Indirect Interdependence:

How Ecosystem Structure Affects Firms' Adaptation to Environmental Changes

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Abstract

Firms' performance is affected by their dependence on technologies in an innovation ecosystem. Although researchers have investigated the impact of direct component interdependence (i.e. dependence between ecosystem components and the firm), this paper expands the focus to include indirect interdependence (i.e. dependence among the components themselves). We borrow conceptual tools from graph theory to model the impact of the density of indirect interdependence, modularity, and bottleneck components on firm ability to adapt to environmental change. In the setting of the e-commerce industry following the EU General Data Protection Regulation, we find that indirect interdependence matters for firms' ability to adapt and that modularity and density of indirect interdependence seem to have a stronger effect than bottlenecks.

Success or failure of an organization depends, in a large part, upon its ability to manage dependencies with the external environment (Astley & Fombrun, 1983). Recent research has emphasized the relationship between a firm and the external innovation ecosystem, defined as the components or complements needed for a focal innovation to deliver a coherent value proposition for a user (Adner, 2017; Kapoor, 2018). For example, in the semiconductor industry, lithography equipment is not useful without adoption of compatible lenses and energy sources (Ganco, Kapoor, & Lee, 2019). These three technological components are interdependent and belong to the lithography ecosystem (Jacobides, Cennamo, & Gawer, 2018).

To date, the strategy field has focused on establishing the importance of ecosystems to the ability of firms to create and capture value (e.g., Ansari, Garud, & Kumaraswamy, 2016). We know that ecosystems affect important outcomes such as firms' technology choice (Kapoor & Furr, 2015), innovation effort (Ethiraj, 2007), innovation performance (Adner & Kapoor, 2010) and firm performance (Hannah & Eisenhardt, 2018). To establish the importance of ecosystems, the field has relied, implicitly or explicitly, on a "fish bone" model of innovation ecosystems where upstream components or downstream complements (ribs of the fish) feed into the value stream (the "backbone" of the fish) required to produce an innovation for use by an end consumer. This analogy establishes the direct interdependence between components required to produce an innovation. But the weakness of the analogy is that it under-emphasizes the multitude of potential indirect interdependencies between the technological components or complements themselves. For example, although successful use of lithography equipment depends on availability of lenses and energy sources (a form of direct interdependence described in the fish bone model), the features of lenses and energy sources may also be interdependent with each other in a way that indirectly affects firms.

By putting emphasis primarily on direct interdependencies, the importance of indirect interdependencies remains understudied yet nonetheless has important firm implications. For instance, firms using lithography equipment may arguably find it more difficult to adapt to external changes if lenses and energy sources are indirectly interdependent with one another as compared to a scenario when these two components are not interdependent. Furthermore, whilst a modular structure among a firm's technologies has been found to be essential to its adaptation ability (Baldwin & Clark, 2000; Sanchez & Mahoney, 1996), we know little about how firms' adaptation is affected by their component choices from a single or multiple modules. Furthermore, structures of interdependence reveal ecosystem bottlenecks (Adner, 2012; Ethiraj, 2007; Jacobides & Tae, 2015). A focus on direct interdependence tends to emphasize how function-level, input-output bottlenecks in an ecosystem affect focal firms (Baldwin, 2015). When we focus on direct interdependencies only, we can miss additional bottlenecks that arise from situations when a component might be restricting adaptation of other ecosystem elements that the firm adopted, thereby hampering the firm's efforts to find its place in the changing environment.

Although ecosystem scholars have always implied the importance of both direct and indirect interdependencies, for reasons of conceptual and empirical tractability research has tended to emphasize direct interdependence between components and less so the impact of indirect interdependencies. One of the challenges to such an expanded view has been the additional complexity that modelling the structure indirect interdependencies introduces into the analysis. To address this gap and to explore the potential impact of indirect component interdependencies on firm outcomes, we borrow the apparatus of graph theory (Borgatti & Halgin, 2011). Graph theory and tools have been used to show how indirect interdependencies in other settings affect firms; for example, how interdependencies resulting from the structure of inter-organizational relationships affect firm performance (e.g., Shipilov & Li, 2008) as well as their adaptation to external influences (e.g., Rowley, Behrens, & Krackhardt, 2000). Graph theory offers two broad sets of concepts that may be useful in an ecosystem context: those related to the structure of a focal node's immediate network (e.g., density) and those characterising the network as a whole (e.g., modularity).

If we conceptualize ecosystems as a collection of interdependent components, then by choosing a subset of these components, a firm both establishes direct interdependence with each chosen component and also embeds itself in a pattern of indirect interdependencies among components. We expect that the use of components with high-density interdependence (i.e., high indirect interdependence) will worsen the firm's performance following an external change, while the use of components with low-density interdependence will improve the firm's performance. Second, we predict that firms' performance following external change will improve if it used components from different modules in an innovation ecosystem. Finally, we expect firms to adapt poorly to an external change if they rely on bottleneck components relative to firms which rely on more peripheral components. Performance of firms that integrate bottleneck components in their value proposition should decline relative to firms which use non-bottleneck components.

We find broad support for our theory by looking at variation in performance of nearly 900 e-commerce websites around the world from 2014 to 2019. In this context, a website is a value proposition that is created through the use of components from an ecosystem of e-commerce technologies. Such components can include the choices of JavaScript libraries, website hosting providers, data management platforms or the like. Our performance measure is a website's traffic data collected by Alexa. Between 2014 and 2019, some of these companies experienced an environmental change in the form of the European General Data Protection Regulation (GDPR). This law forced companies dealing with European data subjects to adapt their technologies or face significant fines. Using the triple differences statistical framework, we find that indirect interdependence matters for firms' ability to adapt and that modularity and density of indirect interdependence seem to have a stronger effect than reliance on bottleneck components.

THEORY AND HYPOTHESES

Indirect Interdependence and Adaptation

Recent research has begun to establish that firm performance is shaped not just by the action of firms vis-à-vis direct competitors but also by the structure of interdependence within the ecosystem in which the firm operates (Adner, 2017; Jacobides et al., 2018; Kapoor, 2018). At the heart of ecosystem research is the study of how firms manage this interdependence—that is, the relationships between a focal firm and other firms who produce or control the components and complements necessary to create and capture value (Adner & Kapoor, 2010). As Kapoor (2018) points out, the starting point for ecosystem research is the focal offer (e.g., electric car, phone) and the interaction between "a set of actors that contribute to the focal offer's user value proposition" (Kapoor, 2018).

The relationship between the firm, components, complements and the user can be seamless at times, or at other times, create bottlenecks to value creation and capture (Baldwin, 2015; Kapoor, 2018). Such bottlenecks may arise from many sources, including technological, capacity, or control constraints, that arise during the evolution of the ecosystem (Furr, Kapoor, & Eisenhardt, 2020). Arguably, when the nature of interdependencies is well understood, firms can optimize their position within the ecosystem. If firms can position themselves to take advantage of this interdependent structure, or proactively occupy a bottleneck, they may gain a performance advantage (Adner & Kapoor, 2010; Hannah & Eisenhardt, 2018). But when the nature of component interdependencies changes, such as through an externally induced regulatory change or radical technological discontinuity, firms must also be flexible and adjust to the new structure of interdependence to sustain performance of their value propositions. However, firms may differ in their ability to adapt depending on their earlier strategic choices made in relation to the ecosystem.

For example, in the early air taxi industry, companies like DayJet chose to be tightly coupled with the components and complements whereas Linear Air remained more loosely coupled with these components. While DayJet focused its business model on a single type of aircraft, Linear Air was happy to operate different types of aircraft. Likewise, DayJet worked with a pre-selected set of airports and invested heavily in the development of these complements, whereas Linear Air invested less in complements and maintained more flexibility. Although DayJet arguably was better positioned for robust growth in the industry because of their tight coupling with ecosystem components and complements, when an economic downturn shocked the industry, Linear Air was better able to adapt to the new environment (Tripsas, Chow, Prewett, & Yttre, 2009). After DayJet filed for bankruptcy because it overextended itself while not being able to receive the fleet it needed, Linear Air set up an online travel platform where it could satisfy customer requests either through its own fleet or using the fleet of over 600 other operators.

However, such classic examples of ecosystem interdependence—what we would classify as "direct interdependence" because the focal firm has a direct input/output dependence on the component or complement in question (Kapoor, 2018)— are not the only form of interdependence that may affect the firm. In addition to direct interdependence, there exists a second set of interdependencies that has not been adequately studied, namely indirect interdependencies. Indirect interdependencies are dependencies between the components or complements themselves, rather than between the focal firm and the component or complement. For example, the relationship between air traffic controllers and the capacity of an airport would be an indirect interdependency between complements necessary to commercialize air taxis but which may be overlooked when considering only the direct interdependencies between the airport capacity, air traffic control and the focal firm.

Such indirect interdependencies may have an impact on the ability of firms to adapt when a change affects the ecosystem, particularly if the indirect interdependencies are strong. To maximize value, a change in one component with indirect interdependencies often demands a change in another component. To understand how indirect interdependencies may affect firm performance after an environmental change, we draw a distinction between the structure of interdependence among the sets of components chosen by a firm (i.e., firm-level interdependence) and the structure of interdependence among the entire set of components in the larger innovation ecosystem (i.e., ecosystem-level interdependence). For example, while ecosystem-level interdependencies may have a modular structure, the firm might draw components either from a single or from multiple modules of this ecosystem. In the former case, the firm value proposition will include components that exhibit higher interdependence and in the latter case the components coming from multiple modules will exhibit lower interdependence. Likewise, while most components in the ecosystem may be highly interdependent, the firm may avoid such a structure by purposefully choosing components that are less interdependent with one another.

Given the need to extend our focus to indirect interdependencies, we require a set of conceptual tools to systematically think about the impact of these interdependencies on firm performance. Relationships among components can be conceptualized as design structure matrixes (Baldwin & Clark, 2000). Although these matrixes have been used to understand interdependencies among components of a single product, such as an engine manufactured by a single organization (Sosa, Eppinger, & Rowles, 2007), one can extend this thinking both conceptually and empirically to interdependencies at the level of an entire ecosystem (Shipilov & Gawer, 2020). Ecosystem-level interdependence matrixes would consist of components in the rows and columns with numbers in the cells representing the presence or absence of interdependencies of these components. Figure A1 in the Online Appendix portrays the location of indirect interdependencies in an ecosystem. This ecosystem may consist of *N* components. In every period, the firm borrows *n* components from the ecosystem to build a given value proposition (e.g. an e-commerce website) and these components have some indirect interdependence with each other. These components don't have to be fixed, i.e.

a firm can change some (or all) of them over time. Whereas direct interdependence between a firm and the components arises when the firm picks them from the ecosystem, indirect interdependence arises as a function of relationships between the chosen components themselves. In turn, relationships between components at the level of an ecosystem are reflected and determined by the firms' collective component usage choices. That is, if a sizable proportion of firms already uses a pair of given components together, one can assume that such components are interdependent at the level of the ecosystem.

Although ecosystem interdependence matrices provide a valuable tool to map direct and indirect interdependencies, the related challenge is how to examine such relationships. Conceptually, such depictions of interdependencies among components at the level of an ecosystem should be amenable to using graph theory to understand archetypical dependence structures and their impact on firm outcomes. Graph theory has been extensively used to model the link between firms' positions in networks of inter-organizational relationships and performance (Shipilov & Gawer, 2020). Just like the applications of graph theory has been useful to understand different archetypes of indirect relationships that could exist between a firm and its partners (e.g., Gulati & Gargiulo, 1999), it could also help to understand different archetypes of indirect interdependencies among components chosen by the firm.

Graph theory offers ways of conceptualizing interdependence at the local and global level. Local interdependence reflects the extent to which the elements around a focal actor are loosely or tightly coupled. An example of a loosely coupled structure involves a node that is surrounded by sparsely connected alters; whereas a tightly coupled structure involves a node that is surrounded by tightly connected alters. In inter-organizational networks, the former structure is called low density network and the latter structure is called high density network. Coupling between alters has implications for the flexibility of the system: the higher the coupling, the more rigid the system and resistant to adaptation (Rowley et al., 2000). As an example of how methods from graph theory can be applied to understand component interdependence, Sosa, Eppinger and Rowles (2007) examine the probability of component redesign as a function of its relationships with other components. The authors find that the more linked a given component is to the other components, the less likely the focal component is to be redesigned. This is because the redesign of a given component is highly likely to affect its compatibility with the other components.

Aggregation of nodes and their alters in a social system leads to the emergence of modularity, i.e. the presence of neighborhoods in which members are more tightly connected internally than they are connected to the outside. A large variety of complex systems--be that networks of investment banks, neural networks of living beings or even power grids--all contain modular topologies (Watts, 1999). Design structure matrixes consist of modules, too: these are groups of components that have higher internal interdependence as compared to their interdependence with external components (Baldwin & Clark, 2000). Rather than understanding a set of components as more or less modular in terms of its own structure, we conceptualize a firm's components as a set of elements that can be drawn from a single or multiple modules of the innovation ecosystem.

Finally, indirect interdependencies can be observed at the global level of the ecosystem as a whole. When one knows how all components in an ecosystem relate to one another, one can uncover central and peripheral components. As Shipilov and Gawer (2020) point out, graph theory is particularly suited to identify bottleneck components from a pattern of interdependencies within an ecosystem. Centrally located components are likely to constitute bottlenecks that limit the growth or the performance of the ecosystem. Subsets of components that a firm has taken from an innovation ecosystem can vary in the extent to which they include bottlenecks.

Design structure matrixes and similar analytical tools have been used to understand interdependencies between components (or tasks) within organizations. When these components are found outside of the organization in its ecosystem, a firm's components are best understood as a subset of that ecosystem. In the sections that follow, we develop theoretical predictions regarding the impact of using components, characterized by a particular interdependence density, concentration within modules and bottleneck locations, on firms' ability to produce high performing value propositions following changes in the external environment.

Density of Component Interdependence Networks

As changes to business environments are becoming increasingly frequent and dramatic, a key question of strategic management is how to enhance firms' ability to adapt. In periods of relative stability, firms make strategic choices in relation to their interdependence with the ecosystem and these choices may establish a performance baseline. But environmental changes can affect the network of interdependencies at both the firm and ecosystem level. Firms are then faced with the strategic question how to structure their interdependencies in order to improve performance following environmental changes.

The interdependencies at the level of an ecosystem can arise from two sources: actions of component suppliers and actions of firms that use the components. First, suppliers can attempt to change their components (or introduce new components), which potentially impacts indirect interdependencies in the ecosystem. For example, technological innovation can affect the interdependence between air traffic controllers and airports which comprise the air travel ecosystem. In the past, air traffic control was done manually. At some point, developers wrote software to automate air traffic control which increased the number of planes that controllers can safely follow, thereby enabling larger airports to handle more air traffic. The appearance of a new component created a three-way indirect interdependence among between traffic control, airports and software, from the standpoint of an airline. Second, firms can adopt and abandon components. For example, this software might have been compatible only with newer airplanes, therefore airlines may have discontinued the use of older planes when flying to large airports.

At the level of the ecosystem, prior research has alluded to the notion that high interdependence among ecosystem activities affects adaptation. Although in certain circumstances, high interdependence among components can facilitate coordinated adaptation among suppliers (Kapoor & Lee, 2013), high interdependence both increases the complexity of the search for an optimal configuration (Kapoor & Agarwal, 2017) and the costs of adapting the component, since any change in one component affects many other components. If air traffic control protocols change, due to changes in international regulations, not only the airports have to change, but also the software providers. Such challenges only increase further when suppliers need to adjust to technological changes in multiple components, which further increases the complexity of their adaptation. Such ecosystem-level interdependence affects both the suppliers' ability to adapt their components, and also the performance of the firms using these components.

In addition to the effect of ecosystem-level interdependencies on suppliers' ability to adapt their components, interdependencies arising from firms' choices of components and activities influence their ability to adapt as well (Siggelkow, 2001, 2002). On the firm level, it is important to have a fit among an organization's activities that comprise its value proposition (Kapoor, 2018; Milgrom & Roberts, 1990; Porter & Siggelkow, 2000). Highly interdependent activity systems are, however, difficult to adapt to changing environments (Levinthal, 1997; Siggelkow, 2001). As Siggelkow (2001, 2002) found in his qualitative research on interdependence of firm activities, there are often non-simple interdependencies between components that sustain a firm's advantage. Changing such interdependencies can come at great cost, with the need to often disassemble and reassemble the network of interdependencies to renew performance. Research that has explicitly measured firm-level interdependencies corroborates such findings, suggesting, for example, that product-related interdependencies reduce adaptation performance following an exogenous shock (Aggarwal & Wu, 2015).

Thus, we expect indirect interdependencies to affect the ability of the firm to adapt after a change in the firm's external environment. When a firm builds its value proposition from highly interdependent components (i.e. components exhibiting high density interdependence in graph theory parlance), a change to one of these components in response to environmental shifts may generate considerable uncertainty and disruption for the other components. When a firm organizes its value proposition around less interdependent components (i.e. components exhibiting low density interdependence in graph theory terms), any change to these components will be associated with low uncertainty and disruption because any single component doesn't depend on many others. More formally:

H1: Following an environmental change, the use of components with high-density interdependence reduces a firm's performance relative to the use of components with low-density interdependence.

Modularity

Although high interdependence between components at both the ecosystem and firm-level may limit the ability of firms to adapt to an environmental change, modular design, by contrast, may facilitate adaptation. Modular design, or the decomposition of a complex technical system into modules with defined interfaces (Baldwin & Clark, 2000; Simon, 1962) has multiple potential benefits. First, by decomposing a technology into modules, actors can engage in parallel, autonomous adaptation within modules, increasing the speed and flexibility of adaptation (Ethiraj & Levinthal, 2004). Furthermore, firms can specialize and focus their search for an optimal configuration within each module, without having to consider all the interactions within the entire system, which simplifies coordination (Pil & Cohen, 2006) and thus by extension, adaptation. Moreover, modularity increases the ability to recombine modules in new ways, creating new options for adaptation while also decreasing the penalties associated with the coordination of interdependencies associated with that recombination (Baldwin & Clark, 2000). Not surprisingly, modularity in product architecture and organization design have been associated with greater adaptivity (Hoetker, 2006; Sanchez & Mahoney, 1996), but also with increased interfirm product modularity (Schilling, 2000; Schilling & Steensma, 2001). Although modularity admittedly comes with costs, during periods of change, adopting modular structures help firms avoid dependence that limits the firm's ability to adapt.

At the firm-level, one critical choice firms make in terms of their technical design is whether to draw on few or many modules found within their ecosystem to create value propositions. Modules are typically composed of interdependent components, with the benefits of modularity created by the interfaces between modules. Firms have a choice of whether to draw upon fewer or a larger number of modules, thereby capturing the benefits of integration and interdependence between components within the modules, or to draw upon more modules. For example, in the early personal computer industry, firms had to make choices about whether to use an integrated chipset and motherboard module, such as that offered by Intel, or whether to use multiple different smaller modules, such as drawing on a chip, motherboard, and related components from multiple suppliers.

Firms choosing to draw upon more modules when designing value propositions may capture several benefits related to adaptation. First, when firms have drawn from a larger set of modules, they have a larger set of potential solutions to draw upon when encountering an adaptation challenge, both decreasing search costs for new solutions and increasing their capability at adopting those solutions they already have experience with (Furr, 2019). Second, when firms have drawn upon several rather than a single module, there are more opportunities to recombine components or modules in new ways, in response to the new environment, further increasing their ability to adapt to a technological change (Ganco, 2013; Grant, 1996; Kogut & Zander, 1992). Third, when firms have invested in understanding more modules rather than fewer, they are more likely to have developed greater absorptive capacity regarding both the technologies they use and those that they might use, further increasing their ability to use technologies in new ways or use new technologies (Brusoni, Prencipe, & Pavitt, 2001; Cohen & Levinthal, 1990; Zahra & George, 2002). Fourth, when firms have experience with more rather than fewer modules, they are more likely to have developed integrative knowledge about how to disassemble and reassemble the interdependencies between the technological components and business activities (Furr & Kapoor, 2018; Helfat & Campo-Rembado, 2016; Moeen, 2017), further increasing firms' ability to adapt to a changed environment.

In addition to firm-level choices, at the ecosystem-level there can exist a second layer of integration/modularity tradeoffs that affects the ability of the firm to adapt. Specifically, modules may co-specialize at the ecosystem level in a manner that affects direct and indirect interdependencies. For example, groups of suppliers may make different choices that lead to the clustering of different modules, or sub-systems, that influence the adaptation benefits of a modular system (Murmann & Frenken, 2006). Real world examples include the modularity within the two competing personal computing ecosystems (i.e., Windows and Apple) but not between them. In such cases, it isn't just the modularity of the firm's technical design but also the modularity within the larger ecosystem that creates interdependence that shapes the ability of the firm to adapt. When considering the tradeoffs around interdependence and modularity at the ecosystem-level, firms drawing upon more rather than fewer modules may capture all the benefits listed above, namely, lower search costs, greater recombination opportunities, higher absorptive capacity, and higher integrative capability. But in addition, the firm that has borrowed its components from many rather than from the few modules is less likely to be captive to any one ecosystem-supplier level interdependency. In sum, there are multiple reasons why firms that have drawn upon more rather than fewer modules may have a greater ability to adapt when the environment changes. Thus, we can hypothesize that:

H2: Following an environmental change, the use of components from a higher number of modules enables firms to improve their performance compared to the use of components from a low number of modules.

Bottlenecks

In addition to the impact of interdependence and modularity, a dependence on an ecosystem bottleneck may also shape the ability of the firm to adapt to an environmental change. Bottlenecks can limit the performance of a technology, industry emergence surrounding the technology, and value capture related to the technology (Baldwin, 2015; Furr et al., 2020; Kapoor, 2018). Bottlenecks have been shown to shape where firms invest their innovation efforts (Ethiraj, 2007; Kapoor & Furr, 2015) and the performance of firms in both emerging and stable industries. (Hannah & Eisenhardt, 2018; Jacobides & Tae, 2015). Bottlenecks also play an important role in the ability of firms to adapt to changing markets. Prior research has underscored that bottlenecks in the ecosystem shape how firms survive technology transitions, acting as buffers for incumbents if there is a bottleneck to the emergence of a threatening technology generation, thereby providing firms with additional time to learn and adapt in the face of a potential substitution (Adner & Kapoor, 2010, 2016).

But when not in the context of technology generational change, bottlenecks may play a different role. In particular, when an environmental shift requires a change in components, reliance on the bottleneck can be detrimental to adaptation, and by consequence to firm performance. When considering the role of bottlenecks within a technology generation, it can be useful to adopt Baldwin's (2015) analogy of a bridge within a larger transportation network. Baldwin argues that the bridge acts as a constraint to the performance of the transportation system as a whole, since traffic has to pass over the bottleneck constraint of the bridge. In the context of an environmental change, firms using such a bottleneck suffer the negative impact of the environmental change on the bottleneck. For example, in the bridge analogy, a change that shifts the traffic over the bridge from railway to cars takes time to adapt to (e.g., introducing the need to widen or strengthen the bridge) and thereby negatively impacts the ability of car users to cross that bridge. However, there is an important exception: if someone using the transportation system does not rely on the bridge (e.g. takes a boat), the negative impact upon their travel will be much less. In an analogous manner, firms relying on bottleneck technologies—that is technologies at the center of network of components that can act as a constraint to the performance of a whole—are more exposed to the negative consequences of an environmental change than those not relying on a bottleneck.

Moreover, the owner of a bottleneck technology, because of their monopoly-like position in the technology ecosystem may hold the users of the bottleneck more captive than those not depending on the bottleneck. Abandoning central components tends to be more harmful to system performance and is thus also less likely. They therefore limit the firm's flexibility by anchoring the firm's configuration into components that might have become obsolete following environmental change (Ghemawat & Levinthal, 2008). Finally, the challenge is that the bottleneck is interdependent with so many other technologies that these dependencies become constraints further slowing the ability of firms to adapt bottleneck technologies in response to environmental changes. Adaptation increases in complexity when the firm uses multiple bottleneck components, especially if they also interact with each other. Hence, we predict:

H3: Following an environmental change, the use of bottleneck components reduces a firm's performance relative to the use of other components.

METHODS

Empirical Context and Sample

We test our arguments in a longitudinal study of 893 e-commerce startups. We examine the interdependencies among web technologies with which their websites are developed. Prominent examples of web technologies are Ubuntu (open source operating system), Facebook for Websites (integration tool), Magento (open source e-commerce platform), WordPress (content management system), Google Analytics (web analytics service) or Angular JS (java-script enabled front-end web framework). A website is presumably the most rapidly diffusing system of technologies in recent years. Web technologies have enabled the emergence of a global e-commerce industry, that recorded sales of around $2.9trillion in 2018 (Statista, 2019). The industry underwent rapid technological change in the period under consideration (2014-2019), requiring firms to frequently update their websites in order to stay competitive.

We empirically test our hypotheses by taking advantage of a policy change which regulates data protection for all individual citizens in the European Union and European Economic Area. The new regulation in EU law was adopted on April 14, 2016 and became enforceable with significant fines on May 25, 2018. The General Data Protection Regulation (GDPR) requires data protection measures to be designed into the development of business processes (Article 25). The regulation applies to all firms which collect data on EU/EEA citizens. Similar to regulatory changes which alter interdependencies in organizations (Aggarwal & Wu, 2015; Stan & Puranam, 2017), the GDPR altered the pattern of interdependencies among web technology components.

Whilst the regulatory change itself was foreseeable, the manner in which it shifted interdependencies once companies started to comply with it was difficult to predict. Anecdotal evidence in the media suggests that most companies were not well prepared for the new regulation at the time it became enforceable (e.g., London Chamber of Commerce and Industry, 2019; Thomson Reuters Legal, 2019). Customers received a high number of emails in May 2018 and new cookie consent banners appeared on many websites. The Google search trend of the keyword "GDPR" increased rapidly in the first quarter of 2018 and spiked in the second quarter of 2018, right around the time of GDPR's enforceability (Google Trends, 2019). This evidence indicates that firms did not intentionally change the structure of their web technologies in anticipation of the regulatory change. Even if firms predicted suppliers' changes in components and components' subsequent relative importance, it is unlikely that firms could predict architectural changes (Henderson & Clark, 1990), that is changes in the indirect interdependencies between web technologies.

We identified all e-commerce startups on Crunchbase that were founded since 2011. The global data set was limited to the 893 firms for which data on page views were available on Alexa. We obtained longitudinal data on the adoption and abandonment of web technologies. The components are developed by suppliers, i.e. software companies or open source communities. We had a sample of 4405 web technologies, which existed at any point during our observation period. For 98 firms, our data on their use of web technologies starts after the beginning of our sample period (181 missing firm-quarter observations). Our resulting unbalanced panel dataset thus consists of 893 companies in 58 countries over the quarters 2014 Q3 – 2019 Q1 (15,000 firm-quarter observations), including four quarters after the new regulation was enforced.

Dependent Variable

Web traffic is the main measure of performance of e-commerce firms, which is widely used by managers and investors (Demers & Lewellen, 2003). Traffic generates sales to customers and influences advertising revenues. Prior research shows that web traffic measures are associated with market value and future revenues (Rajgopal, Kotha, & Venkatachalam, 2000; Trueman, Wong, & Zhang, 2001). Alexa tracks a global representative sample of users. It records the number of page views per million users in this sample over three-month periods. We use the logged value of average page views per million in each quarter as a dependent variable. Our unit of analysis is a firm-quarter observation. The web traffic variable is always based on data in the next two quarters following the independent variables. For example, independent variables ending in Q1 of a given year predict traffic in Q2-Q3 of the same year.

Construction of Component Interdependence Networks

We define an innovation ecosystem as all technological components that all firms in our sample used in a given time period. Our main independent variables are based on the structure of interdependencies among components. Analogous to the approach taken in organizational networks research (e.g., Gulati & Gargiulo, 1999), formal models of complex adaptive systems (Ghemawat & Levinthal, 2008; Rivkin & Siggelkow, 2007) and design structure matrices (Baldwin, MacCormack, & Rusnak, 2014; Eppinger, Whitney, Smith, & Gebala, 1994; Sosa, Gargiulo, & Rowles, 2015), we construct symmetric adjacency matrices that reflect interdependencies between components on the level of a whole innovation ecosystem.

Like design-structure matrices used in technology and innovation research (e.g., Batallas & Yassine, 2006; Sosa et al., 2007), our matrices had technological components (e.g. WordPress, Ubuntu) in rows and columns. We use moving windows to construct 17 matrices that capture interdependencies in a given year as a function of components' joint use. Moving windows come into play when, for instance, the variables for Q3 of 2017 are computed based on the network that reflects interdependence of components for the prior 4 quarters, that is from Q4 of 2016 to Q3 of 2017. Subsequently, variables for Q4 of 2017 are computed based on the interdependence of components between Q1 and Q4 of 2017.

Follwing Godart and Galunic (2019), as well as social network measures that use the frequency of collaboration as an indicator of a relationship between entities (e.g., Gulati & Gargiulo, 1999), we use the frequency with which two components are used together as a measure of their interdependence. We consider two components to be interdependent at the level of an ecosystem if more than 10% of the firms in the ecosystem use both components at any time during the four quarters. As an example, if 10% of firms in our sample built their websites with both WordPress and Facebook for Websites between Q1 and Q4 of 2017, we would add a value of 1 in the matrix with row id “WordPress” and column id “Facebook for Websites” for the 2017 Q4 network. In a supplementary analysis, we confirmed that our results remain very similar when we use a 5% cutoff.

Depending on the time period, our 17 matrices include from 730 to 1803 components each, a total of 2471 unique components that firms used for the minimal duration of 1 year. The remaining 1934 components are not used for an entire year by any firm and are thus only used for the computation of control variables. Joint use of components reflects their interdependence for a number of reasons. First, when two components are complementary, they are more likely to be used together. Complementarity may be of a technological nature. In the extreme case, using one component may be a necessary technological requirement for using another component. There may also be social expectations or normative pressures for complementarity. For example, the use of two open source technologies may come from the developers’ “ideological” belief that they should not rely on proprietary software. Second, when components are frequently used together, they are certainly technologically compatible, otherwise they would not have been used together by at least some proportion of ecosystem members. Third, when components are frequently used together by the ecosystem members, component suppliers are more likely to invest in enhancing complementarity between the components. Forth, there are network effects that increase the value of joint component use. Software developers are more likely to find information online about how to use two components together and how to solve occurring technological problems, if a high number of other developers already use the two components together.

Independent Variables

To operationalize *Interdependence Density* of components on the firm level, we borrow the ego density measure used by network scholars (e.g., Rowley et al., 2000). For each firm and quarter (e.g., casper.com, Q4 2017), we determine the set of components that the firm has used. We then look at the interdependence matrix calculated on the four quarters (e.g., Q1-Q4, 2017) and observe the pattern of interdependence that exists among these components based on the technological choices of the entire ecosystem. *Interdependence Density* is then computed as the ratio of interdependencies among components to the maximum number of possible interdependencies among the firm's components using the following formula:

$$Interdependence\ Pattern_{it} = \frac{Component\ Linkages_{it}}{\frac{1}{2}(Number\ of\ Components_{it}^2 - Number\ of\ Components_{it})} \quad (1)$$

For example, if the website casper.com used three components A, B, C and more than 10% of firms in the ecosystem used components A-B and A-C together, then *Interdependence Density* will take a value of 2/(0.5*[3[2]-3])=0.66. If more than 10% of firms in an ecosystem used A, B and C together, then *Interdependence Density* will take a value of 3/(0.5*[3[2]-3])=1. A low value of this measure would indicate that a firm has a low density of interdependence while a high value on this measure would indicate high density interdependence.

To capture *Cross-Module Component Use (CMCU)*, we start by decomposing our ecosystem's matrix of interdependencies into modules (Clement, Shipilov, & Galunic, 2018; Zhou, 2013) using the unipartite version of the algorithm developed by Guimerà and Amaral (Guimerà & Amaral, 2005b, 2005a). It partitions a network into groups of components with as many internal links and as few external links as possible. The resulting partition of the 17 networks varied from 2 to 4 modules. Newman and Girvan (2004) define a statistic M as a fraction of the links in the network that connect nodes within the community less the expected value of the same quantity in a network with the same community divisions but random connections between the nodes. M equals zero if they are placed at random into the modules Amaral (Guimerà & Amaral, 2005b, 2005a). We obtain M values ranging from 0.12 to 0.17. While networks with community structures have typically fallen in the range from 0.3 to 0.7 (Newman & Girvan, 2004) and have therefore been viewed as indicative of modular structures, Guimerà, Sales-Pardo and Amaral (2004) suggest a more nuanced approach using a formula to calculate expected M for a random network that has the same number of nodes and the same average connectivity as the actual network. If M for the actual network exceeds the expected M for a random network, then we can consider modularity in the actual network to be non-random. Table 1 provides a summary of modularity values for different quarters. It shows that, starting from Q1 2016, M from the actual network exceeds that of a random network.

--- Insert Table 1 about Here ---

Our M is not high in this context possibly because there are no systematic social processes that shape the network of interdependencies, unlike what has been observed in the networks formed through collaboration between individuals (e.g., Clement et al., 2018). For example, if we have three components A, B and C -- such that A is interdependent with B and C -- there may be no pressures (at the level of the entire ecosystem) for an interdependence between B and C to emerge. However, even modules at relatively low values of modularity can be constraining for firms. That is, if a firm chooses components from a single module, where all components have a higher degree of interdependence relative to the components in other modules, it may have less flexibility in adapting to an external change relative to a firm which is choosing components across different modules and which thus needs to accommodate fewer component interdependencies. The "Number of Nodes" in Table 1 refers to the number of technological components which are connected in a main cluster (i.e. a connected subgraph of interdependencies) through a set of interdependence relationships for that specific time period and the values of "Density" and "Modularity" in Table 1 are also computed on the network in the main cluster[1].

We followed two strategies to verify whether our modules were "real", despite their modest modularity values. First, we initialized modularity analysis from different initial conditions (started

[1] *Interdependence Density* and *Bottleneck Components* are computed on the full matrix of interdependencies that includes both components that belong to the main cluster and those that don't belong to the main cluster.

the algorithm with different random numbers) and this resulted in very similar modules. Second, we checked whether modules, identified by the algorithm, were relatively stable over time. We found that the median percentage of components that remain in the same module is 91% when comparing modules resulting from network change quarter to quarter; and 74% when comparing modules resulting from network change year to year.

Given that our modules were stable, we then computed the Herfindahl-Hirschman Index of component use concentration by the focal firm:

$$\mathrm{HHI} = \sum_{\mathrm{m}=1}^{\mathrm{N}} \left(\frac{(\text{Number of Components in Module m})_{\mathrm{it}}}{(\text{Number of Components})_{\mathrm{it}}}\right)^2 \qquad (2)$$

Finally, we calculated *CMCU* as one minus the Herfindahl-Hirschman Index. A higher value of *CMCU* means that the firm picks technologies from a high number of modules, whereas a lower value of *CMCU* means that the firm picks technologies from a low number of modules.

To measure a firm's use of *Bottleneck Components*, we proceed in two steps. We first computed the eigenvector centrality of each component in the ecosystem-level network (Bonacich, 2007). The higher a component's ecosystem eigenvector centrality, the higher the likelihood that it constitutes a bottleneck in the ecosystem as a whole. Second, we identify which components, that the firm has chosen from the ecosystem, are the most important to the firm itself. To this end, we compute local eigenvector centrality of each component based on the matrix of interdependencies that includes only the components which the firm has chosen. Finally, we identify the ecosystem eigenvector centralities of the technologies that comprised the top 25% of the local eigenvector centralities and compute the median of their ecosystem level centralities. A high score thus indicates that the firm has chosen interdependent components that constitute bottlenecks on the ecosystem level. Figure A2 (adapted from Shipilov and Gawer (2020)) in the Online Appendix illustrates our approach to constructing the *Bottleneck Components* variable. It contains an illustration for interdependencies in a simple ecosystem with seven components (A-G), a graphic representation of ecosystem component interdependencies and three different scenarios to illustrate how we would have operationalized *Bottleneck Components* depending on the firm's technological choices.

To account for the exogenous change introduced by the coming into force of the General Data Protection Regulation, we include a binary variable, *Post-change*, indicating whether the observation occurred after (i.e., *Post-change*= 1) or prior to the enforcement of the regulation in the second quarter of 2018 (i.e. *Post-change*= 0). Moreover, we include a binary variable, *Treatment Country*, indicating whether the firm is located in a country in which it is likely to be affected by the regulation (i.e., equal to 1) or not (i.e., equal to 0). Since the regulation applies to all firms that collect data on EU/EEA citizens, firms located in the EU and EEA, Switzerland, the USA and Canada are likely to be affected by the regulation. Firms less likely to be affected are located in Brazil, China, India, Indonesia, Mexico or Singapore, for example.

Control Variables

Since our theoretical framework revolves around indirect interdependencies, we also have to control for direct interdependencies between the firm and the innovation ecosystem. We construct our variable *Direct Interdependence* in the following way: For each technological component, we identify the number of components in the same category, which constitute potential substitutes. All components are classified into 200 categories, with an average of 22 components each. Examples of categories are Cloud Hosting, Affiliate Programs and Digital Video Ads. For each firm and quarter, we compute the inverse of the average number of substitutes of the technological components that the firm uses in the given quarter. The higher the *Direct Interdependence*, the lower is the average number of substitutes of the components that the firm uses.

A firm can adapt to external changes merely through changing its technologies without any regard for their interdependence. We captured this process with a variable *Technological Change*.

For each firm and quarter, we construct a vector of all components whose elements equal one if the firm uses the component in the given quarter and zero if the firm does not use the component in the given quarter. We calculate the Euclidean distance between the current quarter's vector and the previous quarter's vector. For example, if the entire ecosystem consists of 4 components (A, B, C and D) and the firm uses only components A and B in Q1 and then it uses components C and D in Q2, then this measure will be 2. However, if this firm continues using components A and B in Q2, then this measure will be equal to zero.

Firms may build more or less centralized component networks to support their value propositions to the customers. Our measure (*Component Centralization*) is computed in two steps. For each component, we first compute the number of interdependencies within the matrix that includes only the components which the firm is using. In the language of network research, we are computing degree centrality of all components used by the firm. The degree does not include interdependencies with components that the firm does not use. Then, *Component Centralization* is calculated as the variance (the average of the squared deviation from the mean) in the degree centrality of the firm's components. High *Component Centralization* means that the firm's components exhibit a core periphery structure such that there are components with a relatively high degree centrality and the other components have low degree centrality. Low *Component Centralization* means that the firm's components have a more or less uniform degree distribution.

Identification Strategy

To identify causal estimates and rule out the possibility that there are some unobserved time variant firm-level characteristics that drive our results, we used a triple differences design (differences-in-differences-in-differences). We also incorporated firm-level fixed effects in our models to account for time-invariant unobserved factors as well as clustered standard errors on the level of the firm. The latter approach to standard errors, even though it is the most conservative, is suggested by Bertrand, Duflo and Mullainathan (2004) when estimating DiD models.

We track 893 firms for every quarter from 2014 Q3 to 2019 Q1. Since GDPR became legally enforceable in Q2 2018, we need to ensure that control and treatment groups are comparable both in terms of their theoretical / control variables and in terms of trends in web traffic. Table 2 provides descriptive statistics and correlations on the full sample. Table 3 compares the treatment with the control group based on their observable characteristics in Q4 2017, which is the period before firms were affected by GDPR in 2018 Q1-Q2. Estimate and standard error results refer to the point estimate in a univariate regression with *Direct Interdependence*, *Component Centralization*, *Interdependence Density*, etc. as a dependent variable and assignment to the treatment or control condition as an independent variable. The resulting p-value and t-statistic show whether there was significant difference between the mean of control and treatment group. The effect of the assignment to the treatment condition is not precisely estimated and no single variable has significantly different means across the control and treatment group.

--- Insert Tables 2 and 3 about here ---

Our approach allows comparison in differences before and after the regulatory change, between firms located in countries affected by the regulation and firms located in countries not affected by the regulation and differences between firms with respect to our covariates. The equations used to test the hypotheses have the general form:

$$\ln y_{it} = \beta_1 * PC + \beta_2 * x_{it} + \beta_3 * PC * TC + \beta_4 * PC * x_{it} + \beta_5 * TC * x_{it} + \beta_6 * PC * TC * x_{it} + \beta_7 * [Controls_{it}] + v_i + u_{it}$$

where subscripts refer to firm i and quarter t, PC denotes the binary *Post-change* variable, TC denotes the binary *Treatment Country* variable, and x_{it} denotes the independent variable. v_i are firm fixed effects, which include the main effect of *Treatment Country* since a firm's country does not change over time in our sample, and u_{it} is a random error. The dependent variable is the log transformation of a firm's quarterly average page views. The interaction between *Treatment Country*, *Post-change* and the independent variable is the term of interest in our models. This interaction term captures the difference between firms in treatment and control countries in the change in average page views for the same firm before and after the environmental change as a function of their differences in interdependence density, cross-module component use or reliance on bottleneck components.

A differences-in-differences design would require the assumption of a parallel trend in performance when comparing firms in the treatment countries with firms in the control countries (or alternatively, when comparing firms with high levels of the covariates, e.g. interdependence density, with low levels of the covariates). If the trends are not parallel in the differences-in-differences design, then one can still deploy a triple differences design assuming that there is a parallel trend in the *interaction* between the treatment group and the covariate of interest prior to the treatment. Following Muralidharan and Prakash (2017), we first test for the parallel trends in the differences-in-differences and reject it. That is, firms in countries which were more likely to be affected by GDPR enforcement had different trends in web traffic as compared to firms in countries which were less likely to be affected by GDPR enforcement. This is indicated by a precisely estimated interaction of *Treatment Country* and *Quarters* in all models in Table A3 in the Online Appendix, which are based on all observations in the pre-treatment period. However, when we estimate whether the trends are parallel with respect to interdependence density, cross-module component use or reliance on bottleneck components, we find that triple interactions of these variables with *Treatment Country* and *Quarters* in Models 1-3 are not precisely estimated. Hence, we can still leverage the GDPR enforcement as an identification strategy for the purposes of testing our specific hypotheses.

Analyses and Results

Our linear regression results with firm fixed effects are shown in Table 4. To reduce collinearity, we compute z-scores for theoretical variables (i.e., *Interdependence Density*, *Cross-Module Component Use* (CMCU) and *Bottleneck Components*). Model 1 is a baseline. In Model 2 we add the *Post-change* variable. In Model 3 we test Hypothesis 1 by entering a three-way interaction of *Interdependence Density* with *Treatment Country* and *Post-change* as well as all the lower level interactions. This effect is negative and precisely estimated (b=-0.12, p=0.015, 95% CI -0.225 to -0.025), suggesting support for Hypothesis 1. In Model 4, we enter a three-way interaction of *CMCU* with *Treatment Country* and *Post-change.* This effect is positive and precisely estimated (b=0.20, p=0.034, 95% CI 0.015 to 0.382), which provides support for Hypothesis 2. Finally, in Model 5 we enter a three-way interaction of *Bottleneck Component* with *Treatment Country* and *Post-change*. While this effect is negative, as we expected, it is not precisely estimated (b=-0.09, p=0.242, 95% CI -0.232 to 0.059). Models 6-8 show that the random-effects model results are consistent with the fixed-effects model results.

Three-way interactions are best interpreted using plots. This is what we do on Figure 1 using the point estimates. Since *Treatment Country* is a fixed characteristic, it drops out from models with firm fixed effects. This is why *Treatment Country* is not included in Table 4. While margins command in STATA is unable to compute marginal effects in the absence of this variable, for plots, we use the random effects versions of Models 3-5 reported as Models 6-8 in Table 4.

--- Insert Figure 1 about here---

These plots highlight marginal effects of transition from the control group to the treatment group. In other words, they show the effect of being located in Europe/Canada/U.S. rather than India/China/rest of the world, and thus being impacted by the enforcement of GDPR. Since our results are the same with and without firm fixed effects, these plots are not confounded by unobserved heterogeneity stable within the firm[2]. Horizontal axes on these figures capture z-score values of corresponding variables.

Panel A, Figure 1 shows that, once the GDPR became enforceable, the performance of firms with high density interdependence decreased in treatment countries relative to the performance of firms in control countries. In contrast, the performance of firms with low density interdependence increased in treatment countries relative to control countries. More specifically, before the regulatory change (line post_change=0), firms with low density interdependence performed worse in treatment countries relative to firms in the rest of the world. In contrast, firms with high density interdependence performed better in treatment relative to control countries. After the regulation became enforceable (line post_change=1), the relative advantage of high-density firms in the treatment countries was reversed. Following the regulatory change, such firms performed slightly better in control countries than in treatment countries. The before vs. after change effect differences are significant up until the mean value of *Interdependence Density*, supporting Hypothesis 1.

Panel B, Figure 1 shows that, after the introduction of GDPR, firms which build their value propositions from components belonging to multiple ecosystem modules performed better in treated countries than in the rest of the world. In contrast, firms which build their value propositions with components from few modules performed worse in treated countries than in control countries (more so than before the environmental change). This pattern supports Hypothesis 2.

While point estimates did not show support for Hypothesis 3, we still plotted the corresponding three-way interaction in Panel C, Figure 1. Essentially, there is no difference between

[2] Such heterogeneity might have arisen from different socioeconomic conditions as well as web browsing patterns in the control and treatment group for example. Since firms don't change countries, firm fixed effects fully account for these factors.

control and treatment groups before and after the regulatory change with respect to the effect of *Bottleneck Components* on firm performance[3].

Given that GDPR was adopted in May 2016 and came into force in May 2018, we tested whether firms reacted to this change in 2016 instead of 2018. To that end, we changed the treatment period to start from Q2 2016. Table A4 in the Online Appendix reports the resulting models. The three-way interactions of *Independence Density x Treatment Country x Post-change* (Model 3), *Cross-Module Component Use x Treatment Country x Post-change* (Model 4) or *Bottleneck Components x Treatment Country x Post-change* (Model 5) were not precisely estimated. This result is robust to a random-effects specification (Models 6-8).[4]

DISCUSSION AND CONCLUSIONS

There has been limited research on how indirect interdependencies among technological components chosen by a firm from an innovation ecosystem can affect the firm's ability to adapt to external changes. Our analysis of e-commerce websites' performance, following the implementation of GDPR, has shown that the density of indirect interdependencies among components was consequential for firm performance. Specifically, before environmental change, firms that chose components with low-density interdependence performed worse relative to firms that chose

[3] These figures use 85% percent confidence intervals (CI). The use of 95% CI on the plots for interactions is a rather conservative measure. According to Asgari et al. (2018: appendix p.8) "if two CIs do not overlap, the estimates are necessarily different. However, the converse of this proposition is not true: we cannot necessarily state that overlapping CIs are not significantly different… When comparing CIs, there is a space where the difference in the means is significant but the CIs overlap; within the CI overlap space, one cannot determine if the difference is significant". Hence, to see if there are significant differences between the means of different groups, one evaluates the precision of point estimates and not the visual representation of the effects. Payton, Greenstone and Schenker (2003) suggest that the use of 95 % CI in the plots corresponds to testing whether the two groups are different with a Type I error rate of 0.01. If one knows the ratio of standard errors in two samples (that can be approximated by a ratio of square roots of sample sizes), one can compute the CI that corresponds to two group mean difference tests with Type I error rate of 0.05 applicable to one's samples. In our case, the pre-treatment sample size is 11 428 and the post treatment sample size is 3572. The ratio of square roots of two sample sizes approximately gives us 1.8. This value approximately corresponds to 85% CI on the graphs in their simulations, so that we can obtain a Type I error rate of 0.05.

[4] In supplementary analyses, we changed the treatment period to any quarter in our sample period and found that the effects are strongest for the treatment period Q1-Q2 2018 that is already used in the main regressions.

components with high-density interdependence. Yet, it seems that low-density interdependence enables firms to improve their performance in fast-paced environments. Whilst firms with high-density interdependence performed better in treated countries than in control countries before the environmental change, this effect disappeared after the environmental change.

Our second finding suggested that firms can enhance their ability to adapt to environmental changes by using components from multiple modules, as opposed to using components from a single module. These modules are formed at the level of an ecosystem as a function of indirect interdependencies involving multiple components. Whereas prior to the environmental change, there was essentially no impact of the number of modules from which firms drew components, following the change firms drawing components from multiple modules clearly outperformed firms drawing from fewer modules. Finally, we did not find evidence that the use of bottleneck components has hindered firms' adaptation to external change. Possibly, suppliers of bottleneck components leverage their position to facilitate coordinated adaptation. Their ability to engage in standard-setting, for instance, may enhance adaptation abilities of components interdependent with bottleneck components. This mechanism offers an explanation for countervailing forces which may have reduced the hypothesised effect.

Whereas bottleneck components arise from the global pattern of interdependencies at the ecosystem level, modularity and density of interdependence are more strongly related to interdependencies between the firm's components or the components with which these components are directly interdependent. Ultimately, indirect interdependencies between the firm's components influence firm's ability to adapt in times of environmental instability, whereas indirect interdependencies of the firm's components in the global ecosystem, in the form of bottlenecks, do not affect firm performance following environmental change. This pattern suggests that, while the structure of interdependencies within an ecosystem matters, indirect interdependencies are more impactful when they involve more “proximate” components to those adopted by the firms in the ecosystem interdependence matrix, as opposed to components that are “further away” in the matrix.

By zeroing in on the pattern of indirect interdependencies, these findings contribute to the literature on performance consequences of firms’ positions within innovation ecosystems. While prior research on technology and innovation has acknowledged that firms deal with interdependencies among technologies, components or processes (e.g., Baldwin & Clark, 2000; Collins, Yassine, & Borgatti, 2009), it was rarely acknowledged that the structure of component interdependencies can come from an innovation ecosystem and that this structure can affect the firm’s performance. Quantitative studies linking a firm’s technological choices from an innovation ecosystem, their interdependencies and a firm’s performance are rare. Most studies examine innovation outcomes due to performance data availability issues. For example, Kapoor and Lee (2013) examine the strength of alliances between complementors and the firm’s propensity to innovate, likewise Ethiraj (2007) links the firm’s use of bottleneck technologies to the firm’s inventive efforts. In a few notable exceptions, Kapoor and Adner (2012) examine how firms’ adaptive behaviours, in the form of changes in components or changes in architectures, affect firm performance defined as the speed with which technologies are brought to market. Likewise, Kapoor and Agarwal (2017) examine performance of complementors, i.e. game developers competing within iOS or Android ecosystems and they examine ecosystem complexity as one of the drivers of variability of complementor performance. Our study joins this small but growing body of knowledge on how firms’ performance is affected by interdependencies between the ecosystem’s technological components.

Our second contribution is the incorporation of graph theory concepts such as density, modularity or centrality, to studying the patterns of indirect interdependencies among components at the level of an innovation ecosystem. Although Collins, Yassine and Borgatti (2009) as well as

Sosa, Eppinger and Rowles (2007) already used graph theory tools to analyse properties of technological (or business process) modules within a single firm, we apply this approach to the level of the entire ecosystem. We distinguish between structure at the ecosystem level and structure at the firm level and show that density and modularity, which capture firm-level structure, are more consequential to firm performance than the use of bottleneck components. As Shipilov and Gawer (2020) point out, further applications of graph theory to the studies of ecosystems can bring novel intellectual stimuli to think about not only the consequences of firms' positions within ecosystems, but also about where these positions come from or how technological interdependencies at the ecosystem level are formed in the first place.

Our study is built on several assumptions. First, firms discover "true" interdependencies among components. That is, if a sizable number of firms uses the two components together, these components are interdependent. Our analysis was robust to different cut-off points for what the "sizable number" actually meant, i.e. while we report results using 10% of firms in the sample as a cut-off score, we find broadly similar results using a less restrictive 5% cut-off. However, we don't know whether there are "true" interdependencies between technologies which the firms have not yet discovered. Had we studied technologies based on patents, we would have used the text of patents (e.g., Kaplan & Vakili, 2015) to infer a different source of interdependencies among technologies and then overlaid these interdependencies upon those which the firms have actually discovered.

Second, as Table 1 shows, our ecosystem's modularity was not very high. We assume that modules in a structure with relatively low modularity can still be constraining for firms. While for the most quarters modularity was higher than that of a random graph, some of the earlier quarters had modularity values that were equal to those of a random graph. Given that this is the first study to apply graph theoretical methods to detect modularity in a network formed by interdependencies among technological components of an ecosystem, as opposed to a network formed by social relationships among economic actors, we don't know how well this finding generalizes. Unlike a centralized ecosystem formed around a single dominant technological platform, such as iOS or Android, our innovation ecosystem has multiple suppliers of technologies and firms are not forced to use bundles of components from one or the other provider. Furthermore, many components are open source, which gives developers a lot more opportunities to mix and match them. Finally, there is no social pressure to "find" interdependencies within a set of components if at least some of them are already interdependent. Maybe it is normal for an innovation ecosystem to be less modular than a network formed among companies or individuals. Despite the relatively modest modularity, we still found that firms subject to environmental change benefited from drawing components out of multiple modules, as opposed to drawing components form a single module.

We assumed that component interdependencies arise both from the actions of suppliers that "build" the interdependencies into their offerings and from the actions of the firms that "discover" component interdependencies. Theoretically, one might believe that supplier induced interdependencies constrain adaptation more than those discovered by firms; however, regardless of their origins all interdependencies will affect firm adaptation. While we could not separate these origins of interdependencies empirically, we hope that future research would be able to do so.

Taken together, our findings highlight the importance of studying the structure of interdependence of a firm's technological components and their position in the broader innovation ecosystem. Firms depend on their ecosystem, but not all components from that ecosystem are equally useful at all times. When faced with an environmental change, firms suffer from using components that exhibit high density interdependence as well as those coming from a single technological module. More broadly, we hope that the paper demonstrates that the application of graph theoretic methods and concepts to ecosystems research is a promising direction to examine new drivers of a firm's competitive advantage in dealing with its external environment.

Table 1. Comparison of Modularity Scores with Those from Random Networks

Independent Variable	Number of Nodes	Density	Modularity (M)	Modularity (M) of Random Graph with Same Density
2014 Q3	46	0.3440	0.1464	0.1776
2014 Q4	55	0.3387	0.1265	0.1650
2015 Q1	63	0.3088	0.1241	0.1642
2015 Q2	69	0.3163	0.1239	0.1543
2015 Q3	79	0.2960	0.1395	0.1504
2015 Q4	90	0.2931	0.1300	0.1414
2016 Q1*	91	0.3267	0.1367	0.1307
2016 Q2*	102	0.3178	0.1477	0.1252
2016 Q3*	108	0.3233	0.1514	0.1200
2016 Q4*	111	0.3320	0.1447	0.1161
2017 Q1*	111	0.3458	0.1415	0.1130
2017 Q2*	117	0.3507	0.1424	0.1088
2017 Q3*	115	0.3571	0.1553	0.1085
2017 Q4*	120	0.3261	0.1641	0.1126
2018 Q1*	118	0.3387	0.1605	0.1108
2018 Q2*	115	0.3219	0.1715	0.1163
2018 Q3*	98	0.3774	0.1644	0.1141

* Modularity (M) greater than modularity of random graph

Table 2. Descriptive Statistics and Correlation Matrix

	Mean	S.D.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Direct Interdependence	0.029	0.008	1	-0.169	-0.584	0.110	0.333	-0.087	0.037	-0.561
(2) Technological Change	2.795	1.375	-0.169	1	0.270	-0.262	0.082	-0.124	0.039	0.149
(3) Component Centralization	196.015	138.105	-0.584	0.270	1	-0.012	-0.123	0.043	0.013	0.365
(4) Interdependence Density*	0.000	1.000	0.110	-0.262	-0.012	1	-0.112	0.516	-0.022	0.046
(5) Cross-Module Component Use*	0.000	1.000	0.333	0.082	-0.123	-0.112	1	-0.050	0.042	-0.463
(6) Bottleneck Components*	0.000	1.000	-0.087	-0.124	0.043	0.516	-0.050	1	0.002	0.137
(7) Treatment Country	0.635	0.481	0.037	0.039	0.013	-0.022	0.042	0.002	1	-0.001
(8) Post-change	0.238	0.426	-0.561	0.149	0.365	0.046	-0.463	0.137	-0.001	1

* z-scores as in the regressions

Table 3. Comparison of Control and Treatment Groups in Quarter Before Treatment

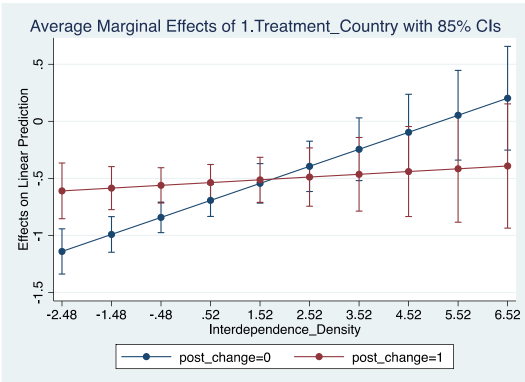
	Means Treated	Means Control	Estimate	S.E.	P-Value	T Statistic
Direct Interdependence	0.0213	0.0211	0.0003	0.0003	0.432	0.787
Technological Change	3.0785	2.9765	0.1020	0.0943	0.280	1.081
Component Centralization	290.0249	289.4740	0.5509	9.9203	0.956	0.056
Interdependence Density	0.2781	0.2864	-0.0083	0.0064	0.192	-1.306
Cross-Module Component Use	0.4771	0.4764	0.0063	0.0025	0.801	0.252
Bottleneck Components	0.9521	0.9554	-0.0033	0.0034	0.341	-0.952

Table 4. Regression Results

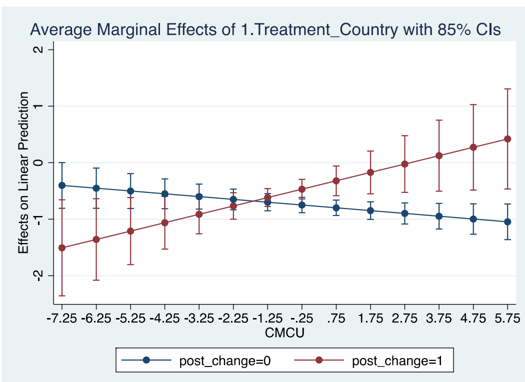
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Direct Interdependence	5.04	1.92	2.59	2.10	2.30	2.88	2.41	2.59
	(2.45)	(2.85)	(2.84)	(2.79)	(2.82)	(2.81)	(2.76)	(2.79)
Technological Change	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Component Centralization	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Interdependence Density	−0.13	−0.13	−0.23	−0.13	−0.13	−0.23	−0.13	−0.14
	(0.02)	(0.02)	(0.04)	(0.02)	(0.02)	(0.04)	(0.02)	(0.02)
Cross-Module Component Use	0.05	0.04	0.04	0.07	0.04	0.04	0.07	0.04
	(0.01)	(0.01)	(0.01)	(0.03)	(0.02)	(0.01)	(0.03)	(0.02)
Bottleneck Components	0.04	0.05	0.05	0.05	−0.00	0.05	0.05	−0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.03)	(0.03)	(0.05)
Post-change		−0.10	−0.25	−0.21	−0.23	−0.24	−0.22	−0.23
		(0.03)	(0.04)	(0.07)	(0.04)	(0.04)	(0.07)	(0.04)
Treatment Country X Post-change			0.22	0.33	0.21	0.22	0.33	0.21
			(0.05)	(0.09)	(0.05)	(0.05)	(0.09)	(0.05)
Interdependence Density X Treatment Country			0.15			0.15		
			(0.05)			(0.04)		
Interdependence Density X Post-change			0.13			0.13		
			(0.04)			(0.04)		
Interdependence Density X Treatment Country X Post-change			−0.12			−0.13		
			(0.05)			(0.05)		
Cross-Module Component Use X Treatment Country				−0.05			−0.05	
				(0.04)			(0.04)	
Cross-Module Component Use X Post-change				−0.01			−0.01	
				(0.07)			(0.07)	
Cross-Module Component Use X Treatment Country X Post-change				0.20			0.20	
				(0.09)			(0.09)	
Bottleneck Components X Treatment Country					0.10			0.10
					(0.06)			(0.06)
Bottleneck Components X Post-change					0.04			0.04
					(0.06)			(0.06)
Bottleneck Components X Treatment Country X Post-change					−0.09			−0.09
					(0.07)			(0.07)
Constant						−0.70	−0.67	−0.68
						(0.13)	(0.12)	(0.13)
Treatment Country						−0.77	−0.76	−0.76
						(0.09)	(0.09)	(0.09)
Observations	15 0000	15 0000	15 0000	15 0000	15 0000	15 0000	15 0000	15 0000
R-squared overall	0.0341	0.0351	0.0227	0.0229	0.0237	0.0876	0.0857	0.0890
R-squared within	0.0302	0.0328	0.0451	0.0404	0.0421	0.0451	0.0404	0.0428

Figure 1: Plots of interaction effects

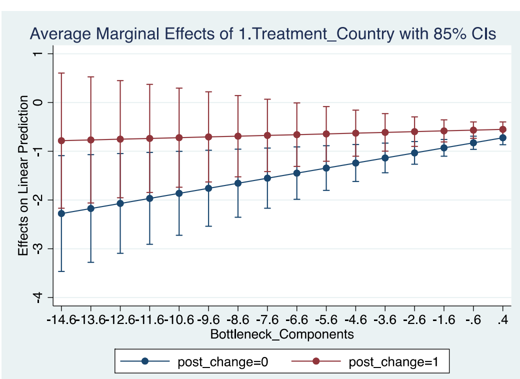
Panel A: Effects of Interdependence Density



Panel B: Effects of Cross-Module Component Use



Panel C: Effects of Bottlenecks



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ONLINE APPENDIX

Figure A1: Innovation Ecosystem Interdependence Matrix

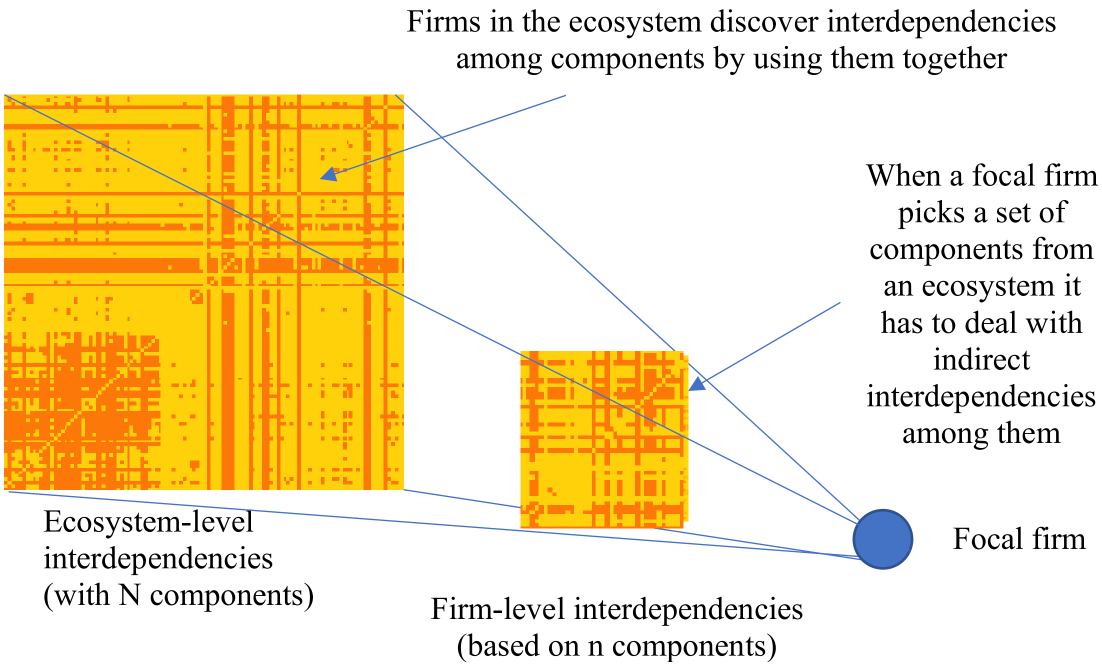
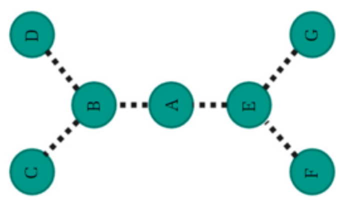


Figure A2: Computation of Bottleneck Component Variable

Panel A: Ecosystem Matrix of Interdependencies

	A	B	C	D	E	F	G
A		1			1		
B	1		1	1			
C		1					
D		1					
E	1					1	1
F					1		
G					1		

Panel B: Visual Representation of the Ecosystem Matrix of Interdependencies



Panel C: Three Scenarios of Computing Bottleneck Component Variable

Let's assume that three different firms have selected three different sets of components (ABE, BCD and CDE) from the ecosystem depicted in panels A and B. Each choice represents a particular scenario. Zero values in the matrixes below indicate that there are no interdependencies between selected components at the level of the ecosystem.

Scenario 1

	A	B	E
A		1	1
B	1		
E	1		

Component A has high centrality in the ecosystem and in the firm network. We use A's eigenvector centrality from the ecosystem matrix to operationalize a firm's Bottleneck Component, because it belongs to top 25% of centralities among A, B and E

Scenario 2

	B	C	D
B		1	1
C	1		
D	1		

Component B has high centrality in the ecosystem and in the firm network. We use B's eigenvector centrality from the ecosystem matrix to operationalize a firm's Bottleneck Component, because it belongs to top 25% of centralities among B, C and D

Scenario 3

	C	D	E
C			
D			
E			

Component E has high centrality in the ecosystem but not in the firm network. We use median eigenvector centralities from C, D and E to operationalize a firm's Bottleneck Component

Table A3. Parallel Trends Results

	Model 1	Model 2	Model 3
Direct Interdependence	−0.86	−0.87	−1.25
	(3.01)	(2.91)	(2.94)
Technological Change	0.02	0.02	0.02
	(0.01)	(0.01)	(0.01)
Component Centralization	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)
Interdependence Density*	−0.19	−0.09	−0.08
	(0.06)	(0.03)	(0.03)
Cross-Module Component Use*	0.01	−0.03	0.01
	(0.01)	(0.06)	(0.01)
Bottleneck Components*	0.08	0.07	0.09
	(0.03)	(0.03)	(0.06)
Quarters	−0.06	−0.06	−0.05
	(0.01)	(0.01)	(0.01)
Treatment Country X Quarters	0.06	0.06	0.05
	(0.01)	(0.01)	(0.01)
Interdependence Density* X Treatment Country	0.04		
	(0.07)		
Interdependence Density* X Quarters	0.02		
	(0.01)		
Interdependence Density* X Treatment Country X Quarters	−0.00		
	(0.01)		
Cross-Module Component Use* X Treatment Country		0.03	
		(0.07)	
Cross-Module Component Use* X Quarters		0.00	
		(0.01)	
Cross-Module Component Use* X Treatment Country X Quarters		−0.00	
		(0.01)	
Bottleneck Components* X Treatment Country			−0.03
			(0.07)
Bottleneck Components* X Quarters			−0.01
			(0.01)
Bottleneck Components* X Treatment Country X Quarters			0.01
			(0.01)
Observations	11 428	11 428	11 428
R-squared overall	0.0083	0.0109	0.0080
R-squared within	0.0626	0.0570	0.0573

* z-scores as in the main regressions

Table A4. Alternative Treatment Period (2016 Q2)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Direct Interdependence	5.04	3.34	5.03	3.41	4.17	5.30	3.72	4.45
	(2.45)	(2.44)	(2.36)	(2.28)	(2.40)	(2.34)	(2.26)	(2.38)
Technological Change	0.03	0.02	0.02	0.03	0.02	0.02	0.03	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Component Centralization	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Interdependence Density	−0.13	−0.11	−0.20	−0.11	−0.11	−0.21	−0.11	−0.11
	(0.02)	(0.02)	(0.05)	(0.02)	(0.02)	(0.05)	(0.02)	(0.02)
Cross-Module Component Use	0.05	0.06	0.05	0.02	0.05	0.05	0.02	0.05
	(0.01)	(0.01)	(0.01)	(0.05)	(0.01)	(0.01)	(0.04)	(0.01)
Bottleneck Components	0.04	0.05	0.06	0.06	0.06	0.06	0.06	0.06
	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.03)	(0.03)	(0.05)
Post-change		−0.13	−0.38	−0.40	−0.39	−0.37	−0.40	−0.39
		(0.03)	(0.06)	(0.05)	(0.06)	(0.06)	(0.05)	(0.06)
Treatment Country X Post-change			0.41	0.42	0.41	0.41	0.42	0.41
			(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Interdependence Density X Treatment Country			0.03			0.04		
			(0.06)			(0.06)		
Interdependence Density X Post-change			0.13			0.13		
			(0.05)			(0.05)		
Interdependence Density X Treatment Country X Post-change			−0.02			−0.02		
			(0.06)			(0.06)		
Cross-Module Component Use X Treatment Country				0.01			0.01	
				(0.05)			(0.05)	
Cross-Module Component Use X Post-change				0.10			0.10	
				(0.05)			(0.05)	
Cross-Module Component Use X Treatment Country X Post-change				−0.08			−0.07	
				(0.06)			(0.06)	
Bottleneck Components X Treatment Country					0.00			0.00
					(0.06)			(0.06)
Bottleneck Components X Post-change					−0.05			−0.05
					(0.05)			(0.05)
Bottleneck Components X Treatment Country X Post-change					0.07			0.07
					(0.06)			(0.06)
Constant						−0.62	−0.50	−0.53
						(0.12)	(0.11)	(0.12)
Treatment Country						−1.01	−1.03	−1.03
						(0.10)	(0.10)	(0.10)
Observations	15 000	15 000	15 000	15 000	15 000	15 000	15 000	15 000
R-squared overall	0.0341	0.0321	0.0000	0.0000	0.0000	0.0858	0.0878	0.0878
R-squared within	0.0302	0.0334	0.0617	0.0582	0.0563	0.0616	0.0581	0.0563