Hop to it! The impact of organization type on innovation response time to the COVID-19 crisis

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ABSTRACT

The COVID-19 pandemic has led to a changing environment posing many challenges that call for innovative solutions, leading to a changing innovation landscape. We explore particular organizational actors' innovation response time by analyzing data from a commercial innovation database. Arguing that innovation response time mostly depends on how organizations perceive time, we expect innovative start-ups to be the quickest and universities to be the slowest in responding to the crisis. Controlling for a set of external drivers of structural change, we find support for our hypothesis about start-ups. Contrary to our expectations, universities do not significantly differ in their innovation response time compared with incumbents. To underpin the robustness of our findings, we provide a specification curve analysis. Our results indicate the significance of start-up–corporate collaboration and open innovation, especially in the aftermath of the crisis.

1. Introduction

Any crisis comes with the potential to solve its associated problems through innovative solutions. The global crisis that emerged following the discovery of the novel coronavirus SARS-CoV-2 (Zhu et al., 2020) and the subsequent spread of COVID-19 is at least a two-fold crisis (Kuckertz et al., 2020). Not only has the health crisis generated the necessity to develop new therapies and vaccines. Equally, the infection control practices taken by many governments worldwide to manage the health crisis have caused an economic crisis (Verma & Gustafsson, 2020), as indicated, for instance, by the reaction of financial markets (Al-Awadhi, Alsaifi, Al-Awadhi, & Alhammadi, 2020; De Vito & Gómez, 2020; Zhang, Hu, & Ji, 2020). Both aspects of the COVID-19 crisis are likely to trigger innovative behavior addressing the consequences of these measures.

Prominent commentators such as Bill Gates (Gates, 2020) primarily consider innovation as an answer to the health crisis that will result in innovative solutions for testing, treatment, vaccines, and disease control measures. Beyond that, the crisis caused by the infection control practices poses a multitude of other unexpected problems for individuals, organizations, and nations alike. These unforeseen problems lead to new behaviors and novel needs that, in turn, can trigger innovative solutions. COVID-19 is potentially changing society beyond health issues, and

innovation is likely to respond to these changes. Initial COVID-19–related research already indicates that innovative start-ups are pivoting and aiming to exploit the emerging entrepreneurial opportunities (Kuckertz et al., 2020; Manolova, Brush, Edelman, & Elam, 2020). More established firms are adjusting their business models in innovative ways as well (Kraus et al., 2020; Breier et al., 2021).

With the present study, we aim to provide a deeper understanding of those innovative actors driving the innovative response to the challenges created by COVID-19. That is, we aim to answer the research question: What type of innovator is the quickest to react to the challenges and opportunities resulting from the COVID-19 crisis? When innovating in response to crises, time seems crucial (Bessant et al., 2012, 2015), and we argue that innovation response time depends on how different types of organizations perceive time. Understanding how quickly different actors align their innovative offers to address the new and unforeseen needs that are consequences of the medical crisis and the general infection control policies is necessary for innovators wanting to shape their crisis response and valuable for informing innovation policy.

In particular, we explore actors' innovation response time and compare universities and higher education institutions and innovative start-ups with incumbent firms. We address our research question with an empirical analysis of 136 innovations triggered by the COVID-19 crisis that we identified in a comprehensive database tracing

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innovation activity worldwide. First, this analysis allows us to contribute an evidence-based perspective on the changing innovation landscape during the COVID-19 pandemic. By illustrating the key drivers of structural change related to COVID-19–induced innovation (i. e., so-called megatrends), we provide a unique characterization of innovation activity in times of crisis. Second, we provide a theoretically grounded description of innovative actors during the crisis based on their innovation response time. Given that the COVID-19 crisis presents the rare opportunity to exactly pinpoint an event potentially triggering innovation, we can go beyond earlier accounts of innovation in crises by introducing the concept of innovation response time. Both contributions could further the theorizing on the relationship between innovation and crises and encourage additional empirical analyses.

2. Background and hypotheses

2.1. Innovation and (the COVID-19) crisis

Although the COVID-19 crisis is unique, we can base our reasoning about innovation in situations of crises on experiences and research in the context of human-made crises such as the 2008 financial crisis (e.g., Archibugi, 2011) or natural crises such as the humanitarian crises resulting from earthquakes or tsunamis (e.g., Bessant, Rush, & Trifilova, 2012). In general, crises seem to have a negative effect on the overall innovation activity in economies (Filippetti & Archibugi, 2011), which is likely to be the case with the COVID-19 crisis as well (Dachs & Peters, 2020). Brem, Nylund, and Viardot (2020), for instance, illustrate how the 2008 financial crisis hampered the emergence of new dominant designs following innovation.

However, at the same time, crises bear the potential for new entrants to cater to new needs with innovative solutions (Archibugi et al., 2013a, 2013b). Furthermore, innovation seems to be an essential driver of firm success, especially in the aftermath of economic crises (Devece, Peris-Ortiz, & Rueda-Armengot, 2016; Naidoo, 2010). Innovation can also significantly contribute to firm recovery from the effects of crises (Hausman & Johnston, 2014).

However, for many firms, there is a danger of missing the opportunities arising from the changing innovation landscape. For instance, firms often reacted to the 2008 financial crisis with rationalization efforts (Laperche, Lefebvre, & Langlet, 2011). Cutting down on innovation activities is a pitfall to avoid because during the COVID-19 crisis, protecting not only a firm's substance and key value creating activities but also its knowledge base will be important (Zouaghi, Sánchez, & García Martínez, 2018). Reducing innovation expenditures to protect the core business activities would thus be myopic, particularly because prior research (Devece et al., 2016) has identified innovation activity as an essential driver of success throughout a recession. In a first bibliometric analysis of the emerging academic literature on business and the COVID-19 pandemic, Verma and Gustafsson (2020) document innovative technologies (e.g., big data and digital healthcare) and their consequences for business as an important theme in the emerging academic discourse.

2.2. Innovation and time

Given that a crisis of the size of the COVID-19 pandemic is accompanied by many pressing challenges, investigating how quickly organizations can react to the challenges seems to be of utmost importance. Because new challenges call for new solutions, how quickly organizations can introduce innovations is just as important as other managerial measures that need to be taken during a crisis. In general, time is an important characteristic of all human activities. The potential for high innovation speed accompanies quick innovation response time. We define innovation response time as follows:

Innovation response time is the time from the first identification of new needs to launching an innovation.

We posit that the innovation response time is mainly affected by how organizations perceive time as a scarce resource. Ellwood, Grimshaw, and Pandza (2017) suggest three dichotomies of time orientation in organizations that seem especially relevant for innovation in times of crises.

First, clock time as opposed to event time is an objective view of time as measurable by a clock. Clock time is quantitative, objective, and universal. It relates to activities and deadlines being precisely scheduled. On the contrary, event time is conceptualized as a social construct within and by the organization. Events are not scheduled in a fixed or regular manner. They flow more dynamically and unevenly. Thus, event time "paces activities by a sense of readiness …, not by dates," as Dougherty, Bertels, Chung, Dunne, and Kraemer (2013, p. 236) suggest. The COVID-19 crisis developed in a way that generated a high level of uncertainty for all economic actors, where organizations with a strict clock time orientation seemed unequipped for innovating at a high innovation speed.

The second time-related dichotomy is linear versus cyclical time orientation. Organizations that maintain a linear time orientation see the dynamics of the external environment in a way that considers the past to be of low value for guiding the future (Cunha, 2004), and these organizations prefer to create their own future. However, organizations that have cyclical time orientation believe that the past provides sufficient guidance for future activities and rely on experience and given knowledge. As a consequence, the unfolding of the COVID-19 crisis in an unprecedented way that surprised many economic actors (Donthu & Gustafsson, 2020) may hamper the innovation process of organizations with a strong cyclical time orientation. In the midst of a crisis, the past does not provide sufficiently valuable information about the future and its development. Of course, this holds for the unfolding of the health crisis and for the development of policy measures imposed to restrict the crisis's spread and their effects on economic activity.

Last, Ellwood et al. (2017) provide a distinction between internal and external time orientation. This distinction describes whether external events or circumstances internal to the organization drive the development of innovations. Internal and external time orientation can be linked to external and internal entrainment, where Khavul, Pérez-Nordtvedt, and Wood (2010) see entrainment as an "organization-environment temporal fit" (p. 106). External entrainment refers to the synchronization of an organization's activities to the dynamics of an external environment, and internal entrainment relates to understanding and orchestrating the pace of internal function (Dibrell, Fairclough, & Davis, 2015). Because the COVID-19 crisis dramatically changed the environment in which organizations and their customers operate, innovation speed depends on an organization's external entrainment.

2.3. Start-ups, universities, and innovation response time

We have argued that some time orientations are more supportive in times of the dynamic unfolding of the COVID-19 crisis than in others. Also, tensions that exist within or between organizations that derive from different views on the timing of activities can result in low innovation speed (Dougherty et al., 2013). In general, start-ups have been considered the key to rapid innovation in crises (Bessant et al., 2012, 2015). Archibugi et al. (2013a, 2013b) consider start-ups' innovation activities as less affected by crises.

The reason for this can be seen in their respective time orientation, as they maintain event time orientation, focus on linear time orientation, and show high external time orientation. Nowadays, in particular, innovative start-ups embrace iterative, discovering approaches to define their business models (e.g., the lean start-up approach (Frederiksen & Brem, 2017) or effectual logic (Sarasvathy, 2001)). Such iterative approaches do not lend themselves to classic project management. Instead, they aim to achieve key milestones and events over the venture creation process, hence making event time orientation more suitable. Moreover, accepting that it is more reasonable to create the future than to predict it

is a key tenant of effectual logic and entrepreneurial thinking (Frederiksen & Brem, 2017), suggesting that linear time orientation is prevalent in start-ups. Last, start-ups' small size limits their self-referentiality. They usually define themselves as part of an entrepreneurial ecosystem (Kuckertz, 2019; Spigel, 2017) and rely heavily on external stakeholders such as key customers, investors, or economic development agencies. Consequently, their time orientation needs to be external rather than internal. Given these favorable time dispositions for innovation and innovation response time, we hypothesize the following:

H1: Relative to incumbents, start-ups are characterized by a faster innovation response time.

We argue that universities as research institutions are at a relative disadvantage to quickly introducing innovations as a response to the COVID-19 pandemic. This disadvantage is at least partially attributable to their respective time orientation. They can be seen as low on event time orientation, low on linear time orientation, and low on external time orientation. Altogether this creates a high degree of organizational inertia.

In principle, universities as knowledge hubs in the innovation system (e.g., Youtie & Shapira, 2008) would be well-positioned to contribute innovative solutions to the problems triggered by the COVID-19 pandemic. They are in command of diverse knowledge and maintain networks that could enable them to contribute to innovations in the complex situation of the COVID-19 crisis that demands interdisciplinary efforts.

However, given that universities are strictly managed and exhibit a high degree of administration and procedural rules, they can be seen as oriented toward clock time rather than event time. For instance, when implementing performance-based research funding with regular reviews and assessments, university governance firmly maintains a clock time orientation. This perception of time often collides with scientists' event time orientation. Eventually, the tensions between the university governance and scientists lead to less economic relevance of research (Hicks, 2012). It also results in negative implications for technology transfer and innovation and—if any—longer innovation response time.

Moreover, universities are highly cyclical organizations, taking in cohorts of new students at fixed times, managing teaching in reoccurring semesters, and conducting research in projects. This shapes the time orientation as cyclical rather than linear, which may cause opposition when the cycles are violated. Consequently, innovative responses can often address pressing issues only when included in these cycles. This slows down universities' innovation response time.

Finally, referring to internal versus external time orientation, universities are inward-looking organizations: if they look outward, they primarily focus on other actors within the scientific cosmos but tend to neglect, for instance, economic actors. Embracing the third mission of (technology) transfer is meant to mitigate this perception. Nevertheless, university technology transfer shows a typical weakness in external entrainment, mainly when external actors and not actors within the university initiate the process (Markman, Gianiodis, Phan, & Balkin, 2005). Given these unfavorable time dispositions for innovation and innovation response time, we consequently hypothesize the following:

H2: Relative to incumbents, universities are characterized by a slower innovation response time.

3. Data and method

3.1. Data collection

To analyze the effect of organization type on the generation of COVID-19–induced innovation activity, we use data on the innovation level. To this end, we take the object-oriented approach and present an alternative to the so-called subject-oriented approach, which analyzes, for instance, firms on the micro-level. The object-oriented approach bases on innovations or innovation projects as the unit of analysis (e.g., Patel, Fernhaber, McDougall-Covin, & van der Have, 2014; Sjöö, 2016).

We identified COVID-19–induced innovations in *Trendone*'s commercial *Trendexplorer* database (Trendone, 2020). *Trendexplorer* is a proprietary database covering more than 46,000 global innovations that are beyond the pure invention stage. The organizations responsible for the innovations have introduced them to the market and publicly communicated it. Utilizing the search term "corona-virus OR coronavirus OR covid-19 OR covid19 OR corona" on May 1, 2020, and after correcting for false hits (e.g., marketing innovations related to the Mexican beer brand *Corona* and hits referring to innovations before the discovery of SARS-CoV-2), we identified n = 136 innovations. The regional breakdown shows 23 innovations from Asia and Oceania, 39 from Europe, and 74 from North America. The first and last innovations in the dataset were observed, respectively, on February 12, 2020, and April 30, 2020.

3.2. Variables

3.2.1. Dependent variables

In our analysis, we are interested in how quickly organizations respond to emerging needs triggered by the COVID-19 crisis by investigating the *overall response time*. We conceptualize this as the time between the occurrence of a need and the introduction of the innovation. We approximate the overall response time by the number of days between January 24, 2020—when academic literature (Zhu et al., 2020) reported SARS-CoV-2 for the first time—and the date the innovation registered in the *Trendexplorer* database. The overall response time assumes that COVID-19 is an international phenomenon wherein the change of customer needs has been transparent right from the start.

By relaxing this assumption and assuming that the change of needs was only transparent when the respective country experienced a sizeable exposure to the virus, we integrate the *local response time* into our analysis. We approximate this by the number of days between the date when the innovation's country of origin reached 100 confirmed cases of COVID-19, as reported by the Johns Hopkins Coronavirus Resource Center (2020), and the date the *Trendexplorer* database reports a particular innovation.

3.2.2. Independent variables

The *Trendexplorer* database also contains information about the organization(s) in charge of the innovations. We identify whether the innovations are developed by or in collaboration with universities and higher education institutions based on the organizations listed as being in charge of developing or introducing the innovations. In this case, the *university* variable is one; otherwise, it is zero. Whereas a university's responsibility for a particular innovation is already directly coded in the database, identifying start-ups responsible for an innovation requires a more elaborate procedure. We identify start-ups in three different ways. First, we code the *start-up* variable as one if the innovation's description explicitly mentions that it originates from a start-up. Second, we examine the list of organizations associated with the innovation and establish whether the organization is five years or younger by consulting its website. Third, if the information on the organization's website is inconclusive, we follow suggestions by Nagaraj and Wang (2016) and determine the organization's age by searching their web domain registration. We use the date of the initial registration of the domain as an approximation of the organization's founding date. We code organizations that we find to be five years or younger as start-ups.

3.2.3. Control variables

In selecting the control variables, we recognize that innovation does not happen in a social vacuum. Instead, it is embedded in and refers to broader and long-run social, technological, and economic developments because these provide information about the future states of the market environment. Innovation both benefits from and amplifies these developments that we call megatrends. Essentially, firms' ability to understand and exploit trends separates the successful innovators from the

Table 1
Definitions and frequencies of megatrends related to COVID-19–induced innovations.

(1) Megatrend (abbreviation)	(2) Definition	(3) Absolute Frequency	(4) Relative Frequency	(5) Core/ Periphery
Health Style (hea)	All innovations catering to the needs of a society increasingly concerned by health issues and actively managing individual physical conditions	56	40.9%	Core
Attention Economy (att)	All innovations related to business models requiring the constant and recurring attention of users, customers, and consumers	45	32.8%	Core
Connected World (con)	All innovations building on digital networks	36	26.3%	Core
Outernet (out)	All innovations related to the rising integration of the online and offline spheres	29	21.2%	Core
Seamless Commerce (sea)	All innovations creating a seamless customer journey across channels	25	18.2%	Core
Urbanization (urb)	All innovations enhancing the quality of life in growing urban centers	19	14.6%	Core
Data Era (dat)	All innovations making smart use of (big) data	18	13.1%	Core
Distrust Society (dis)	All innovations mitigating the consequences of the growing disenchantment with politics and big business	14	10.2%	Core
Artificial Intelligence (art)	All innovations related to intelligence demonstrated by machines	12	8.8%	Core
Future Work (fut)	All innovations enabling to work and access information everywhere	12	8.8%	Core
Virtual Experiences (vir)	All innovations related to immersive worlds enabling different forms of interaction	12	8.8%	Periphery
Individualization (ind)	All innovations addressing the consequences of more flexible and differentiated lifestyles and life choices	8	5.8%	Periphery
Industry 4.0 (i40)	All innovations enhancing the digitization of production	8	5.8%	Periphery

Table 1 (*continued*)

(1)	(2)	(3)	(4)	(5)
Transhumanism (tra)	All innovations targeting the biological and device-enabled improvement of humans	8	5.8%	Periphery
Food Culture (foo)	All innovations related to new ways of food consumption and food production	1	0.7%	Periphery
Sustainability (sus)	All innovations enabling the present generation to meet their needs while enabling future generations to meet theirs.	1	0.7%	Periphery

n = 136 (multiple assignments of an innovation to a megatrend are possible). Own calculations are based on Trendone (2020).

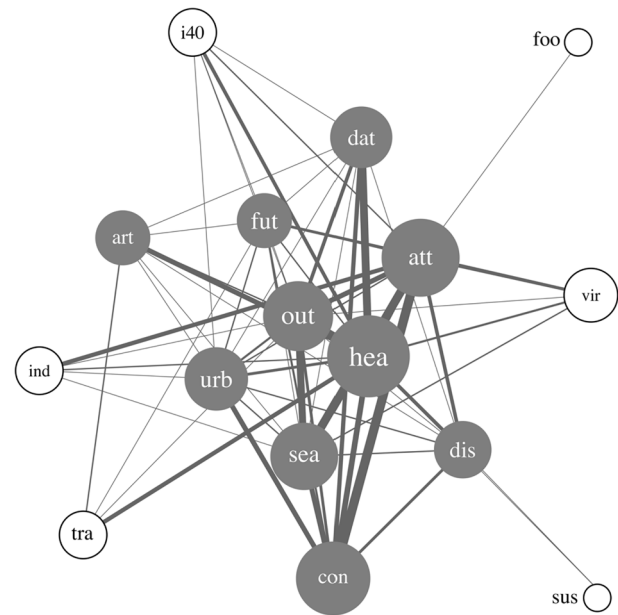**Fig. 1.** Network visualization of the trends' co-occurrence in our sample of innovations. Abbreviations can be found in Table 1. Gray shaded nodes are the core of the network. Force-directed layout (Frick, Ludwig, & Mehldau, 1994).

unsuccessful ones (Manson, Mattin, Luthy, & Dumitrescu, 2015). As a commercial database targeted at tracking and identifying trends, *Trendexplorer* assigns each innovation to 1 or more of 16 megatrends. Considering these megatrends allows us to further control for the characteristics of a particular innovation. Table 1 presents the definitions of these megatrends and their respective absolute and relative frequencies of occurrence in our sample. The regressions below only include a limited set of the most important megatrend control variables to conceive parsimonious models. We utilize the fact that each innovation is assigned to one or more megatrends for selecting the control variables. This co-occurrence of megatrends gives rise to a network (see Fig. 1), where we use a k-core algorithm (Borgatti, Everett, & Johnson, 2013) with k = 19 to identify the core and periphery trends in the network. We only use the core trends as control variables.

The database contains information about the type of innovation, the innovation's country of origin, and an industry classification of 12 industries. It also classifies each innovation into one of three types of innovations: product innovation, marketing innovation, and technological

innovation. We build three dummy variables (*product innovation, marketing innovation,* and *technology*) based on this classification. Also, we construct the mean of the dependent variable by industry.[1] We also build three regional dummies based on the innovation's country of origin (*Asia, Europe,* and *North America*). Table A1 in the Appendix provides the descriptions for the variables.

3.3. Method

Because our dependent variable is count data, we use a Poisson quasi maximum likelihood (QML) regression to regress the overall response time and local response time. We choose the Poisson QML estimation because it allows for overdispersion. With respect to the conditional specification, it is consistent under weaker assumptions, as compared with the Poisson or negative binomial regression (Cameron & Trivedi, 2009). As a traditional robustness check, we use OLS regressions of the log of the overall and local response times. We report these estimations alongside the Poisson QML estimates. As a more comprehensive robustness check, we implement a specification curve analysis (Simonsohn et al., 2015, 2020) to visualize the robustness of our findings. This approach is relatively new and has not yet been implemented in business research but is gaining prominence in psychology and related fields (Orben & Przybylski, 2019; Orben, Dienlin, & Przybylski, 2019; Rohrer, Egloff, & Schmukle, 2017).

4. Results and robustness

4.1. Context

Before discussing the findings of the regression analysis, establishing the context of the innovations in the dataset seems appropriate. We report the frequencies of occurrence of the megatrends related to COVID-19 innovations in Table 1 and analyze the trends' co-occurrence via network visualization in Fig. 1. The network visualization places nodes closer to each other when they exhibit more edges. The size of the node in Fig. 1 captures the frequency of a trend appearing in the sample. If an innovation relates to more than one trend, these trends are pairwise linked by edges in the diagram, which are thicker the more often two megatrends are related.

Unsurprisingly, the network of COVID-19–related megatrends has *health style* at its center. Our procedure to identify the core and periphery trends in the network reveals nine additional core megatrends around health style. Innovations are associated with *outernet*, which bridges the online and offline worlds and provides, for instance, real-time information for individuals on COVID-19–related issues. Infection control practices imposed by governments to reduce the spread of COVID-19 strengthen megatrends such as *future work*. These practices seem to only slightly affect rural areas, whereas the problems in metropolitan areas amass; innovations hence relate to the *urbanization* megatrend. In addition, the COVID-19 crisis provides the opportunity for organizations to show good corporate citizenship in the fight against the growing *distrust* toward politics and big businesses that may result from the infection control practices and orders to practice social distancing. *Attention economy* and *seamless commerce* point to new ways of consumption and fulfillment. Finally, innovations seem to be enabled by technology-driven megatrends that support innovative COVID-19 solutions related to health, work, and consumption with *artificial intelligence*, the utilization of big data (*data era*), and network technologies (*connected world*).

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[1] Trendexplorer provides a comprehensive and unique industry classification of 12 industries: Transportation & Mobility; Tourism & Leisure; Financial Services; Retail; Materials, Manufacturing & Engineering; Energy & Environment; Health & Life Sciences; Food & Beverages; Media & Entertainment; IT & Telecommunication; Non-Profit & Public Services; and Consumer Goods.

Table 2
Determinants of response time.

	(1)	(2)	(3)	(4)
	Poisson QML		OLS	
Dependent variable	Local Response Time	Overall Response Time	Ln(Local Response Time)	Ln(Overall Response Time)
Independent variables	b/std. err	b/std. err	b/std. err	b/std. err
Startup	−0.244**	−0.135**	−0.402*	−0.136**
	0.115	*0.055*	*0.229*	*0.065*
University	−0.022	−0.009	−0.029	−0.007
	0.110	*0.052*	*0.135*	*0.064*
Controls				
Marketing innovation	−0.207	0.004	−0.311	−0.022
	0.149	*0.072*	*0.217*	*0.092*
Product innovation	−0.144	−0.035	−0.076	−0.068
	0.129	*0.069*	*0.178*	*0.088*
Region: Asia	0.094	−0.372***	0.019	−0.440***
	0.127	*0.084*	*0.172*	*0.100*
Region: North America	−0.025	−0.037	−0.055	−0.035
	0.079	*0.038*	*0.131*	*0.045*
Industry	0.074***	0.023**	2.466	2.096**
	0.023	*0.010*	*1.769*	*0.897*
Trend: health style	−0.041	0.002	−0.022	−0.016
	0.091	*0.054*	*0.118*	*0.067*
Trend: Outernet	−0.104	−0.037	−0.154	−0.025
	0.093	*0.053*	*0.110*	*0.067*
Trend: data era	−0.056	0.011	−0.008	0.011
	0.109	*0.057*	*0.131*	*0.074*
Trend: distrust society	−0.116	−0.136***	−0.059	−0.105*
	0.098	*0.050*	*0.134*	*0.057*
Trend: attention economy	0.132	0.003	0.128	−0.002
	0.106	*0.054*	*0.161*	*0.064*
Trend: artificial intelligence	−0.150	−0.165*	−0.213	−0.160
	0.167	*0.092*	*0.191*	*0.111*
Trend: seamless commerce	−0.037	−0.061	0.034	−0.098
	0.095	*0.055*	*0.124*	*0.079*
Trend: connected world	0.044	−0.009	0.024	−0.008
	0.078	*0.040*	*0.110*	*0.049*
Trend: future of work	−0.122	−0.027	−0.222	−0.017
	0.160	*0.065*	*0.224*	*0.076*
Trend: urbanization	−0.034	−0.026	0.012	−0.031
	0.127	*0.058*	*0.160*	*0.071*
Constant	1.021	2.826***	−5.234	−4.500
	0.920	*0.716*	*6.510*	*3.849*
N	136	136	136	136
pseudo-R^2	R^2	0.097	0.171	0.15	0.407
Chi^2	F	52.40***	98.35***	2.60***	5.96***

Standard error in italics; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$, reference category for startup and university is established firms, reference category for marketing and product innovation is technology innovation, reference category for regions is Europe. Industry is the mean dependent variable by industry. VIFs for all variables included are well below 4.

4.2. Regressions

Analyzing the effect of start-up as the origin of innovation on response time, we report a series of regressions in Table 2. Columns (1) and (2) contain the Poisson QML regressions, and Table 3 reports the marginal effects of the *start-up* and *university* variables and of some control variables. As an initial robustness check, we report the OLS

Table 3
Determinants of response time (marginal effects).

Dependent variable	(1)	(2)
	Poisson QML	
	Local response time	Overall response time
Start-up	−9.514[**]	−9.844[**]
	4.438	3.976
University	−0.840	−0.633
	4.289	3.801
Marketing Innovation	−8.062	0.295
	5.798	5.260
Product Innovation	−5.600	−2.582
	5.039	5.029
Region: Asia	3.820	−24.464[***]
	5.329	0.084
Region: North America	−0.972	−2.89
	3.045	0.038

regressions of the log of the local response time in columns (3) and (4) of Table 2.

For the control variables, we observe that the local response time is not different across regions: Asian, European, and North American innovations were equally swift in reacting to evolving local needs. Concerning the overall response time, we find that responses in Asia were significantly earlier by more than 24 days (see the marginal effects in Table 3), which is unsurprising because the overall and local response times converge for Asia. The regressions also show that there is no difference between the types of innovations.

Across all regressions, we find that compared with innovations originating from incumbents, those originating from start-ups reveal a significantly shorter response time, thus supporting H1. The marginal effect is sizeable (Table 3). Even when controlling for the type of innovation, the region of origin, the industry, and the trend this innovation relates to, innovations from start-ups are introduced 9–10 days faster to the market than innovations that do not involve start-ups. Universities,

however, are not significantly faster or slower in responding to the COVID-19 crisis with innovation, and the response time is unaffected by universities' contribution to their development, as the parameter estimate for university is not different from the reference category, which is established firms. H2 is thus not supported.

Different model specifications to check for moderation based on the types of innovation lead to qualitatively identical results. The types of innovation are not found to be moderating. The significant effects of start-ups and the non-significant effects of universities are maintained.

4.3. Robustness

The estimated negative marginal effect of *start-ups* is highly significant. In general, regression findings are contingent on the selected model represented, for instance, by the selected dependent variable and control variables. Other configurations of the regression model might lead to different, potentially conflicting results. By implementing a specification curve analysis (Simonsohn et al., 2015, 2020), we address the findings' dependence on our decisions, leading to the models in Table 2. This analysis makes these decisions transparent and examines how different choices would have affected the findings. In particular, we investigate how the results about the negatively significant marginal effects of *start-up* and the non-significant marginal effects of *university* would have changed in different model configurations. The specification curve helps us to address the selection of the dependent variable, and we address our decisions in selecting the control variables.

For the specification curve, we estimate all $2^7 = 128$ potential models that can represent the two different dependent variables (*overall response time* and *local response time*) and the control variables (all *Trend Dummies*, *Region: North America*, *Region: Asia*, *Product Innovation*, *Marketing Innovation*, and *Industry*). All regression models include the variables capturing *start-ups* and *universities*. We use the Poisson QML regression for estimation.

In the specification curves in Figs. 2 and 3, we show the marginal effects of *start-up* and *university*, respectively, across all of our 128
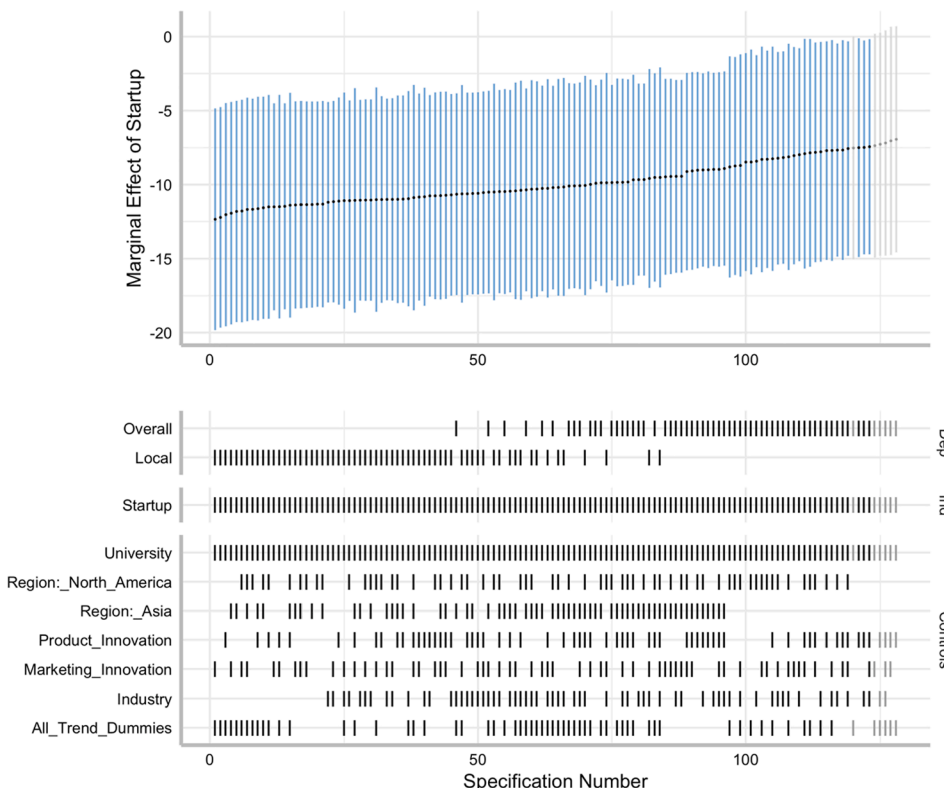

Fig. 2. Specification curve of the results of the Poisson QML regressions of response time (overall response time or local response time). The upper panel shows the estimated marginal effect of *start-up* on the response time for each of the 128 models. The lighter shaded area indicates the 90% confidence intervals. Each model represents a different combination of decisions about dependent variables and control variables. The confidence intervals indicate that for 122 of the 128 models, the estimated marginal effect of *start-up* is significant. In the lower panel, the dashboard depicts the details about the regressions. *All Trend Dummies* indicates where all trend dummies are included in the regressions.
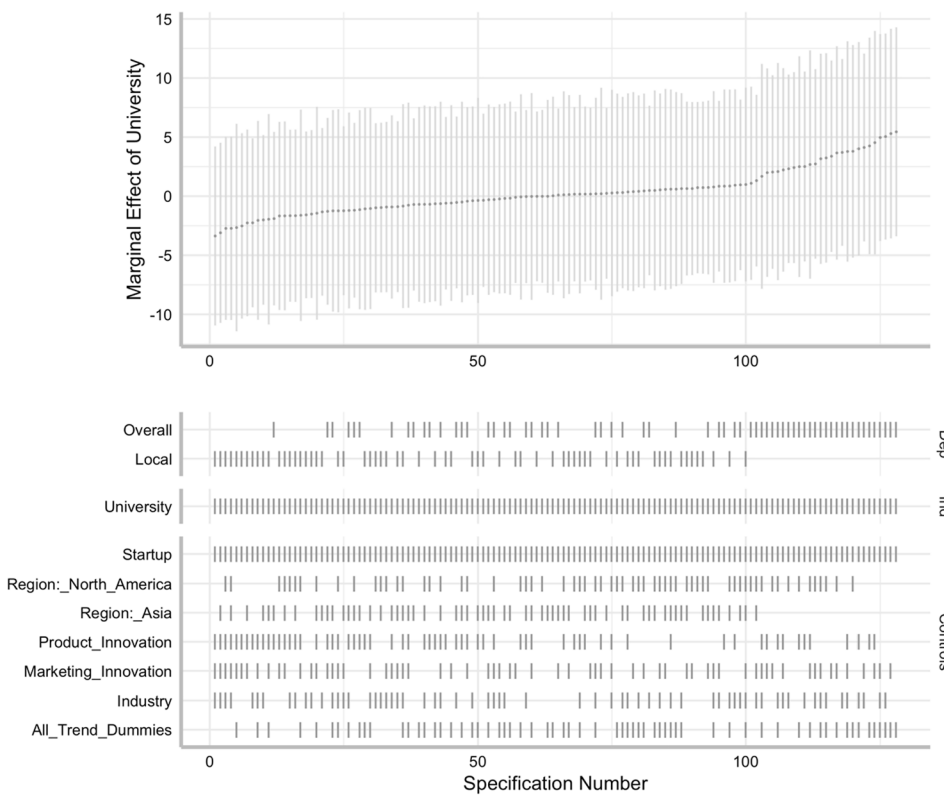
Fig. 3. Specification curve of the results of the Poisson QML regressions of response time (overall response time or local response time). The upper panel shows the estimated marginal effect of *university* on the response time for each of the 128 models. The lighter shaded area indicates the 90% confidence intervals. Each model represents a different combination of decisions about dependent variables and control variables. The confidence intervals indicate that the estimated marginal effect of university is significant for none of the models. In the lower panel, the dashboard depicts the details about the regressions. *All Trend Dummies* indicates where all trend dummies are included in the regressions.

models, sorted by the magnitude of the marginal effects. The lighter shaded bars indicate the respective confidence intervals, whereas the blue error bars indicate significant marginal effects to the 10% level of significance. Gray error bars indicate non-significant marginal effects. Below the specification curves, we provide a dashboard-like visualization of the models' composition. This visualization allows us to assess the variability of the marginal estimate depending on different model specifications. With the specification curves, we present a visual assessment of our findings and how strongly the findings depend on our modeling choices.

The confidence intervals in Fig. 2 clearly show that the negative marginal effect of *start-up* on the response time is robust across the 128 different models. Only six models indicate a non-significant marginal effect. However, closer inspection of these models reveals that they do not appropriately control for the geographical region when regressing the overall response time. This modeling decision would be rather difficult to defend, given the pandemic's temporal and geographical development pattern. We also observe some variations in the marginal effect's magnitude, ranging from a response that is up to 12 days faster to a response that is about 7 days faster than the reaction of the reference category of established firms. On the contrary, the specification curve of *university's* marginal effect on the response time highlights that the non-significant findings in Table 2 are rather robust. None of the 128 models yields a significant estimate of the marginal effect.

5. Discussion

5.1. Implications

The innovation literature seems to be undecided, whether economic crises force firms to reduce their innovative activities (cyclical nature of innovation) or whether crises provide opportunities for innovation (counter-cyclical nature of innovation) (Filippetti & Archibugi, 2011). In general, counter-cyclical behavior in crises can lead to positive performance effects (Özturan, Özsomer, & Pieters, 2014). The case of the

COVID-19 crisis seems very clear in this regard: being not only an economic crisis characterized by reduced and changing demand and supply (Manolova et al., 2020) but also a health crisis significantly shaping how individuals think, behave, and consume (Clark, Davila, Regis, & Kraus, 2020), the pandemic makes counter-cyclical innovation necessary. Our sample illustrates that firms deliver to this.

Based on our descriptive network analysis, innovation management should especially consider the identified megatrends at the core of our network analysis to build on their innovation activities. These go beyond what the emerging COVID-19 literature on technology (and innovation) has documented (Verma & Gustafsson, 2020). Whereas all megatrends have been important before the COVID-19 pandemic, their nature and the concrete innovations related to them seem to have changed. For instance, a megatrend such as health style could be described as a luxury phenomenon when considering pre-pandemic times. Then it was associated with innovations such as performance food or wearables enabling the "quantified self" (Swan, 2013), especially in developed and innovation-driven economies. Now, the health style megatrend dramatically turned toward addressing humanity's basic needs in every type of economy. Establishing the core of the trends also highlights that COVID-19 innovation is happening at the intersection of health, data, urbanization, connected worlds, offline and simultaneously online, and commerce.

Our findings suggest that innovative start-ups are the quickest to react to the changing innovation landscape regarding our research question. This finding is in line with and goes beyond the studies by Archibugi et al. (2013a, 2013b), which found crises to generally offer smaller enterprises opportunities to enter the market. Bessant et al. (2012, 2015) highlight start-ups' role in a crisis when considering humanitarian innovation. Going beyond these findings and adding to the literature on entrepreneurial decision-making theory (Ferreira, Fernandes, & Kraus, 2019), the present analysis suggests that the COVID-19 crisis offers opportunities for innovative start-ups and that these start-ups respond faster than established firms and research institutions do.

Only, at first sight, this might be astonishing. Start-ups are usually

Table 4

Actionable measures for start-ups, incumbents, universities, and innovation policy.

	Objectives	Measures
Start-ups	• Secure start-ups do not lose their time orientation (which is conducive to swift response) while growing and maturing.	• Actively manage entrepreneurial culture over the company life cycle to avoid the emergence of organizational inertia.
Incumbents	• Learn from start-ups to change some dimensions of their time orientation, which is similar to that of start-ups	• Allow entrepreneurial thinking and the utilization of iterative process models in innovation management (e.g., effectual logic and lean start-up approach).
	• Reap the benefits from the response speed of start-ups in the innovation process.	• Collaborate with start-ups (asymmetric collaboration).
University	• Adjust dimensions of time orientation.	• Follow the model of an entrepreneurial university—increase the importance of transfer without compromising on the quality of research and teaching.
Innovation policy	• Support asymmetric collaboration to create systemic structures for swift response.	• Adjust supply side innovation policies (e.g., funding schemes) to support asymmetric collaboration.
	• Utilize the speed of start-ups' innovation response.	• Adjust demand side innovation policies (e.g., procurement) to support the governmental and private procurement of innovations from start-ups.
	• Foster universities' responsiveness.	• Help universities to develop entrepreneurial spirit in the sense of an entrepreneurial university by stipulating and supporting technology transfer.

said to suffer from the liabilities of newness (Stinchcombe, 1968), which should make them more vulnerable in times of crises than the more established actors in the market. The reasons for this can be the comparatively lower levels of resources and the missing legitimacy of new market actors from the perspective of many stakeholders.

However, the liabilities of newness are complemented by the assets of newness (Choi & Shepherd, 2005)—that is, the organizational characteristics resulting from newness give start-ups a competitive edge over incumbents. In particular, organizational flexibility and organizational energy (Nagy, Blair, & Lohrke, 2014), which partially result from a start-up's time orientation, can be considered assets of newness that start-ups are very likely to exhibit at a higher level than incumbents. And these assets seem to matter throughout a crisis, thus allowing for faster innovation.

The non-significant finding for universities' innovation response time could, in fact, be interpreted as a positive sign. There were reasons to assume that research institutions such as universities would exhibit a competitive disadvantage relative to incumbents. However, it seems that recent third-mission–related developments have helped to put universities at least on par with established firms. In particular, narrative evidence suggests that universities can quickly respond to changing societal, economic, and environmental needs when they find the appropriate format for transfer (such as the Virtual Idea Blitz discussed by Bacq, Geoghegan, Josefy, Stevenson, and Williams (2020)). Such a format would be internally initiated but externally oriented and breaks down the cyclical time orientation and clock time orientations universities typically have. In this regard, it seems important for university leadership or even governmental funding bodies to encourage academics to embrace unorthodox actions to respond to uncertainty (Fisher, Stevenson, & Burnell, 2020). Standard processes in universities would run counter to what seems necessary in times of crises.

The consequence of our analysis for established firms and their

innovation management could thus be not only to avoid cutting down on innovation activities but also to ensure that start-ups will continue to be part of a "holistic and overarching corporate innovation system" (Kötting & Kuckertz, 2020, p. 90). Conceptual arguments (Chesbrough, 2020) have already pointed to open innovation as an important approach that might enable fast and innovative answers to COVID-19–related problems and could thus be critical in answering to the pandemic's challenges.

Moreover, research into how firms dealt with the 2008 financial crisis found that the firms that decided to open up their innovation management were successful in the long run (Laperche et al., 2011). Evidence provided in the present paper suggests that there could be value in dealing with the COVID-19 crisis in a similar manner. Alliances are suggested to be a standard response to increased uncertainty (Marino, Lohrke, Hill, Weaver, & Tambunan, 2008), and diversifying the innovation alliance portfolio has proven valuable in the past (Chung, Kim, & Kang, 2019). Engaging in asymmetric partnerships (Allmendinger & Berger, 2020) with innovative start-ups will thus be a promising route for innovation management to benefit from those fast innovators' organizational characteristics. Also, considering how an organization perceives time and taking measures to change its culture toward time perception as event time, linear time, and external time seems promising.

Supply-side innovation policy measures could also support the creation of asymmetric partnerships to build systemic structures for swift innovation response. Demand-side measures impacting innovation could more explicitly include start-ups, for instance, in procurement practices in times of crises. Table 4 summarizes these implications and presents some actionable measures for start-ups, incumbents, universities, and innovation policy.

5.2. Limitations and future research

Several limitations of this research make interesting future research possible. First, the analysis allowed us to characterize single innovations by the megatrends they relate to and the actors that realize them. There is, however, no information that describes the degree of innovativeness. The difference between radical innovation and incremental innovation, in particular, might be an interesting factor that potentially explains innovation response time. Future research could thus use additional concepts describing an innovation's characteristics to illustrate how organizational flexibility and organizational energy contribute to the realization of such innovations. Moreover, no information is yet available regarding the market performance of the scrutinized innovations in our dataset. Prior research suggests that although innovation can be beneficial in turbulent environments, fast movers are not necessarily the most successful firms (Bruton & Rubanik, 2002). Therefore, it is important to follow up on the innovative initiatives started during the COVID-19 crisis and to assess the relationship between innovation response time and performance in the aftermath.

Second, the concept of a megatrend suggests that trends will continue. This is obviously not necessarily the case; thus, continuously following the development of potential structural changes in the innovation landscape will be useful to decide whether the COVID-19 crisis only had short-term effects on innovation or whether it was the defining moment of an entire generation, as some already assume (Gates, 2020).

Finally, it is astonishing to see that a megatrend such as sustainability is only in the periphery of the current innovation activity. This does not seem to be a limitation of the present analysis; instead, it seems to be a limitation of the current innovation activity. Pressing issues such as climate change and limited fossil resources will continue to be relevant despite the health crisis, and future research should factor in how COVID-19–related innovation could add to the sustainable transformation of consumption, firms, and economies (Bogner, Mueller, Pyka, Schlaile, & Urmetzer, 2020).

Table A1
Descriptive statistics.

Variable	Obs.	Mean	Std. Dev.	Min	Max
Overall response time	136	73.074	18.816	19	97
Local response time	136	38.971	16.869	1	90
Start-up	136	0.169	0.376	0	1
University	136	0.118	0.323	0	1
Marketing innovation	136	0.169	0.376	0	1
Product innovation	136	0.728	0.447	0	1
Technology innovation	136	0.103	0.305	0	1
Region: Asia	136	0.169	0.376	0	1
Region: Europe	136	0.287	0.454	0	1
Region: North America	136	0.544	0.500	0	1

6. Conclusions

Our analysis points to a potentially changing innovation landscape triggered by the COVID-19 pandemic. This change goes beyond merely addressing health issues because the crisis affects society as a whole. To benefit from the numerous opportunities for innovation resulting from this changing innovation landscape, innovation management should not only consider addressing the identified trends. It should also strive for the continuity and involvement of innovative start-ups, given that these flexible and energetic actors seem to be capable of helping to considerably speed up the innovation process. Equally, it seems that universities are not as inert as widespread prejudices suggest. From a societal perspective, it thus seems desirable to address challenges resulting from the COVID-19 crisis with a balanced combination of all types of innovators.

CRediT authorship contribution statement

Bernd Ebersberger: Conceptualization, Data curation, Formal analysis, Visualization, Writing - original draft. **Andreas Kuckertz:** Conceptualization, Validation, Writing - original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

Appendix A

See Table A1.

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