building blocks of CA in macroeconomic models I: endogenous growths models (EGMs)		
Consideration of CA	**Effect of CA**	**Seminal papers**
Firms invest into ***R&D*** to acquire ***better inputs***, such as machines, processes and skills	Reduction in production costs	Rivera-Batiz and Romer (1991)
Firms invest into ***R&D*** to develop ***new variants*** of products, which may come with temporary monopoly rents due to consumers' preferences for variety	Temporary monopoly rents	Grossman and Helpman (1991a,b)
Firms invest into ***R&D*** , but the carriers of CA (e.g. scientists) are 'scarce', so sustained growth is possible only due to ***knowledge spillovers***: CA happens cumulatively and via interpersonal knowledge diffusion	Increased productivity	Romer (1990)
Firms invest into **R&D** and **recombine existing knowledge** to advance productivity; CA happens cumulatively and mainly via recombination of existing, rather than the creation of new knowledge as such.	Increased productivity	Weitzman (1998)
Entrant firms invest into ***R&D*** and ***replace incumbents***, mostly by offering higher-quality versions of existing products; in effect, CA is enforced by the danger of ***creative destruction***	Temporary monopoly rents (for successful innovators)	Aghion and Howitt (1992)
An important set of growth models formalizes ***barriers to technology adoption***, (such as extractive institutions), and focus on why CA does *not* take place	Persistent differences in levels of income and capabilities across the world	Howitt (2000), Acemoglu *et al.* (2007)
People learn to use particular technologies, thereby closing the possible ***mismatch between knowledge and technologies***; in effect, CA happens cumulatively	Slow or no CA taking place; this implies lack of catch-up across countries	Atkinson and Stiglitz (1969), Acemoglu and Zilibotti (2001), Acemoglu (2002b)

Table 1: Implementation of the CA process in selected macroeconomic endogeneous growth models.

A slightly different perspective is offered by the models in the spirit of Grossman and Helpman (1991a,b), where CA is also the result of investment into R&D, but where it leads to the production of new product varieties. Thus, for firms, CA pays off not by the reduction of production costs but because of temporary monopoly profits on the market. This mechanism is more similar to *product innovation*, although it is only about the development of new varieties of existing products, rather than the invention of brand new products.[5] Temporary monopoly rents are also the main implication of CA in the models building upon Aghion and Howitt (1992), where R&D investments lead to the production of better products, which then eliminate their predecessors. Because of the resulting competition between incumbent and entrant firms as well as the resemblance of a process of *creative destruction*, these models are often labeled as 'Schumpeterian models'. Here, CA is something firms must strive for in order to survive in the market.

In much of the newer literature, the main interest of researchers has shifted to the explanation of uneven CA on the global level. Starting with the contributions of Howitt (2000) and Acemoglu *et al.* (2007), the investigation of *barriers* to CA, such as incomplete contracts, extractive institutions or social conflicts, is now an active area of research. While these models are less concerned with the question of how CA takes place, their treatment of barriers to CA allows to

[5]This distinction has relatively little impact on the mathematical structure of the models, yet represents very different aspects of the real world innovation and CA process, which is why we consider it important to highlight this difference.

derive conjectures on these processes as well. The same applies to models dealing with the *mismatch between skills and technology* (e.g. Acemoglu and Zilibotti, 2001; Acemoglu, 2002b), which also consider processes of *learning-by-doing*.

While EGMs continue to be very successful in macroeconomics and have highlighted important systemic implications of CA processes on the firm level, they necessarily take a birds eye perspective on the process of CA: they abstract away most of the particular learning activities on the firm and employee level. This helps to focus on the macroeconomic implications of CA, yet also shallows the concrete mechanisms underlying CA on the micro level. This is potentially different in the case of agent-based models (ABM), which have grown in popularity over the previous years due to their success in replicating a respectable number of stylized facts on the micro, meso and macro level (for a survey see, e.g., Dawid and Delli Gatti, 2018; Dosi and Roventini, 2019). These models consist of an artificial population of agents whose interactions are simulated directly and analyzed numerically without an *a priori* equilibrium assumption. One of the main advantages lies in the straightforward consideration of agent heterogeneity (Hidalgo *et al.*, 2007; Syverson, 2011, which matters because agent heterogeneity affects diffusion of knowledge, and countries and firms differ considerably in terms of their level of accumulated capabilities[) and out-of-equilibrium dynamics (which matter in the context of innovation or technological change, seee, e.g., Dosi and Roventini, 2019), which is why ABM have become a popular tool to study CA.

In contrast to EGMs, ABM necessarily contain explicit protocols for all processes taking place within the model. On the one hand, this might entail the danger of *ad hoc* specifications of these processes. On the other, the flexibility of ABMs and the required explicitness might facilitate the inclusion of results of the specialized literature on CA. In the following, we ask to what extent this inclusion has already taken place. To this end we discuss five different models, each representative for a particular 'family' of macroeconomic ABM.[6] An overview is given in table 2.

Macroeconomic ABMs usually distinguish between a production sector for consumption and for capital goods. Dosi *et al.* (2019b, representative for the 'Keynes-meets-Schumpeter' models) and Caiani *et al.* (2019, representative for the 'Benchmark' models) locate CA processes only in the consumption good sector. Firms invest into R&D to increase the probability of successful *innovative* or *imitative* activities. If the former is successful, the firm may discover better ways to produce their final products, resulting in an increase of labor productivity. In case the latter is successful, the firm copies the productive technologies of other firms' production, which may also lead to increased productivity. Thus, both processes refer to improved ways to produce the same product.

Other macroeconomic ABMs locate the CA process in *both* the consumption and the capital good sector: Ciarli *et al.* (2018) consider two types of CA processes: first, capital good firms invest into R&D to develop higher quality versions of their capital good, which are more attractive to final good firms since they feature higher labor productivity. Then, final good firms invest into R&D based on anticipated payoffs and, if successful, produce new products (or, in the jargon of the paper, goods in higher quality). Thus, the model features a kind of CA similar to that in Grossman and Helpman (1991b) with regard to *product innovation*.[7]

Hötte (2020), who extends the Eurace@Unibi-eco model (Dawid *et al.*, 2019), models the CA process both on the level of employees and firms: the firm side is similar to the models discussed above: capital good firms invest into R&D to increase the probability to invent more productive capital goods, which can then be sold more attractively to the final good firms that produce a homogeneous consumption good. On the level of the individuals, employees improve their abilities to work with particular capital goods on the job via a *learning-by-doing* process through which workers acquire *technology-specific* skills. This has important implications: by representing the specificity of employees' skills and the mechanism of *learning-by-doing*, Hötte (2020) is able to study the co-evolutionary character of technological

[6] A 'family' is made up by several versions of the same underlying model. Since all instances of the respective families implement CA similarly, we focus on the most recent instance or the one that pays most attention to the topic of CA.

[7] This also illustrates how the explicit event protocols in ABMs allow for a more explicit and diverse representation of CA processes: in Ciarli *et al.* (2018), for example, firms decide on their R&D expenses based on anticipated payoffs, whereas in Dosi *et al.* (2019b) it is a fixed share of past profits. This introduces more degrees of freedom, but also allows for a more fine-grained alignment of the model specification with the existing empirical literature.

Building blocks of CA in macroeconomic models II: agent-based models (ABMs)				
Model	**Locus of CA**	**Effect of CA**	**Description of CA process**	**Determinants of CA**
(Dosi *et al.*, 2019b, representative for the 'Keynes-meets-Schumpeter' models), (Caiani *et al.*, 2019, representative for the 'Benchmark' models)	Consumption good firms	Increased labor productivity	Firms invest into R&D to increase the probability for successful innovation or imitation which, in turn, may increase productivity	R&D expenses, spillovers
Ciarli *et al.* (2018)	Capital good firms Consumption good firms	Capital goods with higher labor productivity Higher product quality	Firms invest into R&D based on anticipated payoffs; this increases trials for innovation activity per time step	R&D expenses
Dawid *et al.* (2019) and Hötte (2020, representative for the EURACE@Unibi models)	Employees	Better exploitation of high productivity production technologies in the employing firm	Workers have exogeneously given general skills that determine speed of *learning-by-doing*, which increases specific skills (i.e. tacit knowledge that workers can take with them to other firms)	Experience
	Capital good firms	Potentially higher productivity of capital goods, if matched with skilled workers	Firms engage in R&D; success randomly adds higher quality vintage, which might be sold to consumer good firms	R&D expenses
Rengs *et al.* (2019)	Consumption good firms	Reduction of carbon intensity of production Reduction of labor intensity of production	Firms decide to invest into R&D directed at green technology reducing carbon intensity, or at grey technology reducing labor intensity of production; for both technologies, spillovers across firms exist	Spillovers, R&D

Table 2: Implementation of the CA process in selected macroeconomic agent-based models, where it is usually discussed under the label 'innovation'. The column 'determinants' only lists the ultimate drivers of CA. We do not mention 'policies' when they impact CA only via fostering R&D investments.

change: the diffusion of technologies depends on the adoption decisions of the users and the solution of an underlying coordination problem, which is why lock-in effects on inferior, but already widely adopted technologies, might occur.

Finally, Rengs *et al.* (2019) distinguishes between capabilities necessary for two aspects of production: firms can reduce the amount of CO_2 emissions associated with production, or they can increase their labor productivity. When deciding on which competencies to improve upon, firms compare themselves with their competitors and follow the strategy of those firms that are making the highest profits, and they decide on the amount of funds allocated to the improvement of their capabilities based on their past profits. The effect of these investments also depends on spillover effects from other firms: the more firms focus on one particular way of improving their products, the more effective their investments become.

In addition to the CA processes just described, many macroeconomic ABMs also study the effect of institutions and government activity on the processes of CA. For example, Dawid *et al.* (2018) study the effect of innovation policy on the speed of CA in less developed countries. Innovation policy here takes the form of (directed or undirected) subsidies for the R&D investments of firms, thus serving as a second level determinant of CA operating through the channel of R&D investment as explained above. Another example is provided by Dosi *et al.* (2018), where the authors study the effect of an active government investing into R&D activities on its own. Via knowledge-spillovers these R&D activities then affect the rest of the economy as well. Again, in this case the *fundamental* channels of CA are R&D activities and knowledge spillovers, yet it is clearly acknowledged that since the government can engage in these activities itself, its behavior affects CA in the overall economy. Finally, as evidenced by Caiani *et al.* (2019), different institutions of wage determination may also affect CA. They show that coordinated wage growth in the long run can lead to a concentration of firms and, via the channel of 'Schumpeter Mark II', to higher and more targeted investments into R&D activities. As in the two examples above, the institutions determining wages here affect CA via the more fundamental channel of R&D investments. Thus, while it is important to keep in mind that many current ABMs do investigate the role of institutions and policy makers for CA, they do so via reference to the more fundamental determinants of CA explicated before, i.e. mainly R&D investment.

When comparing ABMs and EGMs with regard to the consideration of CA we may conclude that – so far – in both modeling paradigms relatively little attention is given to the precise mechanisms according to which CA takes place. Moreover, in both approaches by far the most prominent determinant for CA is R&D investment (and, to a lesser extent, knowledge spillovers) and the main effect is an increase in firm productivity. Relatively little attention has been given to the role of CA for the invention of radically new products. Models that do feature product innovation consider CA as means to leading to higher quality products.

3 Theory and empirics of CA beyond macroeconomics

We first describe the data used for our literature survey in section 3.1. Then we complement this information by reviewing the empirical (section 3.2) and theoretical (section 3.3) literature directly concerned with the problem of CA .

3.1 Methods and Data

We conducted a bibliographic search to collect papers that focus on the mechanisms underlying CA rather than the implications of these mechanisms. Our focus was on papers that consider CA either as a *dependent* or at least *mediating* variable. Furthermore, we focused on CA in the context of manufacturing, not services. In a first step, we collected a sample of papers by following two strategies. We started by searching the EconLit database for english papers published between 2004 and 2019 (working papers published not later than 2018) containing both keywords *capability* and *accumulation*, as well as the exact phrases *knowledge accumulation*, *technological learning* and *product complexity*.[8]

[8]We deliberately excluded the keyword *innovation* since the keyword 'innovation' is used in a much broader way. Moreover, most relevant contributions focusing on innovation in a sense that is consistent with our definition of CA also use some of the keywords that were used in our search strategy.

This resulted in 570 papers. After deriving a sub-sample of the most relevant results via a content analysis, we divided the papers into 1) theoretical contributions that describe a mechanism of CA, 2) empirical contributions that study a mechanism of CA on the aggregate (mostly regional or national) or 3) the firm level. After conducting a thematic analysis of the mechanisms described in this subset, we arrived at eight main *topoi* that the literature was centered around (see sections 3.2 and 3.3).

Then we searched the Web of Science database for papers published in the same period containing the exact phrases listed above plus *capability accumulation*.[9]. This resulted in 764 papers. The additional results so obtained (especially in the fields of engineering, business, management and organization science) let to a further refinement of our respective *topoi*. Moreover, we applied *purposive searching* ('snowballing')[10] and added further relevant literature referenced in these papers to our overall sample. Finally, we consulted experts from theory and practice and added further literature based on their recommendations. In sum, we selected the 75 representative empirical studies on CA as shown in Tables 3 and 4 and nine representative theoretical models that implement CA processes in specialized models (Table 5).

3.2 Empirical contributions

3.2.1 Empirical results on the aggregated level

Determinants of CA on the aggregated level can be clustered according to three main *topoi*: (1) the *cumulative and path-dependent nature of CA*, (2) the *institutional environment*, and (3) the relevance of *government activity*. Despite the boundaries being not always clear-cut and because a separate discussion of each *topos* might be more helpful in the development of comprehensive models, the *topoi* are now examined one by one. The results are summarized in table 3.

Cumulative and path dependent nature of CA. New capabilities are accumulated step-wise, and new capabilities are similar to existing ones. This means that the set of capabilities that is most likely accumulated in the present is a function of the stock of capabilities that have already been accumulated in the past. Dubbed as the "Principle of Relatedness" (Hidalgo *et al.*, 2018, , hereafter PoR), this general claim has been examined on the basis of different operationalizations that can be considered as different but related attempts to empirically test a rather abstract principle:

- *Skill relatedness* (e.g. Neffke *et al.*, 2017) as measured by inter-industry labor flows: capabilities develop along similar human capital or skill requirements.
- *Technological relatedness* (Acemoglu *et al.*, 2016b; Alonso and Martín, 2019; Balland *et al.*, 2019; Neffke *et al.*, 2011) as measured by plant-level product portfolios, country-level production baskets and/or patent data: capabilities develop along regional paths of production.
- *Export relatedness* (e.g. Bahar *et al.*, 2014) as measured by the composition of export baskets: a country's capabilities converge to the capabilities of neighboring countries, i.e. there are information spillovers between close regions.

Hidalgo *et al.* (2007) formalize this general idea of *relatedness* within the framework of the *product space*, a network based on trade data in which the vertices represent products, and the edges represent the probability that two products are co-exported by the same country. They make the PoR empirically tractable by making two major assumptions: First, the products a country produces proxy the capabilities accumulated by the people in this country: if a country is a producer of computer chips we can conclude that its inhabitants have the capabilities required to produce computer

[9] In contrast to EconLit, we used the exact phrase here since searching for the common occurrence of *capability* and *accumulation* alone would yield more than 4.600 results.

[10] Snowballing often appears to be a more viable approach in identifying the relevant literature compared to conventional database searching (Pawson, 2006).

Empirical findings on the aggregated level	
Findings on the CA process	**Sources**
Cumulative and path dependent nature of CA	
Skill Relatedness: CA happens through worker migration flows	Neffke *et al.* (2017)
Technological Relatedness: CA builds on preexisting capabilities	Acemoglu *et al.* (2016b), Alonso and Martín (2019), Balland *et al.* (2019), and Neffke *et al.* (2011)
Export Relatedness: Spillovers from neighboring regions lead to CA (expressing themselves in more similar export baskets)	Bahar *et al.* (2014)
CA is determined by the "product space"	Hidalgo *et al.* (2007)
CA is determined by a country's knowledge base focus	J. J. Lee and Yoon (2015)
CA is hampered by structures causing institutional "lock-in"	Mirimoghadam and Ghazinoory (2017)
Institutional environment	
CA is supported by securing and deepening intellectual property rights	Ang (2010, 2011)
CA is hampered by excessive intellectual property rights	Dosi *et al.* (2006) and Fernandez Donoso (2014)
CA is supported by protectionism	Figueiredo (2008)
CA is supported by economic integration	Alonso and Martín (2019), Castellacci and Natera (2013), Figueiredo (2008), Habiyaremye (2019), and Molina-Domene and Pietrobelli (2012)
CA is weakened by labor market flexibilization	Vergeer and Kleinknecht (2014), Cetrulo *et al.* (2019)
CA may be supported by financial development but is negatively associated with financial liberalization (policies)	Ang (2010, 2011)
CA is linked with socio-political and socio-economic development: inequality, education, health and public infrastructure	Castellacci and Natera (2013) and Dutrénit *et al.* (2019)
Government activity	
CA is fostered by public R&D investment	Ang (2011), Cai *et al.* (2020), Castellacci and Natera (2013), T. J. Lee (2004), and Mazzucato and Semieniuk (2017)
CA is fostered by public ownership, governance and procurement	Castelnovo *et al.* (2018), Mazzucato and Semieniuk (2017), and Yu *et al.* (2015)
CA is fostered by active industrial policies: training programs, coordination, mediation and collaboration	Figueiredo (2008), Lebdioui (2019), J. J. Lee and Yoon (2015), Mazzucato and Semieniuk (2017), Mehri (2015), and Perez-Aleman and Alves (2017)

Table 3: Central empirical findings on the determinants for well-functioning CA on the aggregated level.

chips.[11] Second, the products that a country exports are a good proxy for the products that a country produces. This assumption is made because there are good data about imports and exports, but not so on actual production[12].

In effect, the product space can be seen as an empirical operationalization of the the PoR when applied to economic activities related to the production of commodities. Although there is no elaborated theory of CA underlying the concept of the product space, it implies that CA happens in a cumulative fashion, with new capabilities being similar to those that have already been accumulated. Hence, CA depends on local experimentation and thereby the exploration of similar, or the re-combination of existing capabilities (see also Hidalgo and Hausmann, 2009; Vermeulen and Pyka, 2014, p. 10575). The framework thus bears much similarity to evolutionary theories of learning, including the idea of technological capabilities as a solution for particular technological challenges (e.g. Silverberg and Verspagen, 2005).

Institutional environment. Numerous studies stress the relevance of regulatory measures and other institutions for CA at the macro, meso and micro level. Determinants include the design of property rights, trade policy, labor market legislation and the overall (public) infrastructure. All this can be summarized under the heading 'institutional environment'. While almost all studies agree on the relevance of the institutional environment, disagreements about the relative strength and the direction of effects, as well as the underlying mechanisms of particular institutions remain.

A determinant of CA that has attracted much attention is the design of policies that foster *economic integration*. Various studies find positive spill-over effects caused by trade liberalization and/or FDI-flows in developing (e.g. Habiyaremye, 2019) and particular in middle-income countries (Castellacci and Natera, 2013), where in the latter case a geographical focus on the Americas stand out (e.g. Alonso and Martín, 2019; Figueiredo, 2008; Molina-Domene and Pietrobelli, 2012). However, there is no consensus on whether trade liberalization is generally beneficial to CA. For instance, Castellacci and Natera (2013) argue that for the development of an economy's innovation system, international trade is important for middle-income countries, yet for advanced and less developed countries other determinants play a more decisive role. Overall, the literature seems to suggest that the effect of openness depends on a countries' development stage and the maturity of the firms in the respective regions (see also, e.g., Radosevic and Yoruk, 2018). For example, in an extensive case study on the "Industrial Pole" of Manaus in Brazil, Figueiredo (2008) finds that protectionist policies triggered various knowledge flows from outside firms into Manaus. These flows led to an accumulation of initial firm-level technological capabilities, which later served as a precondition for successful liberalization reforms in the 1990s and which further boosted CA, but would not have been successful without earlier protectionist measures – an interpretation that aligns well with the work of economic historians on the determinants of catch-up processes after the Industrial Revolution (e.g. Allen, 2011; Chang, 2003).

However, not all contradictions regarding the institutional environment can be solved by taking a dynamic view. For instance, although it is widely agreed upon that financial development generally benefits CA via inducing R&D spending, financial liberalization policies tend to impede the CA process – particularly in developing countries (e.g., Ang, 2010). A reason for this may lie in the reallocation of human capital to the financial sector, resulting in a lack of CA in the technology sector (Ang, 2011). Another example refers to the organization of *intellectual property rights* (IPR): While, several empirical studies suggest a general positive effect of IPR institutions on CA (e.g. Ang, 2010, 2011), Fernandez Donoso (2014) finds an inverted U-shape relationship between patents and technological complexity. Moreover, there is also literature that question the positive effect of IPR, arguing that institutions of *open access* are essential for collective learning and, thereby, CA (Dosi *et al.*, 2006; see also Heinrich, 2013; Marengo *et al.*, 2012)

For other institutions results are less inconsistent, e.g. in the case of *labor market institutions*. The removal of rigidities on the labor market has, for example, been found to create incentives for the creation of low-paid and low-skilled jobs – at the expense of well-paid jobs with a higher innovative potential. Such liberalization policies also tend to discourage

[11] This assumption might be violated whenever countries 'produce' products by only assembling parts that have been imported from other countries.

[12] There are situations in which the assumption might not hold, e.g. if a country does not want to export for political reasons, where a country is at the end of an international production chain or when a country has the capabilities to produce a product, but not to sell it on the competitive world market.

worker training and the accumulation of worker experience. Both of these factors harm an economy's capacity for CA (Cetrulo *et al.*, 2019; Vergeer and Kleinknecht, 2014). Another example is *public infrastructure*, which has been found to play a crucial role for successful CA, but mainly as an 'absorptive capacity variable' (see below) that mediates the positive effect R&D investments, the accumulation of human capital and collaboration efforts among firms (see section 3.2.2 below), particularly in middle-income countries (Castellacci and Natera, 2013; Dutrénit *et al.*, 2019).[13]

Government activity. Many authors stress the relevance of direct government action, with the *entrepreneurial state* as described by Mazzucato (2014) being a recent example.[14] Channels through which more direct government action enhances CA include public R&D investment (Ang, 2011; Cai *et al.*, 2020; Castellacci and Natera, 2013; T. J. Lee, 2004; Mazzucato and Semieniuk, 2017), public ownership and governance of key sectors and enterprises (Mazzucato and Semieniuk, 2017; Yu *et al.*, 2015) but also public procurement in the context of large technology projects (Castelnovo *et al.*, 2018; for limited evidence in a developing context see Ribeiro and Furtado, 2014).

The possibilities for constructive government action beyond the fixing of market failures have been explored in numerous case studies. Mazzucato and Semieniuk (2017) show for the case of greener technologies that public organizations may not only rely on measures such as proactive financing of R&D or absorbing high risk levels and uncertainty often related to exploring radical product innovation. They may also use well-crafted policies that provide incentives to meet quality standards that go beyond what is currently demanded on the markets. Figueiredo (2008) illustrate this in the context of Manaus, where government organizations acted as active development agencies in shaping capabilities of local firms by forcing them to obtain quality standards or to introduce new management and organization techniques beyond what has been demanded on the market. Further examples are provided by Lebdioui (2019), J. J. Lee and Yoon (2015), and Perez-Aleman and Alves (2017) who explore a wide repertoire of active government policies aimed to facilitate coordination, mediation and collaboration between relevant actors (e.g. domestic and foreign firms, universities, research institutions) for triggering CA processes. In most of these cases, the government effectively supports the mechanisms operating on the firm level, as described in section 3.2.2.

3.2.2 Empirical results on the firm level

Research on CA on the firm level has highlighted a broader spectrum of determinants than on the aggregate level, with numerous firm-level studies suggesting a complex interplay of several distinct determinants and channels of CA. These are often in-depth case studies that follow a qualitative approach. Since the main goal of the paper is to distill determinants and channels of CA to integrate them into more comprehensive macroeconomic models, the determinants will be clustered around around six *topoi*: (1) *absorptive capacities*, (2) *relatedness*, (3) firm-level *R&D spending*, (4) *experience*, (5) *external learning*, and (6) *internal learning*[15].

[13] Note that in these studies, public infrastructure encompass more simple indicators such as the degree of electrification and telecommunication but also wider characteristics of socio-political systems such as educational and public health infrastructures, the quality of institutions and governance (corruption).

[14] There is not always a clear line to draw between active government action and regulatory policy, e.g. when it comes to incentive-based policies such as tax incentives for firms, investing a share of their revenues into R&D (Figueiredo, 2008).

[15] The *topoi external & internal learning* were inspired by the framework of Bell and Figueiredo (2012, p.24-25)

Empirical findings on the firm level	
Findings on the CA process	***Sources***
Absorptive capacities	
CA is positively moderated by a firm's absorptive capacity	Chuang and Hobday (2013), Chung and K. Lee (2015), Figueiredo and M. Cohen (2019), and Forés and Camisón (2016)
Relatedness	
Skill Relatedness: CA is determined by the composition of human capital	Neffke and Henning (2013)
Technological Relatedness: CA is determined by preexisting capabilities	Chuang and Hobday (2013), Laurens *et al.* (2017), and Youn *et al.* (2015)
R&D spending	
CA is fostered through R&D spending	Caloghirou *et al.* (2004), Chung and K. Lee (2015), Tsai and J. C. Wang (2007), and Wu and Wei (2013)
CA achieved by *anti-learning*: higher R&D spending over time is linked with quality upgrades of products	Dosi *et al.* (2017)
CA may be retarded by R&D over-investment	L. Li *et al.* (2018)
Experience	
CA is moderated by firm size	Dosi *et al.* (2019a), Molina-Domene and Pietrobelli (2012), and Villar *et al.* (2012)
CA is moderated by firm age	Dosi *et al.* (2019a) and Villar *et al.* (2012)
CA is accomplished by *learning by doing*: cumulative production is linked with increasing production efficiency	Dosi *et al.* (2017)
External learning	
CA is enhanced by *alliances*	L. Li *et al.* (2018), Subramanian *et al.* (2018), Vanhaverbeke *et al.* (2015), and Zheng *et al.* (2013)
CA through *learning by licensing*	Chung and K. Lee (2015), Leone *et al.* (2016), Y. Wang *et al.* (2013), and Li-Ying *et al.* (2013)
CA through intra-industry spillovers: customers, competitors and suppliers	J. Chen *et al.* (2012), Dachs *et al.* (2014), Fassio (2018), J. Li *et al.* (2013), Yap and Rasiah (2017), and Zhai *et al.* (2007)
CA through inter-/extra- industry spillovers: other industries, research and government institutions	Cantwell and Zhang (2013), Figueiredo and Brito (2011), Liefner *et al.* (2019), and Y. Wang *et al.* (2015)
CA through informal spillovers: social interactions, trust and identity	Autio *et al.* (2008), L.-C. Chen (2009), Ciravegna (2011), and A. A. Egbetokun (2015)

Empirical findings on the firm level (continuation)	
Findings on the CA process	***Sources***
Internal learning	
CA is enhanced through firm-level governance: local decision making, autonomy and global value chain architecture	Collinson and R. Wang (2012), Figueiredo (2008), Hobday and Rush (2007), and Marin and Bell (2010)
CA is retarded by *thick* management bureaucracies	Kleinknecht *et al.* (2016)
CA is activated by organizational routines that enable the (re)configuration and (re)combination of internal and external knowledge	Aeron and Jain (2015), Bikfalvi *et al.* (2014), Chuang and Hobday (2013), Forés and Camisón (2016), Freitas (2011), Grigoriou and Rothaermel (2017), Intarakumnerd (2017), Marion and Meyer (2018), Nagle and Teodoridis (2020), Paiva *et al.* (2008), and Zhou *et al.* (2019)

Table 4: Central empirical findings on the determinants for and functioning of CA on the firm level. Although the referenced papers identified the factors listed here as a main determinant for CA, most of these factors are not discussed in isolation.

Absorptive capacities. Various papers highlight the role of *absorptive capacities* (W. M. Cohen and Levinthal, 1990) as an underlying mechanism of CA (e.g. Chuang and Hobday, 2013; Chung and K. Lee, 2015; Figueiredo and M. Cohen, 2019; Forés and Camisón, 2016).[16] Originally, a firm's absorptive capacity was defined as its ability "to recognize the value of new, external information, assimilate it, and apply it to commercial ends" (W. M. Cohen and Levinthal, 1990, p.128). Many present studies have departed from the original definition, yetwith regard to the actual impact of absorptive capacities, most of them agree that (1) they have a *moderating* effect on CA by positively influencing the impact of other determinants (such as R&D investment or alliances) and (2) are important for the firm to absorb external knowledge. Therefore, Chuang and Hobday (2013) define them as a "deeper level of capability" (p. 1062). This means that any analysis of the effect of absorptive capacities on CA must include an analysis of those determinants that are being moderated. Examples for such studies include Cantwell and Zhang (2013), Chung and K. Lee (2015), Figueiredo and M. Cohen (2019), and Subramanian *et al.* (2018) who find that firm-level absorptive capacities are crucially affect the impact of firm-level *alliances*, and different forms of *internal* and *external learning*.

Relatedness. As on the aggregated level, relatedness also appears as a relevant determinant of CA on the firm level. In particular, Neffke and Henning (2013) show that firms are more likely to diversify into industries that are skill-related with the firms' core activities, i.e. with the human capital that the firm has already accumulated, and Laurens *et al.* (2017), find a robust positive association between knowledge capital accumulated in the past and the number of new inventions in the field of clean energy technologies (for similar results see, e.g., Chuang and Hobday, 2013). Youn *et al.* (2015) come to similar conclusions after studying a large-scale sample of patent records in the US. They identify technology *combination* as a main driver of modern invention implying that technological change is in most cases incremental. In all, the relevance of the principle of relatedness finds considerable empirical support and its save the assume that CA takes place in a cumulative way on the firm level as well (see also Hidalgo *et al.*, 2018).

R&D investment. Not surprisingly, the – mostly positive – link between R&D spending and CA has also been found on the firm level (e.g. Caloghirou *et al.*, 2004; Chung and K. Lee, 2015; Dosi *et al.*, 2017; Tsai and J. C. Wang, 2007; Wu and Wei, 2013). But there are also more nuanced results: Dosi *et al.* (2017), for example, not only find for Indian manufacturing firms that R&D also has a positive impact on the degree of *learning-by-doing*, but also that there

[16] Castellacci and Natera (2013) and Criscuolo and Narula (2008) introduce models that translate the idea on an aggregated level.

are cases of a positive relationship between production costs (and prices) and produced quantities (experience), an observation they label *anti-learning*. They rationalize this observation as a result of quality improvements and ongoing product innovation rather than process innovation. Others even find adverse effects of R&D on CA: L. Li *et al.* (2018), for instance, analyze U.S.-based small and medium enterprises (SMEs) in the biopharmaceutical sector and find that the in-house R&D stock is initially conducive for the accumulation of intellectual resources. However, later R&D played only a minor (or even negative role) for further CA. They argue that in a dynamic and complex global environment, other factors such as strong alliances might, overall, play a much more important role for successful CA.

Experience. Another important set of processes underlying CA is the accumulation of experience, the precise effect of which is often also dependent on firm size and age. While firm size appears to correlate with higher production and linkage capabilities (Molina-Domene and Pietrobelli, 2012), a more nuanced result is given by the analysis of the Spanish ceramic tile production sector (which mainly consits of SMEs) (Villar *et al.*, 2012): Experience – as measured by age – is a significant moderating variable for product innovation while firm size is a significant moderating variable for the degree of complexity of an innovation, such that both relationships are stronger for larger firms. These findings are supported and complemented by Dosi *et al.* (2019a) who analyze Indian manufacturing firms and that diversifying in terms of product scope is a strategy which is pursued by big and mature firms. Moreover, Dosi *et al.* (2017) find robust evidence for *learning by doing* – defined as the negative relation between cumulative production and production costs – as a driver of CA, although mostly for industries in developed economies.

External learning. A major group of firm-level determinants of CA refer to the influence of *external learning* mechanisms (Bell and Figueiredo, 2012) on CA. Depending on factors such as the institutional environment, sectoral specifities and the firm type, firms interact with suppliers, customers, competitors, research institutions and other social networks and are thus able to access external resources. The literature suggests various channels through which external learning happens. *Alliances* and *learning by licensing* represent more active and deliberate forms of gaining access to external resources, while *spillovers* are mostly understood as unintended knowledge transfers.

By forming *alliances*, a firm might achieve CA by drawing on "routines and arrangements embedded in a firm's ties to external parties" (Zheng *et al.*, 2013, p.1209-1210). The positive effect of alliances, however, might also be not uniform across firms and may depend on "alliance capabilities"[17](L. Li *et al.*, 2018), the level of "knowledge base homogeneity"[18](Subramanian *et al.*, 2018) or the stage of the technology life cycle (Vanhaverbeke *et al.*, 2015).

With regard to *licensing*, results are still diverse: Y. Wang *et al.* (2013) and Li-Ying *et al.* (2013) found that Chinese firms have successfully learned from licensing-in foreign technologies, yet Chung and K. Lee (2015) find that for Korean manufacturing firms it *in-house* R&D activities, which were established as a reaction to "know-how licensing" that subsequently lead to product innovation. Licenses may also serve as substitutes for the absorptive capacity of the licensee firm (Leone *et al.*, 2016).

Finally, a wide range of literature emphasize the pivotal role of *knowledge spillovers*, usually understood as the involuntary transfer of knowledge, which may result from a firms interaction with its suppliers, customers or competitors (e.g. J. Chen *et al.*, 2012; Fassio, 2018; Zhai *et al.*, 2007) or outside of the industry (e.g. Cantwell and Zhang, 2013; Liefner *et al.*, 2019; Y. Wang *et al.*, 2015). These spillovers may take place more formally (e.g. service relationship between firm and customer (Dachs *et al.*, 2014)) but also informally (e.g. Autio *et al.*, 2008; Ciravegna, 2011).

[17]Defined as "the abilities to shape and reconfigure firms' resource base by accessing the resources of its partners"(L. Li *et al.*, 2018, p.820).

[18]Knowledge base homogenity (KBH) refers to the similarity of a firms knowledge base, defined as the subset of knowledge a firm is able to consider in the search process for new inventions (Yayavaram and W.-R. Chen, 2014). For partners who have a low KBH, Subramanian *et al.* (2018) find an inverted U-shaped relationship between technological distance and CA, i.e. firms profit from alliances most if they have a medium technological distance. For partners with a high KBH, on the other hand, they find a positive relationship between the two factors, i.e. higher technological distance is associated with a higher level of CA – an intuitive finding since greater similarity allows for the comprehension of relatively more advanced technology.

Internal learning. In addition to external learning, the literature strongly emphasizes the complementary role of *internal learning* mechanisms. More specifically, one may distinguish between mechanisms that can result either in a (re)allocation of resources within the firm or mechanisms that link a firm's internal and external knowledge in ways conducive for CA. In the former case, the precise functioning of CA mechanisms still remains ambiguous: CA may be triggered by both, decentralization (e.g. local decision making and autonomy of subsidiary firms) (Collinson and R. Wang, 2012; Figueiredo, 2008; Hobday and Rush, 2007) or stronger integration within the (global) corporation (Marin and Bell, 2010). In the latter case, there is a clear evidence regarding the pivotal role of organizational routines that enable a firm to (re)configure and (re)combine internal or external knowledge. Since these routines strongly depend on firm characteristics and its environment and can, thus, be operationalized in various ways, one has to refer to a substantial body of literature (see table 4). Zhou *et al.* (2019) for instance argue that "intra-firm" spillovers (which shape the "firm productive struture") are a key source for firm diversification. However, it still remains unclear how these spillovers may be triggered within the firm. Forés and Camisón (2016, p.844) conclude that "the creation of a diverse and rich internal knowledge base through internal knowledge creation capability" is essential for a firms absorptive capacity. However, the building of this capability is dependent on various factors (e.g. employee motivation and commitment, a firms innovative culture, managerial strategies) which makes it difficult to distill a specific mechanism that represents internal learning. On a more concrete level, these routines may be facilitated via human resource management (HRM) practices as part of a firms "technological learning structure" (Freitas, 2011). Broadly speaking, HRM practices include all activities that enable knowledge sharing, integration and codification (Figueiredo and M. Cohen, 2019) such as team work arrangements, team meetings and internal training programs (see also Bikfalvi *et al.*, 2014; Chuang and Hobday, 2013; Marion and Meyer, 2018) but also the utilization of skill diversity and cross-disciplinarity within the firm (Intarakumnerd, 2017; Nagle and Teodoridis, 2020; see also Freeman and Huang, 2014; Wuchty *et al.*, 2007). Conversely, and consistent with what has been discussed for the aggregate level, a deregulation of labor markets may lead to higher rates of job turnover resulting in a destruction of mutual trust, loyalty and commitment (Kleinknecht *et al.*, 2016). In order to monitor and control such counterproductive behavior, bloated management bureaucracies within the firm may evolve which in turn are detrimental to creativity and entrepreneurship.

3.2.3 Taking stock

The empirical literature reviewed in section 3.2 highlights a variety of factors contributing to CA on both the aggregate as well as on the firm level. Noticeably, many papers analyze the determinants of CA in a very context-specific setting (e.g. specific industries such as ceramic tile vs. electronics industry, specific firm types such as MNEs vs. SMEs or specific countries such as catching-up vs. developed countries), and most papers discuss several determinants simultaneously. Not surprisingly, this suggests that CA is a highly complex process, working on both the aggregated and the firm level. This also means that is difficult to identify *main* channels of CA and that there seems to be no catch-all solution for triggering and sustaining CA. Nevertheless, one may cluster the results of the literature into four distinct aspects that are relevant for the construction of macroeconomic models. The first is a rather a general call for caution when it comes to the use of models in general and stresses the *contingency and context-dependency* of CA. Three topical areas – institutions, spill-overs and micro-macro mechanisms – may then serve as a more positive guide for macroeconomic model construction.

Contingency and context-dependency of CA Numerous studies, particularly those employing a case study methodology, stress the contingency and context-dependency of CA processes, i.e. they highlight the relevance of factors that are very specific to the particular place and time (e.g. Chuang and Hobday, 2013; Collinson and R. Wang, 2012; Figueiredo and M. Cohen, 2019; Vanhaverbeke *et al.*, 2015) or stage of development (e.g. Castellacci and Natera, 2013; Dutrénit *et al.*, 2019; Figueiredo, 2008). In each stage, a firm has to pursue another strategy, ranging from the use of preexisting, i.e. *related* capabilities, *internal* and *external learning*. Moreover, singular events often have an important impact on CA: Chuang and Hobday (2013), for example, explain how the financial crises of 1997 has led Japanese firms to enter cooperation agreements with Taiwanese firms, a strategy that has ultimately led to the establishment

of numerous most successful transnational companies. It is hard (and maybe even counter-productive) to consider such events in comprehensive macroeconomic models, but it is important to keep their relevance in mind and to take seriously the limits of modelling when it comes to the explanation of CA processes.

The primacy of institutions. The literature clearly shows that *institutions* – here encompassing both the regulatory environment as well as government activity – are crucial determinants of CA processes. This result is highlighted via both case studies (e.g. Figueiredo, 2008; J. J. Lee and Yoon, 2015; Mazzucato and Semieniuk, 2017; Mehri, 2015) and econometric analyses (e.g. Castellacci and Natera, 2013; Yu *et al.*, 2015; Zhou *et al.*, 2019). Many of these studies also highlight the fact that implementing specific government policies preceded an ongoing and successful process of CA.[19] Institutions are not only relevant on the macro, but also on the firm-level. Considering this insight against the macroeconomic models surveyed in section 2 one may conjecture that for macroeconomic modelers there is the chance to harvest some long-hanging fruits: for example, in both ABM and EBM, institutional aspects of regulation or direct government action are often merely considered in the context of barriers to technology (see 1), being reduced to "Pareto-improving policy interventions" (Acemoglu, 2009, p.483) such as subsidies to research, subsidies to capital inputs, anti-trust and patent policies. In ABMs, various forms of industrial policy (e.g. Dawid *et al.*, 2019), implications of labor regulations (e.g. Caiani *et al.*, 2019) or state-led research (e.g. Dosi *et al.*, 2018) have been considered, yet only via their effect on R&D investment. This leaves room for further enhancement, e.g. with regard to the investigation of the implications of public ownership and governance, the government as a facilitator of alliances among relevant actors or the role of private property and open-access norms.

External learning as inter-organizational processes A second cluster of findings is operating mainly on the firm level and involves *inter-organizational factors and processes* such as *spillovers* or *alliances*. These include both processes by which resources are drawn from various sources *outside* the firm – such as other autonomous players – as well as those from *within* the firm – such as internal R&D oder capacity building. From a methodological viewpoint, it seems to be particularly attractive to study such processes in ABM since these models are by design well suited to study direct interactions across heterogeneous actors.

The micro-macro links of CA A final lesson from the empirical literature is that the close interconnection of aggregated and firm level determinants implies that any satisfactory analysis of CA – in particular, in a modelling context – must take into account determinants on both the micro and the macro level *simultaneously*. Such a challenging task seems to be a natural topic for ABM and outside this literature there are currently only few examples for models taking this mutual interdependency of micro and macro seriously (e.g. Dosi *et al.*, 2019b).

3.3 Specialized models of CA – theoretical contributions

As already discussed in section 2, modeling CA in macroeconomics comes with certain trade-offs regarding the models' complexity. Models that are not macroeconomic by nature and that focus exclusively on the mechanisms underlying CA do not face these trade-offs. One may, therefore, suppose that these models have already formalized a richer set of mechanisms that macroeconomic models, and may, therefore, serve as a useful source of inspiration for the latter. Therefore, this section presents mechanisms that have received particular attention in this more specialized literature (see the summary in table 5).[20]

[19] Figueiredo (2008) is representative for this when they state that "it is important to recognize the relevance of different government policies that have been implemented over the past 40 years, especially since the 1990s in the context of Manaus. In the absence of such government policies, all these firms and some supporting organizations would probably not even have been there in the first place." (p. 84).

[20] We focus on models that study the interplay of several mechanisms. For models focused on one particular form of CA see, e.g., Vermeulen and Pyka (2014), Tur and Azagra-Caro (2018) (alliances), Santos Arteaga *et al.* (2019) (internal learning) or Zhuang *et al.* (2011) (external spill-overs).

Specialized models of CA			
Source	**Determinants**	**Description of the CA process**	**Model type**
Marengo *et al.* (2012)	Patenting and external spillovers, R&D	By investing into (innovative and imitative) R&D, firms assemble products from different components, which can be patented such that other firms cannot produce them for some time. Central result: if the product space is complex, IPRs are an obstacel, rather than an incentive, to innovation.	ABM
Dasgupta (2012)	Spillovers (Human Capital)	International worker mobility leads to knowledge spillovers among workers; CA is related to a reduction in inequality and an increase in individual income.	equilibrium model
Wersching (2010)	R&D Investment, Spillovers, Absorptive Capacities	Aiming for a competitive advantage, firms invest into R&D in order to accumulate internal knowledge and into absorptive capacities in order to gain from knowledge spillovers.	ABM
Savin and A. Egbetokun (2016)	Alliances, Absorptive Capacities, R&D Investment	Through alliances and absorptive capacity, firms (that aim for a competitive advantage) acquire voluntary and involuntary spillovers, respectively; R&D investment can lead to incremental innovation	ABM
Pyka *et al.* (2019)	Alliances, Learning by Doing, R&D Investment	Firms collaborate on the intra-regional and interregional level to acquire implicit and explicit knowledge, respectively. Also, they invest into R&D to expand internal knowledge. Knowledge that is used is intensified, leading to CA (via a radical or incremental increase in product complexity), whereas other knowledge is gradually forgotten	ABM
Caiani (2017)	R&D Investment, Firm-Size, Absorptive Capacities	Firms, which aim for a competitive advantage, move on a technology space. In order to reach certain points, they invest in imitative and innovative R&D with the probability of successfull increases with firm size since larger firms make higher investments. The probability of sucessfull imitation increases with size of the target industry.	ABM
Criscuolo and Narula (2008)	R&D, FDI, Absorptive Capacities, Intra-industry Spillovers	CA on the national level is determined by domestic R&D investment, FDI and international spillovers. The speed of CA (i.e. individual and national knowledge accumulation) is determined by absorptive capacities.	Differential equations
Landini and Malerba (2017)	Absorptive capacities, spill-overs, R&D, national policies	Firms invest into R&D to extract new techniques from a technology space; the extraction gets facilitated by spillovers from domestic competitors. Sometimes the domestic technological frontier expands and firms can use new techniques if their absorptive capacities are high enough. Moreover, firms accumulate new capabilities according to a pre-specified logistic function. National policies can accelerate this process.	ABM

Table 5: Implementation of the CA process in selected specialized models.

The fact that R&D activity fosters CA is taken to be self-evident in many models and the corresponding processes will not be discussed in more detail; the basic mechanisms are similar to those discussed for macroeconomics models (see section 2). Noteworthy are, however, models that enrich this mechanism in an additional dimension, such as Marengo *et al.* (2012), who study the effect of patent systems on CA. In their ABM, firms invest into (innovative and imitative) R&D to discover new products, which are assembled from different components. The overall performance of a product depends on the quality of the single components, as well as how well they fit together. The space containing all products is called a 'product space', and its complexity depends on the strengths of the interdependencies of the components when determining the overall product performance. Marengo *et al.* (2012) then study the effects of different degrees of IPR protection: the stronger the patent system, the more finely-grained can firms protect their innovations. In the strongest case they can prevent other firms from using a single component they have discovered so far. The model indicates that too strong IPR protection hampers overall innovation and welfare when the product space is more complex since patents work as obstacles in the product space and the invention of new products gets aggravated. The key underlying mechanism here is that of external learning and spill-overs across firms. Another determinant underlying CA and often modeled in the specialized literature is the *organization of human capital*. In these models, the skills and the knowledge embodied in each individual worker are the main driver of CA and, therefore, firms have to organize their human capital strategically in order to achieve CA. In a general equilibrium model Dasgupta (2012) studies CA as a learning process which is spurred by the mobility of workers from countries and firms with higher capabilities. By moving to other firms, their knowledge is passed on to the latter firm's workers, thus leading to CA in firms as well as entire regions (as the knowledge is passed on further). Thus, CA is here understood as a social process, propelled by the interaction of people with diverse knowledge.

Savin and A. Egbetokun (2016) introduce a model of CA in which they study the role of *alliances*, *absorptive capacities* and *R&D*. They situate firms on a two-dimensional metric space which they call 'knowledge space' and where the distance between two firms provides information on how similar their production technologies are. A firm's 'proximity radius', which can be extended via R&D investment, determines the knowledge the firm has potential access to. In accordance with the empirical literature (see above) the authors assume that there there is an inverted U-shaped relation between technological distance and CA, i.e. knowledge from technologically close and distant firms is less useful than that of firms with medium proximity. However, to actually absorb the knowledge of other firms in the first place firms must either engage in alliances (leading to *voluntary spillovers*) or invest into their absorptive capacities (leading to *involuntary spillovers*). Involuntary spillovers are purely a function of absorptive capacities of a firm. Voluntary spillovers emerge from alliances, which are formed profit maximizingly, based on the expected R&D investment of the potential partner as well as the disadvantages in competitiveness that arise from the spillovers that go toward the other firm. A partnership will only be formed if the alliance is mutually beneficial. Based on the alliance decision, a firm will split up its (exogenously given) R&D investment, spending as much as needed to benefit from alliances as well as involuntary spillovers. The rest will go to the expansion of internal knowledge. The model indicates that what cooperation strategy is best in terms of competitiveness depends on the current stage of a firm and whether it is currently more dependent on voluntary or involuntary spill-overs.

Pyka *et al.* (2019) model the interrelation of three different mechanisms of CA: *R&D investment*, *alliances* and *learning-by-doing*, as well as the potential role of policies in fostering CA processes. In the model, each firm is endowed with knowledge units that can then combined to invent new products that can then be sold on a market. CA processes are modelled as the acquisition of new knowledge units. There are three options: first, firms can invest into R&D. With a given probability, this creates a new knowledge unit that differs from the existing units only within a pre-specified range, as suggested by the principle of relatedness discussed above. The second option is to copy a knowledge unit from cooperation partners with whom the firm has formed an alliance. This copies only parts of the knowledge unit, however: aspects related to the experience of the firm of applying this knowledge are not copied. Finally, firms improve upon their knowledge by *learning by doing* if they apply their knowledge to produce products. At the same time, they can also forget about knowledge that remains unused in practice. The authors then test various policy scenarios in

which firms are motivated to engage in new alliances of invest more into R&D. They find that CA happens best when firms diversify their channels for CA and if they are supported by nuanced policy programs that provide firms to engage in regional collaboration.

Landini and Malerba (2017) study the catch-up dynamics between technologically lagging latecomers and an advanced incumbent country within a globalized industry. Their major research interest refers to the set of public policies that is best suited to achieve convergence among the two countries. Firms in both countries produce goods, which they can sell on the domestic and foreign market. Prices depend on quality and quality depends on the techniques used by, and the capabilities existent in a firm.[21] Firms invest a fixed share of their profits into R&D, which increases their chance to extract new and better techniques from the technological space. There is also a country specific information effect, which depends on the level of technological knowledge in the country and can be thought of as general spill-overs that facilitate the identification of better techniques. The current technological space gets expanded by chance (a 'radical change'), in which case firms might adopt the enlarged space if they have enough capabilities absorptive capacities to perceive the enlargement. They might decide against it, however, if too many specific capabilities for the old space have been accumulated. Thus, lock-ins in inferior technologies are possible. Firms' capabilities evolve according to a logistic learning equation, which is set as a parameter. Learning can, however, be accelerated by national policies. Aside from such policies that foster CA directly, i.e. speed up the accumulation of new capabilities or the initial level of capabilities for firms, other policies are also helpful, but depend on the technological environment. If radical technological change is relevant, facilitating the entry of domestic firms is highly complementary to other CA-enhancing policies, yet it remains ineffective if radical change is absent. Protectionism on the other hand is found to be helpful only in the absence of radical technological change and then in combination with other CA-supporting policies.

Caiani (2017) discuss an ABM in which CA occurs through innovative and imitative R&D with the firm size determining the success of innovation and the extent of absorptive capacities. Firms move on a network-like technological space where each node that is farther from the starting point is associated with a reduction of production costs via CA. In a first step, each firm chooses a target node. In order to reach that node, firms can either innovate or imitate, whereby costs of imitating are lower than those of innovating. The probability of successful innovation increases with the amount invested into innovative R&D. Since larger firms invest more, they have an advantage. In order to imitate, a firm collects a sample of firms. If any of them has the target node in their portfolio, imitation will be successful. The number of firms that can be sampled depends – just as before – on the amount of R&D investment, giving larger firms an advantage. However, success also depends on the size and structure of the industry, with a larger industry offering a higher probability of success. The sample size represents the size of the region within which firms to imitate can be sampled and can, therefore, be interpreted as its absorptive capacities. In the first instance, the sample is selected randomly. However, if imitation was successful, the imitated firm will be a preferred choice in the next period. Thus, industries have a different branch structure and they develop differently as firms move along, varying in size (i.e. number of firms). Both of these factors influence the benefits that can be expected from innovation and imitation such that it might me easier or harder for firms to become large and for large firms to stay successful.

A similar approach is put forward by Wersching (2010). Here, CA can occur both with respect to processes and products. Firms move on a circular technological space where they take a new spot between two occupied spots if they innovate incrementally and where they take a spot on an enlarged circle that is relatively farther away from the occupied spots if they innovate radically. Firms can invest into internal R&D or absorptive capacities in order to accumulate capabilities. Here again absorptive capacities enable firms to acquire spillovers from more distant points in the technology space. However, it is assumed that the relationship between distance and productivity of new knowledge is inverted U-shaped.

Criscuolo and Narula (2008) take a different approach and propose a differential equations model in which they generalize the original theory of absorptive capacities to the national level. Thus, in their model national CA is depends on domestic and foreign R&D investment, inward FDI and international spillovers, all moderated via national absorptive

[21] This distinction does not fit neatly into our broad definition of capabilities above. Rather, both techniques used and capabilities in the sense of Landini and Malerba (2017) would count as capabilities in the sense of the present paper.

capacities. The latter depends on R&D expenditures, an institutional variable representing the ease of knowledge diffusion, and the technology gap to most advanced countries. This way, the model replicates the stylized fact that individual and national knowledge accumulation is fastest during an intermediate stage of catching-up. This way it also provides a nice formal operationalization of the ambiguous concepts of absorptive capacities.

Finally, there are models that represent the processes underlying the emergence of new technologies and their diffusion, but that are meant as rather abstract illustrations. Nevertheless, they deserve to be mentioned here because they highlight aspects of technological change that themselves affect the way CA does actually take place. One example for such a model is Silverberg and Verspagen (2005), who present a model in which new technologies are assembled from existing technologies and thereby grow in complexity. The model is able to replicate a number of stylized facts of technological change (e.g. that there are many small and few big innovations) and captures the idea of technological relatedness very nicely, yet since it does not feature any concrete firm of market interaction it is more suitable to get a very general idea of 'technological change', rather than illuminating the mechanisms underlying CA. A similar argument holds for Angus and Newnham (2013). Their model consists of finite state automata that process bit-strings (which may be interpreted as products) and that, via evolutionary selection and mutation, produce new bit-strings. This way, the model produces a certain kind of 'novelty', which is currently lacking in most economics models. A slightly different approach is taken by Desmarchelier *et al.* (2018), who propose an ABM where firms are located on the empirical product space of Hidalgo *et al.* (2007) and try to maximize their export opportunities. There is, however, no actual production or consumption taking place in the model and it remains unclear how the firms actually accumulate the capabilities necessary to move to more central parts of the product space.

4 Discussion

The prime objective of this paper was to delineate promising channels for integrating results from the specialized literature on CA into comprehensive macroeconomic models. Starting with a summary of current strategies to integrate CA into macroeconomic models, the empirical literature on CA on the micro- and macroeconomic level and then a selection of specialised models dedicated to the investigation of CA processes was reviewed. The results of this work are summarized in table 6, which provides an overview on how empirical findings on CA have been implemented in specialized and comprehensive macroeconomic models so far.

The first lesson from the table is that the clearest alignment of the empirical and theoretical literature is with regard to the positive effect of R&D expenses on CA. This positive effect has not only been documented empirically, it has also been considered in both specific and macroeconomic models various times. Of course, the empirical literature studies R&D activities on a much more fine-grained level than is acknowledged in the models. Yet, in general there is a close alignment between the empirical and theoretical literature in this dimension.

The second, maybe more surprising, insight is that there is no clear indication on whether specialized or comprehensive macro models tend to implement empirical findings more conscientiously. Noticeably, the mechanisms listed which are related to the government and institutions have received more attention in the macroeconomic models than in the specialized models, most likely since the former include a government by definition. In taking a much narrower focus, specialized models usually do not include a government sector. At the same time, it is easier to integrate more complex processes such as *firm collaboration* or *absorptive capacities* into a model that has its main focus on CA, rather than into an already complex macroeconomic model (for an exception see Hötte, 2020). Also, the empirically highly relevant topic of the *relatedness* of CA has received more attention in the specialized literature. In these dimensions, there is certainly potential in taking the existing specialized models and to think about how they could be integrated into a more comprehensive macroeconomic framework.

Finally, there are also factors that – while having received considerable attention in the empirical literature – have not been considered in the modeling literature at all. The contingency of CA processes (such as time- and space-contingency) is the obvious example in table 6. Modelling contingency is difficult *per se*, since models are mostly used

as a way to formalize general mechanisms. It would, however, be desirable if the mechanisms modelled allowed for the distinct and non-linear development paths that are suggested by the empirical literature. This, obviously, represents a greater challenge for analytical models, leaving the stage clear for simulation models.

Another lesson that is not directly evidenced in table 6 is the role of the modelling framework chosen. General mechanisms such as R&D investment can be deployed in analytical models rather straightforwardly and very general results are available. However, mechanisms that refer to some kind of heterogeneity and interaction among the entities concerned, such as inter-firm or intra-firm functionalities are generally less commonly studied in analytical models. These mechanisms often play an important role in ABMs, which, by construction, are geared towards modelling interactions and heterogeneity - although one might also expect new innovative ideas to emerge in the recent HANK literature (*heterogeneous agent New Keynesian models, see, e.g.,* Kaplan *et al.*, 2018). At the same time, unlike in the analytical modeling literature, we cannot identify general benchmark models in the ABM literature, but rather a number of distinct model 'families' – although the particular implementation of certain key mechanisms, such as R&D investment is quite similar even across model families as well and some general building blocks seem to be emerging.

One crucial difference of how ABMs and analytical models study CA is due to the fact that ABMs include explicit interaction protocols. When it comes to the integration of results from the empirical literature this is a potential advantage that, however, can also turn into a source of *ad hoc* specification: on the one hand, the explicit interaction protocols of ABM allow a more detailed alignment of the model with empirical evidence and expert knowledge. At the same time, the need to be explicit can be a burden when there is no clear empirical guidance on how to build the interaction protocols. Take Dawid *et al.* (2018) as an example: the authors study the effect of directed subsidies paid to firms in poorer countries. In one scenario firms receive subsidies only when they invest money into R&D at the technological frontier. The interaction protocol for the ABM requires them to define exactly when the supervision of the firms takes place, i.e. when the authorities check whether the firms really invest at the technological frontier. Does this takes place before or after granting the subsidies? Or before or after the paid subsidies have been invested? After a particular time frame after granting the subsidies? Sometimes one can get good guidance by looking at the empirical data, talking to decision makers or experts in the field. In other cases, the decision is necessarily *ad hoc*. At the same time, in some instances such implementation decisions matter considerably, in other instances it does probably not matter much. It is, however, hard to make a definitive decision on the precise implementation. This is not a problem if one can easily test for the implications of distinct implementations, yet in larger models one usually faces numerous such challenges, and testing for the implications of all of them becomes infeasible or, at least, very demanding and time consuming. Thus, the enforced explicitness of interaction protocols in ABM can in principle be an advantage, but in practice might also lead to potentially misleading *ad hoc* specifications. In any case it points to the principal possibility to use ABM to test for the systemic relevance of such implementation details and thereby to develop very nuanced policy advice.

5 Summary and conclusion

This paper comprises a comparative survey of CA-related literature in order to identify possibilities to align the macroeconomic modelling literature more with recent insights from the specialized literature. The empirical literature on CA is manifold and shows that CA is not the outcome of a single mechanism but that the determinants are highly diverse. To consider this diversity in macroeconomic models is far from trivial and it is clear that there is a trade-off for models that seek to provide a comprehensive macroeconomic representation of an economy when it comes to the detailed representation of particular mechanisms. Nevertheless, given the high relevance of CA processes both on the micro and macro level we believe that working on a closer integration of them into macroeconomic models is a fruitful avenue for future research, which the present review has hopefully facilitated.

Mechanisms in the literature			
Mechanism	**Level**	**Macro models**	**Specialized models**
'Principle of Relatedness' (cumulative accumuation of capabilities)	Aggregated, firm		
Institutional environment (regulations)	Aggregated		
Government activity (industrial policy)	Aggregated		
Government activity (public research)	Aggregated		
Government activity (other)	Aggregated		
Absorptive capacities	Firms		
R&D investment	Aggregated, firm		
Experience & learning-by-doing	Firm		
External learning	Firm		
Internal learning	Firm		
Governance	Firm		

Table 6: Mechanisms of CA in the sampled literature. (Red stands for nonexistent or rare, yellow for still under-explored and green for frequent implementation in models.)

Acknowledgements

We are grateful to Manuel Scholz-Wäckerle, Muhamed Kudic, Torsten Heinrich, Jakob Kapeller, Steffen Müller and the other disciplinary experts that gave us feedback on the manuscript and our literature search strategy. We also acknowledge the feedback given at seminars and conferences where this work has been presented, particularly the EAEPE Annual Conference, the Rebuilding Macroeconomics Globalization Hub Workshop and the ICAE Research Seminar. We are particularly grateful to Kerstin Hötte for her extensive feedback on the manuscript. All remaining errors are our own. The authors gratefully acknowledge support of the Economic and Social Research Council (UK) under grant reference number ES/R00787X/1. We also acknowledge the role of the National Institute of Economic and Social Research (NIESR) in hosting the Rebuilding Macroeconomics Network.

References

Acemoglu, D. and F. Zilibotti (2001) "Productivity Differences". In: *The Quarterly Journal of Economics* **116**.2, 563–606.

Acemoglu, D. (2002a) "Directed Technical Change". In: *Review of Economic Studies* **69**.4, 781–809.

– (2002b) "Technical Change, Inequality, and the Labor Market". In: *Journal of Economic Literature* **40**.1, 7–72. DOI: 10.1257/0022051026976.

– (2009) *Introduction to Modern Economic Growth*. Princeton: Princeton University Press.

Acemoglu, D., U. Akcigit, and W. R. Kerr (2016a) "Innovation network". In: *Proceedings of the National Academy of Sciences* **113**.41, 11483–11488.

Acemoglu, D., U. Akcigit, and W. R. Kerr (2016b) "Innovation network". en. In: *Proceedings of the National Academy of Sciences* **113**.41. Publisher: National Academy of Sciences Section: Social Sciences, 11483–11488. DOI: 10.1073/pnas.1613559113.

Acemoglu, D., P. Antràs, and E. Helpman (2007) "Contracts and Technology Adoption". In: *American Economic Review* **97**.3, 916–943. DOI: 10.1257/aer.97.3.916.

Aeron, P. and R. Jain (2015) "A study on technological capability among product-based telecom start-ups in India: role of technological learning and bricolage". en. In: *International Journal of Technological Learning, Innovation and Development* **7**.4, 336. DOI: 10.1504/IJTLID.2015.073039.

Aghion, P. and P. Howitt (1992) "A Model of Growth Through Creative Destruction". In: *Econometrica* **60**.2, 323. DOI: 10.3386/w3223.

Aharonson, B. S. and M. A. Schilling (2016) "Mapping the technological landscape: Measuring technology distance, technological footprints, and technology evolution". In: *Research Policy* **45**.1, 81–96. DOI: 10.1016/j.respol.2015.08.001.

Allen, R. C. (2011) *Global Economic History*. Oxford: Oxford University Press.

Alonso, J. A. and V. Martín (2019) "Product relatedness and economic diversification at the regional level in two emerging economies: Mexico and Brazil". en. In: *Regional Studies* **53**.12, 1710–1722. DOI: 10.1080/00343404.2019.1605441.

Ang, J. B. (2010) "Financial Reforms, Patent Protection, and Knowledge Accumulation in India". en. In: *World Development* **38**.8, 1070–1081. DOI: 10.1016/j.worlddev.2009.12.011.

– (2011) "Financial development, liberalization and technological deepening". en. In: *European Economic Review* **55**.5, 688–701. DOI: 10.1016/j.euroecorev.2010.09.004.

Angus, S. D. and A. Newnham (2013) "The bit-economy: An artificial model of open-ended technology discovery". en. In: *Complexity* **18**.5, 57–67. DOI: 10.1002/cplx.21449.

Atkinson, A. B. and J. E. Stiglitz (1969) "A New View of Technological Change". In: *The Economic Journal* **79**.315, 573.

Autio, E., S. Kanninen, and R. Gustafsson (2008) "First- and second-order additionality and learning outcomes in collaborative R&D programs". en. In: *Research Policy* **37**.1, 59–76. DOI: 10.1016/j.respol.2007.07.012.

Bahar, D., R. Hausmann, and C. Hidalgo (2014) "Neighbors and the evolution of the comparative advantage of nations: Evidence of international knowledge diffusion?" en. In: *Journal of International Economics* **92**.1, 111–123. DOI: 10.1016/j.jinteco.2013.11.001.

Balland, P.-A., R. Boschma, J. Crespo, and D. L. Rigby (2019) "Smart specialization policy in the European Union: relatedness, knowledge complexity and regional diversification". en. In: *Regional Studies* **53**.9, 1252–1268. DOI: 10.1080/00343404.2018.1437900.

Baumol, W. J. (2002) *The free-market innovation machine: Analyzing the growth miracle of capitalism*. Princeton University Press.

Bell, M. and P. N. Figueiredo (2012) "Innovation capability building and learning mechanisms in latecomer firms: recent empirical contributions and implications for research". In: *Canadian Journal of Development Studies / Revue canadi-*

enne d'études du développement **33**.1. Publisher: Routledge _eprint: https://doi.org/10.1080/02255189.2012.677168, 14–40. DOI: 10.1080/02255189.2012.677168.

Bikfalvi, A., A. Jäger, and G. Lay (2014) "The incidence and diffusion of teamwork in manufacturing evidences from a Pan-European survey". In: *Journal of Organizational Change Management* **27**.2. Publisher: Emerald Group Publishing Limited, 206–231. DOI: 10.1108/JOCM-04-2013-0052.

Cai, J., W. Chen, J. Huang, R. Hu, and C. E. Pray (2020) "The Evolving Structure of Chinese R&D Funding and its Implications for the Productivity of Agricultural Biotechnology Research". en. In: *Journal of Agricultural Economics* **71**.2. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/1477-9552.12363, 287–304. DOI: 10.1111/1477-9552.12363.

Caiani, A. (2017) "Innovation Dynamics and Industry Structure Under Different Technological Spaces". en. In: *Italian Economic Journal* **3**.3, 307–341. DOI: 10.1007/s40797-017-0049-z.

Caiani, A., E. Catullo, and M. Gallegati (2019) "The effects of alternative wage regimes in a monetary union: A multi-country agent based-stock flow consistent model". In: *Journal of Economic Behavior and Organization* **162**, 389–416.

Caloghirou, Y., I. Kastelli, and A. Tsakanikas (2004) "Internal capabilities and external knowledge sources: complements or substitutes for innovative performance?" en. In: *Technovation* **24**.1, 29–39. DOI: 10.1016/S0166-4972(02)00051-2.

Cantwell, J. A. and F. Zhang (2013) "Do Foreign-owned Subsidiaries in China Follow a Distinctive Pattern of Technological Knowledge Sourcing?" en. In: *Management and Organization Review* **9**.3, 489–512. DOI: 10.1111/more.12026.

Castellacci, F. and J. M. Natera (2013) "The dynamics of national innovation systems: A panel cointegration analysis of the coevolution between innovative capability and absorptive capacity". en. In: *Research Policy* **42**.3, 579–594. DOI: 10.1016/j.respol.2012.10.006.

Castelnovo, P., M. Florio, S. Forte, L. Rossi, and E. Sirtori (2018) "The economic impact of technological procurement for large-scale research infrastructures: Evidence from the Large Hadron Collider at CERN". en. In: *Research Policy* **47**.9, 1853–1867. DOI: 10.1016/j.respol.2018.06.018.

Cetrulo, A., V. Cirillo, and D. Guarascio (2019) "Weaker jobs, weaker innovation. Exploring the effects of temporary employment on new products". In: *Applied Economics* **51**.59. Publisher: Routledge _eprint: https://doi.org/10.1080/00036846.2019.1619015, 6350–6375. DOI: 10.1080/00036846.2019.1619015.

Chang, H.-J. (2003) *Kicking Away the Ladder: Development Strategy in Historical Perspective*. London: Anthem Press.

Chen, J., Y. Guo, and H. Zhu (2012) "Can me-too products prevail? Performance of new product development and sources of idea generation in China an emerging market". en. In: *R&D Management* **42**.3. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1467-9310.2012.00683.x, 273–288. DOI: 10.1111/j.1467-9310.2012.00683.x.

Chen, L.-C. (2009) "Learning through informal local and global linkages: The case of Taiwan's machine tool industry". en. In: *Research Policy*. Special Issue: Innovation in Low-and Meduim-Technology Industries **38**.3, 527–535. DOI: 10.1016/j.respol.2008.10.008.

Chuang, Y.-S. and M. Hobday (2013) "Technological upgrading in Taiwan's TFT-LCD industry: signs of a deeper absorptive capacity?" en. In: *Technology Analysis & Strategic Management* **25**.9, 1045–1066. DOI: 10.1080/09537325.2013.832748.

Chung, M. Y. and K. Lee (2015) "How Absorptive Capacity is Formed in a Latecomer Economy: Different Roles of Foreign Patent and Know-how Licensing in Korea". en. In: *World Development* **66**, 678–694. DOI: 10.1016/j.worlddev.2014.09.010.

Ciarli, T., A. Lorentz, M. Valente, and M. Savona (2018) "Structural changes and growth regimes". In: *Journal of Evolutionary Economics* **29**.1, 119–176.

Ciravegna, L. (2011) "FDI, Social Ties and Technological Learning in New Silicon Valley Clones. Evidence from the Costa Rican ICT Cluster". In: *The Journal of Development Studies* **47**.8. Publisher: Routledge _eprint: https://doi.org/10.1080/00220388.2010.547935, 1178–1198. DOI: 10.1080/00220388.2010.547935.

Cohen, W. M. and D. A. Levinthal (1990) "Absorptive Capacity: A New Perspective on Learning and Innovation". In: *Administrative Science Quarterly* **35**.1, 128–152. DOI: 10.2307/2393553.

Collinson, S. C. and R. Wang (2012) "The evolution of innovation capability in multinational enterprise subsidiaries: Dual network embeddedness and the divergence of subsidiary specialisation in Taiwan". en. In: *Research Policy* **41**.9, 1501–1518. DOI: 10.1016/j.respol.2012.05.007.

Criscuolo, P. and R. Narula (2008) "A novel approach to national technological accumulation and absorptive capacity: aggregating Cohen and Levinthal". en. In: *The European Journal of Development Research* **20**.1, 56–73. DOI: 10.1080/09578810701853181.

Dachs, B. *et al.* (2014) "Servitisation of European manufacturing: evidence from a large scale database". In: *The Service Industries Journal* **34**.1. Publisher: Routledge _eprint: https://doi.org/10.1080/02642069.2013.776543, 5–23. DOI: 10.1080/02642069.2013.776543.

Dasgupta, K. (2012) "Learning and knowledge diffusion in a global economy". en. In: *Journal of International Economics* **87**.2, 323–336. DOI: 10.1016/j.jinteco.2011.11.012.

Dawid, H., P. Harting, and M. Neugart (2018) "Cohesion policy and inequality dynamics: Insights from a heterogeneous agents macroeconomic model". In: *Journal of Economic Behavior and Organization* **150**, 220–255. DOI: 10.1016/j.jebo.2018.03.015.

Dawid, H. and D. Delli Gatti (2018) "Agent-Based Macroeconomics". In: *Handbook of Computational Economics*. Ed. by C. Hommes and B. LeBaron. Springer, 63–156.

Dawid, H., P. Harting, S. van der Hoog, and M. Neugart (2019) "Macroeconomics with heterogeneous agent models: fostering transparency, reproducibility and replication". In: *Journal of Evolutionary Economics* **29**.1, 467–538.

Desmarchelier, B., P. J. Regis, and N. Salike (2018) "Product space and the development of nations: A model of product diversification". en. In: *Journal of Economic Behavior & Organization* **145**, 34–51. DOI: 10.1016/j.jebo.2017.10.020.

Dosi, G., L. Marengo, and C. Pasquali (2006) "How much should society fuel the greed of innovators?" In: *Research Policy* **35**.8, 1110–1121. DOI: 10.1016/j.respol.2006.09.003.

Dosi, G., M. Grazzi, and N. Mathew (2017) "The cost-quantity relations and the diverse patterns of learning by doing: Evidence from India". en. In: *Research Policy* **46**.10, 1873–1886. DOI: 10.1016/j.respol.2017.09.005.

Dosi, G., F. Lamperti, M. Mazzucato, M. Napoletano, and A. Roventini (2018) "The Entrepreneurial State at Work: an Agent Based Exploration". In: *IsIGrowth Working Paper* **41**.

Dosi, G., N. Mathew, and E. Pugliese (2019a) *What a firm produces matters: diversification, coherence and performance of Indian manufacturing firms*. en. Tech. rep. 2019/10. Laboratory of Economics and Management (LEM), Sant'Anna School of Advanced Studies, Pisa, Italy.

Dosi, G. and A. Roventini (2019) "More is different ... and complex! the case for agent-based macroeconomics". In: *Journal of Evolutionary Economics* **29**.1, 1–37.

Dosi, G., A. Roventini, and E. Russo (2019b) "Endogenous growth and global divergence in a multi-country agent-based model". In: *Journal of Economic Dynamics and Control* **101**, 101–129.

Dutrénit, G., J. M. Natera, M. Puchet Anyul, and A. O. Vera-Cruz (2019) "Development profiles and accumulation of technological capabilities in Latin America". en. In: *Technological Forecasting and Social Change* **145**, 396–412. DOI: 10.1016/j.techfore.2018.03.026.

Egbetokun, A. A. (2015) "Interactive learning and firm-level capabilities in latecomer settings: The Nigerian manufacturing industry". en. In: *Technological Forecasting and Social Change* **99**, 231–241. DOI: 10.1016/j.techfore.2015.06.040.

Fassio, C. (2018) "Export-led innovation: the role of export destinations". en. In: *Industrial and Corporate Change* **27**.1. Publisher: Oxford Academic, 149–171. DOI: 10.1093/icc/dtx028.

Fernandez Donoso, J. (2014) "Do complex inventions need less international patent protection?" en. In: *Economics Letters* **125**.2, 278–281. DOI: 10.1016/j.econlet.2014.09.026.

Figueiredo, P. N. (2008) "Government Policies and Sources of Latecomer Firms' Capability Building: A Learning Story from Brazil". en. In: *Oxford Development Studies* **36**.1, 59–88. DOI: 10.1080/13600810701848177.

Figueiredo, P. N. and K. Brito (2011) "The innovation performance of MNE subsidiaries and local embeddedness: evidence from an emerging economy". en. In: *Journal of Evolutionary Economics* **21**.1, 141–165. DOI: 10.1007/s00191-010-0180-6.

Figueiredo, P. N. and M. Cohen (2019) "Explaining early entry into path-creation technological catch-up in the forestry and pulp industry: Evidence from Brazil". en. In: *Research Policy* **48**.7, 1694–1713. DOI: 10.1016/j.respol.2019.03.017.

Forés, B. and C. Camisón (2016) "Does incremental and radical innovation performance depend on different types of knowledge accumulation capabilities and organizational size?" en. In: *Journal of Business Research* **69**.2, 831–848. DOI: 10.1016/j.jbusres.2015.07.006.

Francis, D. and J. Bessant (2005) "Targeting innovation and implications for capability development". In: *Technovation* **25**.3, 171–183.

Freeman, R. B. and W. Huang (2014) "Collaboration: Strength in diversity". en. In: *Nature News* **513**.7518. Section: Comment, 305. DOI: 10.1038/513305a.

Freitas, I. M. B. (2011) "Technological learning environments and organizational practicescross-sectoral evidence from Britain". en. In: *Industrial and Corporate Change* **20**.5. Publisher: Oxford Academic, 1439–1474. DOI: 10.1093/icc/dtr027.

Grigoriou, K. and F. T. Rothaermel (2017) "Organizing for knowledge generation: internal knowledge networks and the contingent effect of external knowledge sourcing: Organizing for Knowledge Generation". en. In: *Strategic Management Journal* **38**.2, 395–414. DOI: 10.1002/smj.2489.

Grossman, G. M. and E. Helpman (1991a) *Innovation and Growth in the Global Economy*. Cambridge, MA: MIT Press.

– (1991b) "Quality Ladders in the Theory of Growth". In: *Review of Economic Studies* **68**, 43–61.

Habiyaremye, A. (2019) "Enhancing productive capabilities through intra-regional trade and cross-border investments in Southern Africa". In: *Development Southern Africa* **36**.4. Publisher: Routledge _eprint: https://doi.org/10.1080/0376835X.2018.1504673, 409–425. DOI: 10.1080/0376835X.2018.1504673.

Heinrich, T. (2013) *Technological Change and Network Effects in Growth Regimes*. London and New York: Routledge.

Hidalgo, C. and R. Hausmann (2009) "The building blocks of economic complexity". In: *Proceedings of the National Academy of Sciences* **106**.26, 10570–10575.

Hidalgo, C., B. Klinger, A.-L. Barabási, and R. Hausmann (2007) "The Product Space Conditions the Development of Nations". In: *Science* **317**.5837, 482–487. DOI: 10.1126/science.1144581.

Hidalgo, C. *et al.* (2018) "The Principle of Relatedness". en. In: *Unifying Themes in Complex Systems IX*. Ed. by A. J. Morales, C. Gershenson, D. Braha, A. A. Minai, and Y. Bar-Yam. Cham: Springer International Publishing, 451–457. DOI: 10.1007/978-3-319-96661-8_46.

Hobday, M. and H. Rush (2007) "Upgrading the technological capabilities of foreign transnational subsidiaries in developing countries: The case of electronics in Thailand". en. In: *Research Policy* **36**.9, 1335–1356. DOI: 10.1016/j.respol.2007.05.004.

Hötte, K. (2020) "How to accelerate green technology diffusion? Directed technological change in the presence of coevolving absorptive capacity". In: *Energy Economics* **85**, 104565.

Howitt, P. (2000) "Endogenous Growth and Cross-Country Income Differences". In: *American Economic Review* **90**.4, 829–846.

Intarakumnerd, P. (2017) "Human resource management and coordination for innovative activities in production networks in Asia: a synthesis". In: *Asian Journal of Technology Innovation* **25**.2. Publisher: Routledge _eprint: https://doi.org/10.1080/19761597.2017.1385957, 199–205. DOI: 10.1080/19761597.2017.1385957.

Kaplan, G., B. Moll, and G. L. Violante (2018) "Monetary Policy According to HANK". In: *American Economic Review* **108**.3, 697–743. DOI: 10.1257/aer.20160042.

Kleinknecht, A., Z. Kwee, and L. Budyanto (2016) "Rigidities through flexibility: flexible labour and the rise of management bureaucracies". en. In: *Cambridge Journal of Economics* **40**.4, 1137–1147. DOI: 10.1093/cje/bev056.

Landini, F. and F. Malerba (2017) "Public policy and catching up by developing countries in global industries: a simulation model". In: *Cambridge Journal of Economics* **41**.3, 927–960.

Laurens, P., C. L. Bas, S. Lhuillery, and A. Schoen (2017) "The determinants of cleaner energy innovations of the worlds largest firms: the impact of firm learning and knowledge capital". In: *Economics of Innovation and New Technology* **26**.4. Publisher: Routledge _eprint: https://doi.org/10.1080/10438599.2016.1193940, 311–333. DOI: 10.1080/10438599.2016.1193940.

Lebdioui, A. (2019) "Chile's Export Diversification since 1960: A Free Market Miracle or Mirage?" en. In: *Development and Change* **50**.6. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/dech.12545, 1624–1663. DOI: 10.1111/dech.12545.

Lee, J. J. and H. Yoon (2015) "A comparative study of technological learning and organizational capability development in complex products systems: Distinctive paths of three latecomers in military aircraft industry". en. In: *Research Policy* **44**.7, 1296–1313. DOI: 10.1016/j.respol.2015.03.007.

Lee, T. J. (2004) "Technological learning by national R&D: the case of Korea in CANDU-type nuclear fuel". en. In: *Technovation* **24**.4, 287–297. DOI: 10.1016/S0166-4972(02)00052-4.

Leone, M. I., T. Reichstein, P. Boccardelli, and M. Magnusson (2016) "License to learn: an investigation into thin and thick licensing contracts". en. In: *R&D Management* **46**.2. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/radm.12187, 326–340. DOI: 10.1111/radm.12187.

Li, J., D. Chen, and D. M. Shapiro (2013) "FDI Spillovers at the National and Subnational Level: The Impact on Product Innovation by Chinese Firms". en. In: *Management and Organization Review* **9**.3, 413–435. DOI: 10.1111/more.12025.

Li, L., D. Li, A. Goerzen, and W. Shi (2018) "What and how do SMEs gain by going international? A longitudinal investigation of financial and intellectual resource growth". en. In: *Journal of World Business* **53**.6, 817–834. DOI: 10.1016/j.jwb.2018.07.001.

Liefner, I., Y.-f. Si, and K. Schäfer (2019) "A latecomer firm's R&D collaboration with advanced country universities and research institutes: The case of Huawei in Germany". en. In: *Technovation* **86-87**, 3–14. DOI: 10.1016/j.technovation.2019.03.002.

Löschel, A. (2002) "Technological change in economic models of environmental policy: a survey". In: *Ecological Economics* **43**.2-3, 105–126.

Marengo, L., C. Pasquali, M. Valente, and G. Dosi (2012) "Appropriability, patents, and rates of innovation in complex products industries". In: *Economics of Innovation and New Technology* **21**.8, 753–773. DOI: 10.1080/10438599.2011.644666.

Marin, A. and M. Bell (2010) "The local/global integration of MNC subsidiaries and their technological behaviour: Argentina in the late 1990s". en. In: *Research Policy* **39**.7, 919–931. DOI: 10.1016/j.respol.2010.04.002.

Marion, T. J. and M. H. Meyer (2018) "Organizing to Achieve Modular Architecture Across Different Products". In: *IEEE Transactions on Engineering Management* **65**.3. Conference Name: IEEE Transactions on Engineering Management, 404–416. DOI: 10.1109/TEM.2018.2790839.

Mazzucato, M. (2014) *The entrepreneurial state: debunking public vs. private sector myths*. Revised edition. Anthem frontiers of global political economy. London ; New York: Anthem Press.

Mazzucato, M. and G. Semieniuk (2017) "Public financing of innovation: new questions". en. In: *Oxford Review of Economic Policy* **33**.1, 24–48. DOI: 10.1093/oxrep/grw036.

Mehri, D. B. (2015) "The role of engineering consultancies as network-centred actors to develop indigenous, technical capacity: the case of Iran's automotive industry". en. In: *Socio-Economic Review* **13**.4. Publisher: Oxford Academic, 747–769. DOI: 10.1093/ser/mwu041.

Mirimoghadam, M. and S. Ghazinoory (2017) "An institutional analysis of technological learning in Iran's oil and gas industry: Case study of south Pars gas field development". en. In: *Technological Forecasting and Social Change* **122**, 262–274. DOI: 10.1016/j.techfore.2015.12.004.

Molina-Domene, M. A. and C. Pietrobelli (2012) "Drivers of technological capabilities in developing countries: An econometric analysis of Argentina, Brazil and Chile". en. In: *Structural Change and Economic Dynamics*. SI: Firm Dynamics and SI: Globelics Conference **23**.4, 504–515. DOI: 10.1016/j.strueco.2011.11.003.

Nagle, F. and F. Teodoridis (2020) "Jack of all trades and master of knowledge: The role of diversification in new distant knowledge integration". en. In: *Strategic Management Journal* **41**.1. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/smj.3091, 55–85. DOI: 10.1002/smj.3091.

Neffke, F. and M. Henning (2013) "Skill Relatedness and Firm Diversification". en. In: *Strategic Management Journal* **34**.3, 297–316. DOI: 10.1002/smj.2014.

Neffke, F., M. Henning, and R. Boschma (2011) "How Do Regions Diversify over Time? Industry Relatedness and the Development of New Growth Paths in Regions: ECONOMIC GEOGRAPHY". en. In: *Economic Geography* **87**.3, 237–265. DOI: 10.1111/j.1944-8287.2011.01121.x.

Neffke, F., A. Otto, and A. Weyh (2017) "Inter-industry labor flows". en. In: *Journal of Economic Behavior & Organization* **142**, 275–292. DOI: 10.1016/j.jebo.2017.07.003.

Paiva, E. L., A. V. Roth, and J. E. Fensterseifer (2008) "Organizational knowledge and the manufacturing strategy process: A resource-based view analysis". en. In: *Journal of Operations Management* **26**.1, 115–132. DOI: 10.1016/j.jom.2007.05.003.

Pawson, R. (2006) *Evidence-based policy: a realist perspective*. OCLC: ocm59138507. London ; Thousand Oaks, Calif: SAGE.

Perez-Aleman, P. and F. C. Alves (2017) "Reinventing industrial policy at the frontier: catalysing learning and innovation in Brazil". en. In: *Cambridge Journal of Regions, Economy and Society* **10**.1. Publisher: Oxford Academic, 151–171. DOI: 10.1093/cjres/rsw038.

Pyka, A., M. Kudic, and M. Müller (2019) "Systemic interventions in regional innovation systems: entrepreneurship, knowledge accumulation and regional innovation". In: *Regional Studies*, 1–12.

Radosevic, S. and E. Yoruk (2018) "Technology upgrading of middle income economies: A new approach and results". en. In: *Technological Forecasting and Social Change* **129**, 56–75. DOI: 10.1016/j.techfore.2017.12.002.

Rengs, B., M. Scholz-Wäckerle, and J. van den Bergh (2019) "Evolutionary macroeconomic assessment of employment and innovation impacts of climate policy packages". In: *Journal of Economic Behavior and Organization* forthcoming.

Ribeiro, C. G. and A. T. Furtado (2014) "Government Procurement Policy in Developing Countries: The Case of Petrobras". en. In: *Science, Technology and Society* **19**.2. Publisher: SAGE Publications India, 161–197. DOI: 10.1177/0971721814529874.

Rivera-Batiz, L. A. and P. M. Romer (1991) "Economic Integration and Endogenous Growth". In: *The Quarterly Journal of Economics* **106**.2, 531.

Romer, P. M. (1990) "Endogenous Technological Change". In: *Journal of Political Economy* **98**, S71–S102.

Santos Arteaga, F. J., M. Tavana, D. Di Caprio, and M. Toloo (2019) "A dynamic multi-stage slacks-based measure data envelopment analysis model with knowledge accumulation and technological evolution". en. In: *European Journal of Operational Research* **278**.2, 448–462. DOI: 10.1016/j.ejor.2018.09.008.

Savin, I. and A. Egbetokun (2016) "Emergence of innovation networks from R&D cooperation with endogenous absorptive capacity". en. In: *Journal of Economic Dynamics and Control* **64**, 82–103. DOI: 10.1016/j.jedc.2015.12.005.

Silverberg, G. and B. Verspagen (2005) "A percolation model of innovation in complex technology spaces". en. In: *Journal of Economic Dynamics and Control* **29**.1-2, 225–244. DOI: 10.1016/j.jedc.2003.05.005.

Solow, R. M. (1956) "A Contribution to the Theory of Economic Growth". In: *The Quarterly Journal of Economics* **70**.1, 65–94.

Subramanian, A. M., W. Bo, and C. Kah-Hin (2018) "The role of knowledge base homogeneity in learning from strategic alliances". en. In: *Research Policy* **47**.1, 158–168. DOI: 10.1016/j.respol.2017.10.005.

Syverson, C. (2011) "What Determines Productivity?" In: *Journal of Economic Literature* **49**.2, 326–365. DOI: 10.1257/jel.49.2.326.

The Growth Lab at Harvard University (2019) *The Atlas of Economic Complexity*. http://atlas.cid.harvard.edu/glossary. [Online; accessed 6-December-2019].

Tsai, K. H. and J. C. Wang (2007) "A longitudinal examination of performance of two ways on innovation in Taiwan: internal R&D investment and external technology aquisition". en. In: *International Journal of Technology Management* **39**.3/4, 235. DOI: 10.1504/IJTM.2007.013493.

Tur, E. M. and J. M. Azagra-Caro (2018) "The coevolution of endogenous knowledge networks and knowledge creation". en. In: *Journal of Economic Behavior & Organization* **145**, 424–434. DOI: 10.1016/j.jebo.2017.11.023.

Vanhaverbeke, W., R. Belderbos, G. Duysters, and B. Beerkens (2015) "Technological Performance and Alliances Over the Industry Life Cycle: Evidence from the ASIC Industry". en. In: *Journal of Product Innovation Management* **32**.4. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jpim.12253, 556–573. DOI: 10.1111/jpim.12253.

Vergeer, R. and A. Kleinknecht (2014) "Do labour market reforms reduce labour productivity growth? A panel data analysis of 20 OECD countries (1960-2004)". en. In: *International Labour Review* **153**.3, 365–393. DOI: 10.1111/j.1564-913X.2014.00209.x.

Vermeulen, B. and A. Pyka (2014) "Technological progress and effects of (Supra) regional innovation and production collaboration. An agent-based model simulation study". In: *2014 IEEE Conference on Computational Intelligence for Financial Engineering & Economics (CIFEr)*. London, UK: IEEE, 357–364. DOI: 10.1109/CIFEr.2014.6924095.

Villar, C., J. Pla-Barber, and J. Alegre (2012) "Unravelling the moderating effects of size and experience on product innovations and exports: a study in a medium knowledge-intensive industry". en. In: *Technology Analysis & Strategic Management* **24**.2, 219–238. DOI: 10.1080/09537325.2012.647650.

Wang, Y., N. Roijakkers, and W. Vanhaverbeke (2013) "Learning-by-Licensing: How Chinese Firms Benefit From Licensing-In Technologies". In: *IEEE Transactions on Engineering Management* **60**.1. Conference Name: IEEE Transactions on Engineering Management, 46–58. DOI: 10.1109/TEM.2012.2205578.

Wang, Y., Z. Zhou, L. Ning, and J. Chen (2015) "Technology and external conditions at play: A study of learning-by-licensing practices in China". en. In: *Technovation* **43-44**, 29–39. DOI: 10.1016/j.technovation.2015.03.006.

Weitzman, M. L. (1998) "Recombinant Growth". In: *The Quarterly Journal of Economics* **113**.2, 331–360. DOI: 10.1162/003355398555595.

Wersching, K. (2010) "Schumpeterian competition, technological regimes and learning through knowledge spillover". en. In: *Journal of Economic Behavior & Organization* **75**.3, 482–493. DOI: 10.1016/j.jebo.2010.05.005.

Wu, A. and J. Wei (2013) "Effects of Geographic Search on Product Innovation in Industrial Cluster Firms in China". en. In: *Management and Organization Review* **9**.3, 465–487. DOI: 10.1111/more.12024.

Wuchty, S., B. F. Jones, and B. Uzzi (2007) "The Increasing Dominance of Teams in Production of Knowledge". en. In: *Science* **316**.5827. Publisher: American Association for the Advancement of Science Section: Report, 1036–1039. DOI: 10.1126/science.1136099.

Yap, X.-S. and R. Rasiah (2017) "Catching up and leapfrogging in a high-tech manufacturing industry: towards a firm-level taxonomy of knowledge accumulation". In: *Knowledge Management Research & Practice* **15**.1. Publisher: Taylor & Francis _eprint: https://doi.org/10.1057/kmrp.2015.21, 114–129. DOI: 10.1057/kmrp.2015.21.

Yayavaram, S. and W.-R. Chen (2014) "Changes in firm knowledge couplings and firm innovation performance: The moderating role of technological complexity". In: *Strategic Management Journal* **36**.3, 377–396.

Li-Ying, J., Y. Wang, S. Salomo, and W. Vanhaverbeke (2013) "Have Chinese firms learned from their prior technology in-licensing? An analysis based on patent citations". en. In: *Scientometrics* **95**.1, 183–195. DOI: 10.1007/s11192-012-0802-x.

Youn, H., D. Strumsky, L. M. A. Bettencourt, and J. Lobo (2015) “Invention as a combinatorial process: evidence from US patents”. In: *Journal of The Royal Society Interface* **12**.106. Publisher: Royal Society, 20150272. DOI: 10.1098/rsif.2015.0272.

Yu, X., G. Dosi, J. Lei, and A. Nuvolari (2015) “Institutional change and productivity growth in China’s manufacturing: the microeconomics of knowledge accumulation and "creative restructuring"”. en. In: *Industrial and Corporate Change* **24**.3, 565–602. DOI: 10.1093/icc/dtv011.

Zhai, E., Y. Shi, and M. Gregory (2007) “The growth and capability development of electronics manufacturing service (EMS) companies”. en. In: *International Journal of Production Economics* **107**.1, 1–19. DOI: 10.1016/j.ijpe.2006.03.009.

Zheng, S., H. Li, and X. Wu (2013) “Network resources and the innovation performance: Evidence from Chinese manufacturing firms”. In: *Management Decision* **51**.6. Ed. by C. C. Williams, F. Más Verdú, and J. A. BelsoMartínez. Publisher: Emerald Group Publishing Limited, 1207–1224. DOI: 10.1108/MD-02-2012-0102.

Zhou, Y., S. Zhu, and C. He (2019) “Learning from yourself or learning from neighbours: knowledge spillovers, institutional context and firm upgrading”. In: *Regional Studies* **53**.10. Publisher: Routledge _eprint: https://doi.org/10.1080/00343404.2019.1566705, 1397–1409. DOI: 10.1080/00343404.2019.1566705.

Zhuang, E., G. Chen, and G. Feng (2011) “A network model of knowledge accumulation through diffusion and upgrade”. In: *Physica A: Statistical Mechanics and its Applications* **390**.13, 2582–2592. DOI: 10.1016/j.physa.2011.02.043.