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DISCUSSION PAPER

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Champions of Digital Transformation? The Dynamic Capabilities of Hidden Champions

Champions of Digital Transformation? The Dynamic Capabilities of Hidden Champions

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Abstract

Hidden Champions (HCs) are small- and medium-sized global market leaders that repeatedly show superior innovation capabilities and economic performance. However, empirical evidence on how the digital transformation may affect their success story remains scarce. I argue that HCs show stronger dynamic capabilities which enables them to be better prepared for the digital transformation than non-HCs firms. To test this hypothesis, I use data from the Mannheim Innovation Panel. This allows me to identify a representative set of German HCs and develop a firm digital readiness index, reflecting the use of important digital technologies and applications. An instrumental variable estimation suggests that higher levels of digital readiness lead to an increase in share of revenue from innovations and productivity. In combination with higher average digital readiness levels of HCs compared to non-HCs, my findings indicate that HCs may indeed be better prepared for the digital transformation.

Keywords: Hidden champions, digital transformation, digital readiness, digital preparedness, performance effects, innovation, dynamic capabilities, instrumental variable estimation

JEL-Classification: L60, L19, M19, O32, O33

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1 Introduction

Since the beginning of the century, advances in computation power and a global access to the Internet have accelerated the digitalization of the business environment. This digital transformation increasingly affects firm strategies, fosters innovation, and creates entirely new business models (Rogers 2016). Studies show that already the digitization of formerly analogous organizational processes can significantly increase efficiency and flexibility within organizations (Markovitch & Willmott 2014; Isaksson et al. 2018). Digitally enabled technologies and applications are the foundation of the internet of things and create substantial amounts of information every day with current estimates expecting an annual growth in worldwide data volume of more than 30% (The Economist 2020). Developments such as big data and increasingly sophisticated machine learning algorithms enable firms to utilize this data and extract valuable new information about customers, markets, and supply chains. This allows companies to streamline internal processes and make more accurate predictions about market trends and customer behavior. In the past, such computation-intensive processes often required significant investments in a capable infrastructure that only few large firms were able to bear. Today, the cloud allows to outsource some of these tasks and significantly reduce investment risks, especially for small and medium-sized enterprises (SMEs) (Bharadwaj et al. 2013; Isaksson et al. 2018). This enables a broad spectrum of firms to access a variety of digital applications and further accelerates the diffusion of digitalization.

The emergence of new revenues streams and improved customer relationships are just a few examples of the potential added benefits of these developments to those firms that are able to quickly adapt their business to this data-driven environment and to build the necessary (digital) innovation[1] capabilities (The Economist 2020). Today, some of the most valuable and profitable firms worldwide primarily base their business around digital products or services and within a few years the share of these '*tech*'-focused firms in the S&P 500 has skyrocketed (Statista 2020). Yet, an increasing number of companies with long successful business models fail to adapt and even former market leaders are not immune to the disruptive impact of digitalization (Hanelt et al. 2015; FAZ 2019; Thangavelu 2020).

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[1] Innovation broadly refers to the, at least attempted, implementation of an idea (Harhoff 2008; Christensen et al. 2015). Baregheh et al. (2009) have identified over 60 different definitions and typologies of innovations. However, in this paper it encompasses major improvements or novel approaches in the context of a firm's processes, products, or its business model (OECD 2018a, 2018b). Digital innovations specifically refer to "the carrying out of new combinations of digital and physical components [in a layered modular architecture] to produce novel products" (Yoo et al. 2010, p. 725). z

A small group of German mid-sized firms may provide insights on how companies can successfully transform from the analogue to the digital world. These so-called hidden champions[2] (HCs) are mid-sized global market leaders that mainly focus on business to business (B2B) niche markets. Even though they may only represent a small group of firms, their continuous economic success in competitive markets has generated a worldwide research, media and policy attention (e.g., Voudouris et al. 2000; Din et al. 2013; Suh & Kim 2014; The Economist 2014; BMWi 2019). Highly dynamic growth rates over the last decades indicate that they have managed to decouple from the national economic development and as a result some even refer to them as prime examples of the German '*Mittelstand*'[3] (The Economist 2014). According to estimates, they have created over 300,000 new jobs from 2000 to 2010 in Germany alone and more than 1,000,000 worldwide (Simon 2012). Highly specialized niche strategies combined with in-depth customer knowledge and continuous innovation efforts are frequently listed as key features that differentiate HCs from most of their global competitors (Venohr & Meyer 2007; Simon 2012; Rammer & Spielkamp 2015). So far, it seems that this strategy has paid off and their sustainable success may suggest that they are also more resilient and adaptable than most firms (Venohr & Meyer 2007).

Nevertheless, the digital transformation and its implications may test the limits of their business models and pose a substantial risk to the future economic success of HCs. Existing studies often remain conceptual and lack any empirical evidence that could provide adequate answers to this central question. Therefore, this study aims at investigating the preparedness of Germany's HCs towards the digital transformation based on representative panel data. To isolate the underlying features that might account for the findings, it specifically focuses on comparing HCs with non-HC firms of similar demographic characteristics.

The remainder of this study is structured as follows. Chapter 2 presents contextual information and emphasizes the potential challenges of digital transformation in the context of HCs. Chapter 3 introduces the dynamic capabilities view as theoretical foundation for my hypothesis and subsequent analysis. Chapter 4 provides an overview of the sample data and the methodology. Moreover, it introduces a measure of firm digitalization that enables the empirical analysis in

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[2] According to Simon (2012), who coined the term hidden champion in the early 1990s, they are defined as firms that, in general, generate below 5 billion Euros in revenues, belong to the top 3 in their respective market globally or are market leading on their continent, and are relatively unknown to the broader public. Estimates of the number of HCs range from approximately 1,300 (Simon 2018) up to around 1,700 (Rammer & Spielkamp 2019).

[3] Mittelstand broadly refers to mid-sized manufacturers, sometimes referred to as the 'backbone' of Germany's economy. They tend to be family-owned and usually sell specialized machineries and components for B2B markets (The Economist 2014).

Chapter 5, where I investigate and discuss the impact of firm digitalization on performance and the digital readiness of HCs. The study concludes with a summary and discussion of the results in Chapter 6.

2 Digital Transformation and Challenges for Hidden Champions

As digitalization advances, it increasingly transforms integral parts of the value creation process (Hess et al. 2016). The *'combinatorial'* effects[4] of digital technologies accelerate the pace and scope of change across various organizational levels and enable new digitally geared business models that overcome existing limitations and create novel channels to address customers across industries (Yoo et al. 2012). This puts existing firms in danger of disruption as they "face challenger[s] that offer far greater value to the customer in a way that [it] cannot compete with" (Rogers 2016, p. 195). Moreover, it radically changes the competitive environment for established firms which often face new competition by more digitally advanced companies outside their own industry. This implies that even long-successful firms may need to be willing to adjust or even abandon existing asset-driven business models in favor of more data- and network-driven approaches (Bharadwaj et al. 2013; Christensen et al. 2015; IW Consult 2018). Ultimately, it urges firms to lay the organizational foundations that enable the development of innovative digital solution.

Research emphasizes that existing innovation approaches may have a limited applicability in the context of digital innovations. The development of products and services with embedded digital capabilities usually involves distributed processes and increasingly relies on external expertise that firms lack internally (Yoo et al. 2012; Müller et al. 2016). In addition, many digital innovations heavily depend on network effects[5] and an interplay of different systems or products (Bharadwaj et al. 2013). This reinforces the importance of platforms, not only as enablers of customer value creation but also as important development environments for collaborative innovations (Yoo et al. 2012; Manyika et al. 2016).

Several reasons suggest that the very characteristics that are considered as the main drivers of HCs' success may in fact impede the necessary structural and strategic adaptations. Although

[4] Combinatorial effect refers to the complementary character of many digital technologies. The transformative effect of combinations of digital technologies is of far greater impact than single technologies alone (e.g., WEF 2020).

[5] Network effects as described in economics and business studies are the effects in which the number of users of a product or network positively affects its value, or in the case of indirect network effects, the value of a complementary product or network. A frequently used example in this context is the invention and expansion of the telephone (Katz & Shapiro 1994).

HCs are regularly referred to as *'drivers of innovation'* and most were founded based on radical and sometimes disruptive new business ideas, they mainly focus innovation efforts on incremental and continuous improvements of their existing product portfolio (Simon 2018; Rammer & Spielkamp 2019). Yet, in the context of digitalization firms have to be able to create radical innovations, leave existing paths and generate new know-how. Along the same lines, specialization strategies and focus on niche markets may allow HCs to develop products and services according to customers' needs but could create limitations in terms of scaling digital innovations and addressing new customer markets (Simon 2009, 2012; Pittrof 2011).

Another characteristic often associated with HCs is an emphasis on strict secrecy measures to protect knowledge and innovations. Accordingly, HCs seem to be reluctant to openly share information along development processes or to innovate in collaboration with external partners. This implies that their innovation activities are still mostly internally driven and reliant on existing internal competences (Rammer & Spielkamp 2015). In the context of digitalization, this strict focus on internal capabilities could limit their ability to rapidly develop sophisticated digital innovations. One particular feature of digital products is that they enable faster development cycles and increase the speed at which firms can evolve ideas into market-ready solutions. However, these processes require novel approaches towards innovation and often involve experimenting and iterative improvements of already marketed products (e.g., minimum viable products). For many HCs, this may require drastic changes within existing innovation processes, as they are usually aligned to hardware-based technologies and aim at providing highly mature solutions to customers. A core requirement for all digitalization efforts is a suitable technological and personnel infrastructure. This often demands large-scale investments and remains one of the main challenges in the context of digital transformation (BMWi 2017b). Rather conservative financing strategies combined with reservations against external ownership are characteristic for HCs (Haussmann 2003; Simon 2012; Rammer & Spielkamp 2019). Often family-owned, HCs typically aim at financial independence and, thus, focus on ensuring relatively high shares of equity. This reliance on internal resources may eventually affect their willingness and ability to provide sufficient funding for digitalization initiatives. Like many other firms in Germany, HCs also struggle to meet the demand in expert personnel, especially in IT-related professions. However, the fact that most HCs are located in rural areas may further decrease their ability to attract suitable experts (Simon 2012).

Despite these potential challenges, research specifically targeting digitalization in the context of HCs remains scarce. Although Simon argues that many HCs engage in digitalization-related fields and indicates that they constantly extend their portfolio, especially in the context of industry 4.0, he does not provide any detailed insights or empirical evidence (Simon 2018, 2019). Others highlight that many HCs (44%) still show low levels of digital performance and the application of digital technologies is often limited to websites and social media (Schmieder 2017). To the best of my knowledge there is only one study that, to some extent, investigates HC digitalization in comparison to other firms. This survey-based study among 82 HCs shows that most of them are aware of the potential profound implications of digitalization for their business models (Freimark et al. 2018). In particular, 42% of the surveyed HCs see an imminent danger of losing market shares due to disruptions caused by the digital transformation. According to the authors, HCs define *'silo thinking'* and a limited willingness to change as the major challenges when it comes to promoting digitalization projects in their organizations. Nevertheless, more than 40% also believe that their business will primarily profit from the digital transformation in the long run. To ensure a successful transformation, more than 60% of HCs allocate the responsibility for its accomplishment at the top management level and more than a third of them actively involve their customers in the process. On average, HCs have already fulfilled half of their self-set transformation targets and 71% of HCs are satisfied with the progress of digital transformation within their firms compared to just 51% of the surveyed SMEs (Freimark et al. 2018). Yet, compared to large corporations, HCs do not seem to outperform in terms of digitalization. This confirms previous findings and indicates that when it comes to the level of digitalization, firm size often matters (BMWi 2018).

Insights from related SME research further show that many established firms still do not have a digital strategy, despite empirical findings supporting a positive correlation between investments in digitalization and firm performance (Kane et al. 2017; The Economist 2020). According to a recent study, the majority of SMEs consider themselves as laggards in the context of digitalization (Bitkom 2020). This is also reflected in the small share of revenues generated via electronic channels of just 10% compared to 28% among larger corporations. Moreover, digital products, services and components only account for 14% of their revenues. Along the same lines, a study by IW Consult (2018) highlights that just 20% of German SMEs possess the necessary capabilities to digitalize their products and processes. Overall, these findings may indicate structural reasons that may impede digital transformation in SMEs and thus may also apply to HCs.

3 Theory and Hypothesis

The aim of this chapter is to provide a theoretical framework that generates insights on how firms may be able to rapidly adapt to the new environment. This framework is then applied to the context of HCs in order to generate a hypothesis about the preparedness of HCs towards digital transformation.

3.1 The Dynamic Capabilities View

The dynamic capabilities view (DCV) is a widely recognized theoretical concept in the context of change and long-term competitiveness (Furrer et al. 2008; Vogel & Güttel 2013). Teece and Pisano (1994) first introduced the theory to explain why some companies show “timely responsive and rapid and flexible product innovation, along with the management capability to effectively coordinate and redeploy internal and external competences” (Teece et al. 1997, p. 515). The idea behind the DCV is that a company’s success is not just based on its resources but that firm-specific capabilities are the main drivers of competitive advantage. These dynamic capabilities (DCs) are defined as “the firm’s ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments” (Teece et al. 1997, p. 516). Some special features about these capabilities include that they are path-dependent (Zollo & Winter 2002), intentionally used (Helfat 1997; Zahra et al. 2006), build over time and, thus, usually cannot be acquired in the market (Teece et al. 1997; Makadok 2001). Overall, this differentiates them from more ordinary capabilities which are supposed to ensure efficiency of existing business functions and resources (Teece 2016).

Even though research remains ambiguous about how DCs exactly enable long-term survival and competitive advantage[6], empirical research regularly confirms their positive impact. Studies show that they increase the ability of incumbents to react to market changes (Helfat 1997), support firms in exploiting new opportunities (Karim & Mitchell 2000), and increase the ability for organizational renewal (Danneels 2002). In particular, high environmental dynamism characterized by rapidly changing market conditions seems to increase the value and necessity of

[6] Some argue that there might be a direct link (Teece et al. 1997; Griffith & Harvey 2001; Lee et al. 2002) while other emphasize an indirect relationship and argue that they enable resource and competence reconfigurations that create value for competitive advantage (Eisenhardt & Martin 2000; Zott 2003).

DCs[7] as they enable firms to create the organizational agility[8] to flexibly adapt to new requirements (Teece et al. 1997; Winter 2003). Eisenhardt and Martin (2000, p. 1107) add that DCs are "the firm's processes that use resources – specifically the processes to integrate, reconfigure, gain and release resources – to match and even create market change".

This indicates that firms should focus on establishing DCs, particularly in the context of digital transformation where companies need to orchestrate multifaceted, data-rich and dynamic digital resources. The presence of sound DCs may allow for business model adjustments in such dynamic environments and eventually improve a firm's long-term competitiveness. Indeed, research frequently highlights the importance of DCs in the context of digitalization. By investigating digital disruptions in the newspaper industry, Karimi and Walter (2015) show that DCs can foster the creation of digital platform capabilities and, thus, help firms to successfully respond to digital transformation. Furthermore, Helfat and Raubitschek (2018) emphasize that DCs enable firms to build ecosystems and design business models in platform-based digital ecosystems. Teece (2017) provides similar insights by indicating DCs a positive impact along digital platform lifecycles and showing their potential in improving competitive outcomes. Along the same lines, Yoo et al. (2012) state that DCs allow firms to share data and processes within networks which, eventually, enable them to apply heterogeneous modules of teams and resources that can be flexibly assigned to specific tasks. However, studies also show that firms often struggle at establishing the necessary level of flexibility for networking between units and organizations required in times of digitalization (Isaksson et al. 2018). This indicates that DCs are actually not common and difficult to create. A possible explanation is that established routines, assets, and resources that support existing business processes create path dependencies which inhibit the development of DCs. Teece (2007) emphasizes that this may explain why established companies often tend to favor more incremental and competence-enhancing improvements instead of competence-destroying, radical innovations. Even if established firms manage to build and integrate the necessary abilities, they frequently fail at reconfiguring their organization according to new market needs due to a persistent focus on ordinary capabilities (Teece et al. 2016). Along similar lines, Zahra et al. (2006) argue that established firms struggle

[7] Firms in markets that are characterized by low dynamism and rates of change, however, should focus on efficiency enhancing ordinary capabilities (Drnevich & Kriauciunas 2011).
[8] Dyer and Shafer (1998, p. 6) define organizational agility as "the capacity to be infinitely adaptable without having to change. It is viewed as a necessary core competence for organizations operating in dynamic external environments".

to build capabilities that leverage their existing business and, simultaneously, enable the creation of a new competence basis.

3.2 Determinants of Dynamic Capabilities

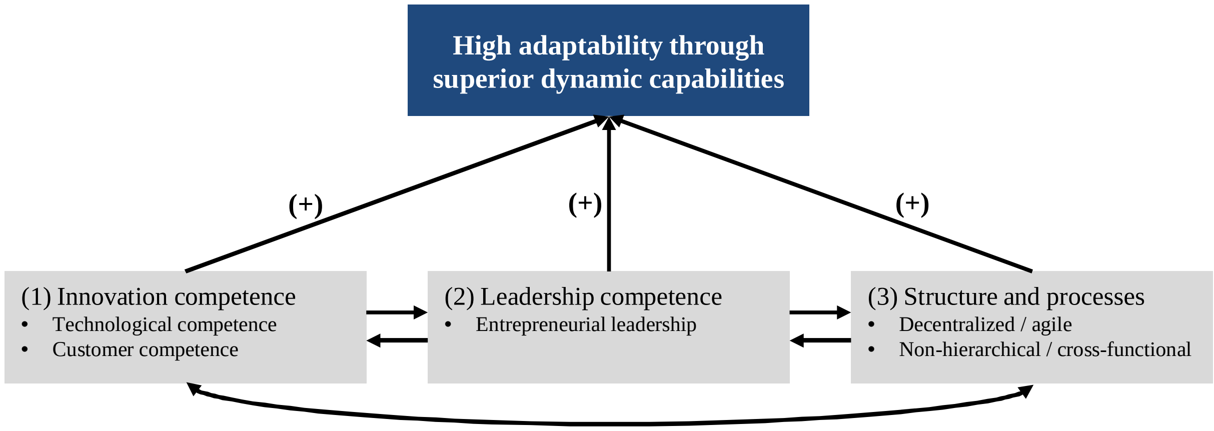
Teece (2007, p. 1319) states that the *'micro foundations'* of DCs are "the capacity to sense and shape opportunities and threats, to seize opportunities, and to maintain competitiveness through enhancing, combining, reconfiguring the business enterprises intangible and tangible assets". These micro foundations usually cannot be directly observed and, thus, are difficult to measure and evaluate. However, research highlights several, often interlinked, factors that can determine a firm's ability for these micro foundations and, therefore, its DCs. In the following, I present three aggregated competences and related abilities that are regularly highlighted as enablers for DCs.

First, research generally identifies ***innovation competence*** as a crucial determinant of DCs. Some argue that dynamic capabilities enable successful innovation (Teece 2007; Drnevich & Kriauciunas 2011), whereas others even treat them as synonyms (Collis 1994; Winter 2003). In this paper, however, I follow the view of Eisenhardt and Martin (2000) who argue that innovation capabilities are key components of DCs, since they permit the renewal and reconfiguration of firm resources. Moreover, they enable the creation of new knowledge and can support managers in sensing and seizing new opportunities. This integral view of innovation capabilities is widely supported in DCV literature (Helfat et al. 2007; Wang & Ahmed 2007). Research in the context of digitalization in general supports the significance of innovation competence and emphasizes the need for digital innovation capabilities (Yoo et al. 2010; Hess et al. 2016). According to Yoo et al. (2010, p. 725), such digital innovations rely on the digitization of physical products and require a firm "to revisit its organizing logic and its use of corporate IT infrastructure". Danneels (2002) further claims that innovation capability itself is closely dependent on an interplay of customer and technological competence. The latter broadly describes the firm's ability to create a certain product based on existing know-how and equipment. Extended to the context of digital transformation, the renewal and reconfiguration of a firm's technological competence towards more digital technology competences seems to be crucial. These digital competences may not only help firms to develop new products or services and business processes but eventually enable new customer relationships and business models (Drnevich & Kriauciunas 2011). Apart from a suitable technology base, strong customer competence allows a firm to create in-depth knowledge of customer needs and processes and to extend its customer base. By covering distribution and communication channels as well as the firm's brand reputation, it further facilitates the marketing of innovations. From a DCV perspective, this may allow firms to not only sense changes in markets earlier than others, but also to successfully seize new (digital) products or services.

Second, Rothaermel and Hess (2007, p. 916f.) emphasize the importance of ***leadership competence*** and state that "managers who take a discerning and discriminating approach towards selecting innovation mechanisms will be most successful in building the dynamic capabilities necessary to continuously innovate". Teece and Augier (2009, p. 417) specifically highlight the role of management in "selecting and/or developing routines, making investment choices, and in orchestrating nontradable assets to achieve efficiencies and appropriate returns". They further suggest that entrepreneurial leadership in particular can help firms to sense new opportunities and, eventually, enable to seize them. Contrary to managerial activities, which tend to concentrate on standardization and optimization, entrepreneurial leadership emphasizes innovation and novel approaches to existing problems (Teece 2012). Rather than maintaining and refining the status-quo, entrepreneurial leaders focus on solutions to future challenges and opportunities. These specific leadership characteristics can directly create and maintain existing DCs within organizations (Teece 2014; Teece et al. 2016).

Third, research highlights the importance of agile ***organizational structures and processes*** in facilitating DCs (Augier & Teece 2009; Teece 2016). In particular, firms should foster exchange between business units and functions as well as limit hierarchical structures, so that sensing, seizing, and resource reconfiguration can be distributed throughout the organization. Teece (2007) further elaborates that decentralized processes and structures may help firms to develop integration and coordination skills, promoting a continuous alignment and realignment of existing assets. Such decentralization efforts should not be limited to the internal organization but explicitly take a firm's external environment into account. This implies that firms enable information and knowledge flows across organizational boundaries (Reitzig & Maciejovsky 2015). In this context, Pitelis and Teece (2010) emphasize so-called co-creation processes. These processes include internal cross-functional as well as joint processes with external partners. Along similar lines, Martin and Eisenhardt (2000) specifically argue that alliances and collaborations are important for the reconfiguration of assets and, thus, represent potential sources of DCs. Figure 1 illustrates the identified determinants and highlights their complementary nature in enabling DCs and creating adaptability.

Figure 1: Overview of the determinants for dynamic capabilities



3.3 Dynamic Capabilities of Hidden Champions

To the best of my knowledge, there is only one study that specifically examines HCs in the context of the DCV. Rammer and Spielkamp (2019) follow the classification of Teece et al. (1997) and focus their investigation on processes, paths, and positions as dimensions of DCs and determinants of business strategies. They argue that these elements represent substantial factors that differentiate HCs from their competitors and build the foundation of their success. In a subsequent empirical analysis, they show that HCs emphasize new technologies, open innovation strategies, and investments in a well-skilled workforce. The authors conclude that these features enable HCs to develop organizational DCs and to create difficult-to-replicate competitive advantages. These findings provide first insights for an investigation of the DC indicators presented in the previous section.

In the context of ***innovation competence***, there seems to be a broad consensus that HCs show superior innovation performance in comparison to other SMEs and large corporations (Pittrof 2011; Simon 2012; Rammer & Spielkamp 2015; Schmieder 2018). Even though empirical findings show no clear pattern regarding the R&D intensity of HCs compared to non-HCs, there is general agreement that HCs exhibit more efficient innovation processes. According to Simon (2018), HCs do not only hold more patents than large R&D intensive firms but also show significantly lower cost per patent[9]. Empirical research further shows that HCs have significantly

[9] The cost of a patent is defined as the total sum of costs beginning with the idea stage until a successful patent grant. According to Simon (2012), HCs have costs of approx. 0.5 million Euros per patent, whereas large corporations spent 2.7 billion Euros per successful patent filing. The average number of patents per employee is 31 for HCs and 6 for large corporations.

higher revenue shares from innovations than other firms (Rammer & Spielkamp 2019). Superior technological know-how and high vertical integration as well as deep customer knowledge are often cited as the main drivers of their innovation capability (Simon 2012; Rammer & Spielkamp 2015). The combination of these factors enables HCs to bring new ideas faster to the market and increase their ability to sense potential threats and seize opportunities earlier than the competitors, allowing them to maintain leading market positions.

Yet, digitalization may change the paradigms of innovations. Digital innovations that go beyond digitizing analogue processes, often require different approaches towards innovation. Firms need to increasingly be able to generate radically new products and services that are embedded in platforms. This transformation may be challenging for HCs who primarily focus on incremental and continuous improvements of their existing portfolio. So far, there is no empirical evidence that shows how this may affect the innovation capabilities of HCs and if their existing technological competences and resources are sufficient to drive radical change. Moreover, in times of changing market structures, customer knowledge limited to their niche might even impede their ability to sense and seize potentially disruptive development from outside this locus. Nevertheless, B2B markets in which HCs are primarily active, significantly differ from B2C markets in terms of customer requirements and process complexity (Simon 2019). Their in-depth customer knowledge and expertise about these industrial processes could support HCs to keep their competitive edge by providing superior digital solutions.

A review of literature on HC ***leadership*** indicates a strong association with entrepreneurial leadership styles (Pittrof 2011; Simon 2012; Hilz 2013). Empirical research suggests that their leaders are driven by long-term visions which increases their propensity to rather focus on innovations and increase of market share instead of short-term cost reductions and profitability (Rammer & Spielkamp 2015). Accordingly, they seem to be primarily driven by intrinsic motivation. Simon (2012) also emphasizes continuity as an important feature of HC leadership leading to relatively few changes in top management positions. This top-level continuity allows HC leaders to actively shape the firm's mission and vision which establishes the credibility necessary to inspire employees. At the same time, HC leaders thoroughly monitor firm performance and stress strict compliance with the firm values to ensure that the entire organization is geared for market leadership and growth. To achieve these ambitious goals, they emphasize decentralized responsibilities and decision-making processes which promotes a culture of individual accountability and autonomy (Pittrof 2011).

The (entrepreneurial) leadership attributes also define the ***organizational structures and processes*** of HCs. Their decentralized and process-focused organization seems to facilitate collaboration across their functional units, leading to improved organizational agility. Moreover, it distributes decision-making authority as well as responsibilities to individual units, which enables close direct customer relationships (Pittrof 2011; Simon 2012). Their focus on few niche products and markets allows HCs to keep simple organizational structures and makes them less prone to innovation inhibiting hierarchical and complex structures (Augier & Teece 2009). Simon (2012) also argues that flexible and digitally backed processes help HCs to effectively manage global businesses.

In summary, this literature review indicates that HCs demonstrate a superior innovation performance, are led by entrepreneurial leaders, and show rather agile organizational structures and processes. In the context of the previously identified DC determinants, this suggests that HCs indeed exhibit superior DCs which differentiates them from other market actors. Even though empirical research specifically targeting the impact of digitalization on HCs is limited, existing literature suggests that HCs may also be able to demonstrate superior sensing, seizing, and reconfiguration of skills in times of digital transformation. Therefore, I hypothesize that *hidden champions are better prepared for the digital transformation than non-HC firms.*

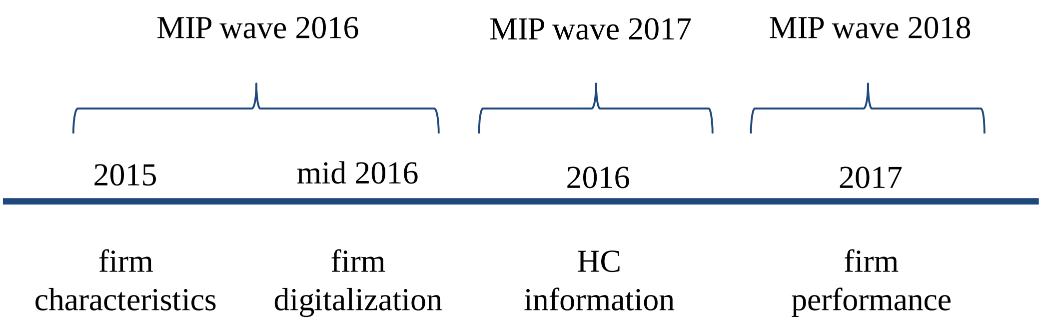
4 Key Variables, Data and Methodology

My main data source are the Mannheim Innovation Panel[10] (MIP) survey waves 2016, 2017 and 2018. The MIP is the official German Innovation Survey (GIS) and represents the German contribution to the Community Innovation Surveys (CIS) of the European Commission. It offers detailed representative firm information and is based on a stratified random sample of all German firms with more than five employees in manufacturing and business-oriented service industries. Each year approximately 7,000 to 8,500 firms provide data with a focus on their

[10] The MIP is a yearly survey conducted by the Center for European Economic Research (ZEW), the Fraunhofer Institute for Systems and Innovation Research (ISI), and the Institute for Applied Social Sciences (infas). It is commissioned by the German Federal Ministry of Education and Research (BMBF) and gathers information on the innovation activities of German firms. The survey allows for extrapolation of the survey results to the total firm population. Every two years, the MIP is part of the CIS of the Statistical Office of the European Commission (EUROSTAT) which serves as the basis for the European Innovation Statistic (ZEW 2019). See, e.g., Rammer and Peters (2013) or visit 'https://www.zew.de/en/research-at-zew/mannheim-innovation-panel-innovation-activities-of-german-enterprises' for general information about the MIP. See Appendix A.1 for an extract of the survey 2016.

innovation activities. The 2016 survey contains information on the *current* state of digitalization of 6,498 firms in mid-2016. All remaining survey questions of interest to this study refer to the end of the previous calendar year. Hence, I use the survey of 2016 to obtain information about firm size, age, and industry affiliation for the reference year 2015. Due to slight changes in the queried firm information every two years, only the MIP 2017 provides enough information to identify HCs within the sample. The 2018 survey provides information on the levels of my main outcome variables measured for the year 2017. Figure 2 illustrates the relationship between the survey years and the variables of interest graphically.

Figure 2: Survey waves, reference years and primary data

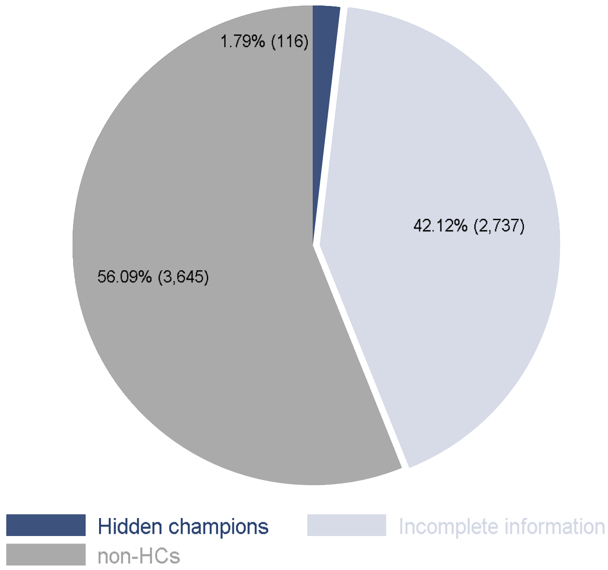


4.1 Hidden Champions and Control Group Firms

Since there is no publicly available list of German HCs, I use a subsample of previously identified HCs within the MIP by Wittenstein (2019) to investigate their digital preparedness. Based on a full sample of 307 HCs and 10,786 non-HCs, I am able to extract 116 HCs and 3,645 non-HCs that have participated in the survey wave 2016 and provide information on firm digitalization. The remaining firms do not provide all information that is necessary for a classification and, thus, are not included for further analysis.[11] Figure 3 summarizes the sample structure.

[11] In terms of age, size and industry classes, the *'unclassified'* firms do not statistically differ from the sample that is used for the analysis. The mean difference in age of 0.046 years and the mean difference in employees of 132 can both be rejected at the 10% level. However, sample firms seem to be 5.6% more likely to be in the wholesale and trade industry, 10.07% more likely to operate in the information and communication sector, and 4.45% more likely to engage in real estate activities. For all other industries no (statistically) significant difference is found.

Figure 3: Number of hidden champions, non-hidden champions in the sample



Notes: This figure presents the firm classification based on MIP wave 2017. Due to incomplete overlap with survey wave 2016, which provides information on firm digitalization, the sample reduces to 6,498 observations.

The industry sector distribution[12] of HCs in the sample reveals that HCs almost exclusively operate within manufacturing related industries. Only 4 of the 116 identified HCs are located outside manufacturing (NACE2 10-33). One operates in wholesale and retail trade (NACE 45-47), another in transportation and storage (NACE 49-53), and two in the area of professional, scientific and technical activities (NACE2 69-75). Overall, this observation matches previous studies that show a similar industry concentration of HCs (e.g., Venohr & Meyer 2007; Simon 2012; Rammer & Spielkamp 2015).

Control group approach

This highly skewed distribution towards manufacturing-related industries indicates that a simple comparison between HCs and non-HCs may not yield meaningful results. Moreover, to adequately analyze HC-specific features and capabilities, age and size distributions also need to be considered. To ensure that such structural characteristics do not affect my subsequent analysis, I use an entropy balance[13] approach. This multivariate reweighting method was first

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[12] See Table C.1 in the appendix for the detailed industry distribution. As most HCs operate in manufacturing, I apply a more fine-grained industry classification, which allows to distinguish between several manufacturing-related sectors, for the analysis. The table also presents the corresponding NACE2 values.

[13] Hainmueller and Xu (2013) provide additional information about the approach and its advantages over earlier control group methods, such as nearest neighbor or propensity score matching techniques that often yield rather low levels of covariate balance.

described by Hainmueller (2012) and allows to "reweight a dataset such that the covariate distributions in the reweighted data satisfy a set of specified moment conditions" (Hainmueller & Xu 2013, p. 1). Accordingly, I apply MIP data on firm age, number of full-time employees, and industry affiliation of firms at the end of 2015 as covariates for the entropy balance approach. By assigning weights to each non-HC I obtain a synthetic control group whose mean, variance, and skewness across these covariates complies with the distribution observed for HCs.[14] Table 1 illustrates how this reweighting of non-HCs improves the structural similarities with HCs. Without entropy balance, HCs and non-HCs significantly differ in terms of firm age and size. By applying entropy balancing weights, these differences reduce to marginal levels, creating a highly similar control group.

Table 1: Comparison of HCs, non-HCs, and control group firms

	Hidden champions			Non-hidden champions (before balancing)			Control group firms (after balancing)		
Variable	Mean	Min.	Max.	Mean	Min.	Max.	Mean	Min.	Max.
Employees 2015	821.87	20	25.000	260,739	0	317,764	821,929	0	317,764
Year of foundation	1968.447	1775	2012	1981.589	1352	2016	1968.184	1352	2016

Notes: Employees 2015 refers to the number of full-time employees at the end of year 2015. For a complete overview of all variables used for entropy balance, inlcluding their mean, variance, and skewness before and after the balancing, see Table C.2 in the appendix.

An investigation of the standardized differences between HCs and control group firms (cf. Table C.2 in the appendix) confirms the validity of the approach. The results show no signs of imbalance in terms of size, age, and industry distribution. After entropy balancing all differences are statistically not different from zero (Normand et al. 2001). Support also comes from graphical illustrations of the density distribution (cf. Figures B.1 – B.3 in the appendix).

4.2 Firm Digital Readiness

Another critical component for the investigation in this study is the development of a valid measurement for firm digitalization. In total, the MIP survey of 2016 contains 11 questions[15] about the usage of digital technologies and applications grouped into four main clusters. Firms are asked to indicate the current prevalence of each individual application area within their organization based on a 4-point Likert scale. The answering possibilities include no use at all

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[14] See Table C.2 in the appendix for the covariate balance table of all applied balancing variables of HCs and control group firms before and after the reweighting created by Stata's ebalance command (Hainmueller & Xu 2013). The table also includes the mean, variance, and skewness for all variables as well as the standardized differences after the entropy balancing.

[15] See Appendix A.1 for an extract of the survey 2016.

(0), low use (1), medium use (2), and high use (3). Taken together, the four clusters cover some of the most crucial aspects of firm digitalization and provide a solid indicator for the digital readiness of a firm. The 11 questions are specifically designed to capture the prevalence of digital applications within the entire spectrum of the economy (Rammer 2017). Therefore, the specific application fields of the digital technologies are defined relatively broadly so that they apply to firms of different size and industry backgrounds.

Digital readiness components

The first cluster covers four questions about the internal as well as external digital connectedness of firms. In particular, firms are asked to state the level of digital interconnectivity (1) within production/service provision, (2) between production/service provision and logistics, (3) with their customers, and (4) with their suppliers. These questions are closely related to the concept of industry 4.0[16], which describes the increasing interconnectivity and exchange of information driven by digital technologies, such as the internet of things (Lichtblau et al. 2015). The second cluster evaluates a firm's digital capabilities in the context of its internal organization and communication. Firms are specifically asked to indicate the prevalence of (5) teleworking possibilities for their employees, (6) software-based communication, and (7) intranet-based platforms. This cluster serves as an indicator for digitally enabled collaboration capabilities of the firm (Digital Intelligence Institute 2015; Berghaus et al. 2016). The third cluster considers digital capabilities in sales and external communication and specifically targets the firm's (8) use of e-commerce and its (9) social media engagement. Both activities are major aspects in creating digital customer experience (Berghaus et al. 2016; IW Consult 2018). Moreover, they may enable new distribution channels and additional information sources that can enhance the firm's operations and create potential for new business models. The fourth cluster analyzes the firm's information processing capabilities in terms of the prevalence of (10) cloud applications and (11) big data analysis. Cloud services can not only significantly increase efficiency and reduce fixed costs for firms, but also grant access to more processing power that is necessary to analyze customer information. Lenka et al. (2016, p. 96) argue that analytic capability encompasses "the ability to transform the data available at hand into valuable insights and actionable directives for the company". In other words, firms that are able to analyze data packages via big data analysis capabilities, have better access to information that can create new business opportunities and support innovation (Bharadwaj et al. 2013).

[16] For more information about the concept of Industry 4.0 see, e.g., BMWi (2017a).

Creating a digital readiness index

While many studies try to cover organizational aspects that are affected by digitalization[17], the digital readiness index used in this paper focuses on particular digital resources and capabilities that are required for more sophisticated digital endeavors. To operationalize the digital readiness of firms, I use the individual values from all questions on digitalization and create an additive index that is normalized to values between 0 and 1. A total *Cronbach's alpha* of .89[18] of the 11 items is well above the suggested threshold of Cortina (1993) and, thus, indicates a high internal consistency of the items. Moreover, the Kaiser-Meyer-Olkin (KMO)[19] measure of sampling adequacy shows solid values with all items being well above the 0.8 threshold. The low p-value of the Bartlett test of sphericity indicates that the null hypothesis of uncorrelated variables can be rejected.[20] An explorative principal factor analysis[21] (PFA) produces a single factor with an eigenvalue larger than 1. According to the Kaiser criterion, only one factor is retained (Mooi et al. 2018). A scree plot analysis[22] confirms this result and graphically shows that an additional factor does not significantly increase the explained variance. The retained factor explains roughly 88% of the variance of the individual items. All 11 factor loadings have the same sign and values above 0.6, which indicates that all variables from the questionnaire may be used to describe the retained factor (Cleff 2015). The results suggest that all 11 items can be combined in one index that describes firm-level digitalization. Hence, I create an index variable comprising the sum of the 11 individual survey responses of each firm. For interpretation purposes, this index is then normalized to values between 0 and 1[23]. A digital readiness score of 0 indicates that the respective firm does not engage in any digitalization activity at all. Correspondingly, firms that reach the maximum index score of 1 must emphasize a high prevalence

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[17] These may include a firm's strategy, leadership, culture, customer experience, products and processes, and technologies (e.g., WiWo & Neuland 2015; Berghaus et al. 2017; Capgemini Consulting & MIT Sloan Management 2017; Microsoft 2017; IW Consult 2018). Moreover, IW Consult (2016) provides a good overview of studies that have measured digitalization in the context of SMEs.

[18] See Table C.3 in the appendix to this chapter for all individual alpha values.

[19] See Table C.3 in the appendix for all individual KMO values.

[20] The Bartlett test shows a Chi-square of 19,018.94 and a corresponding p-value of 0.000. Therefore, the null hypothesis that variables are not intercorrelated can be rejected.

[21] PFA is frequently applied to identify hypothetical higher order factors that explain individual items. I applied this method instead of a principal component analysis, as the latter requires the strict assumption that all variance in the data is common variance. PFA on the other hand allows for unique variances and attempts to partition the common variance (Cleff 2015; Mooi et al. 2018). See Table C.4 in the appendix for an overview of the results of the factor analysis.

[22] Figure B.4 in the appendix shows the respective scree plot.

[23] See Figure B.5 in the appendix for the distribution of the digital readiness variable.

for each of the 11 surveyed applications and technologies within their firms. This makes it a suitable tool for my empirical analysis on a firm's preparedness towards digital transformation.

Description of firm digital readiness

Table 2 presents the mean values for each item within the digital readiness index as well as the average digital readiness across all classified firms in the sample. Among all four clusters, the digitization of production and service processes seems to be the most common and prevalent cluster of firm digitalization activities. This indicates that the sample firms are rather advanced in terms of establishing digital connectivity within their organizations as well as to customers and suppliers. By comparison, the fourth cluster on the prevalence of information processing capabilities shows the lowest scores within the index. This area seems to be either of lower importance to the firms in the sample or may describe more sophisticated digital applications that firms struggle to implement. Since the second and third cluster also show on average much lower scores compared to the first cluster, firms may also find it more difficult to assess their capabilities related to rather specific applications.

Table 2: Description of the digital readiness index and all items

Variable	Range	Mean	Std. dev.	Observations
Joint digital readiness index	0-1[1]	0.322	0.218	3,761
Production and/or provision of services				
(1) Digital connectedness within production and/or provision of services	0-3[2]	1,565	1,067	3,775
(2) Digital connectedness between production and/or provision of services and logistics	0-3	1,286	1,079	3,775
(3) Digital connectedness with customers	0-3	1,472	1,006	3,773
(4) Digital connectedness with suppliers	0-3	1,253	0.968	3,771
Internal organization and communication				
(5) Teleworking	0-3	0.728	0.911	3,773
(6) Software-based communication (Skype etc.)	0-3	0.896	0.967	3,773
(7) Intranet-based platforms (Wikis etc.)	0-3	0.840	0.973	3,774
Sales and external communications				
(8) E-commerce	0-3	0.741	0.897	3,774
(9) Social media (Facebook, Twitter etc.)	0-3	0.660	0.858	3,775
Information processing				
(10) Cloud applications	0-3	0.686	0.903	3,775
(11) Analysis of Big Data	0-3	0.473	0.778	3,776

Notes: [1] Scale is normalized to values between 0 and 1, with 0=no digital readiness and 1=complete digital readiness.
[2] Scale ranges from 0 to 3. Based on the the survey questions 0=no usage, 1=low usage, 2=medium usage, 3=high usage of the respective technology.

The average total digital index score is highly dependent on a firm's industry affiliation. Table 3 on the following page shows that the information and communication sector (0.517) and firms in financial and insurance activities (0.430) demonstrate the highest average digital readiness scores. With an average score of 0.379, manufacturing of transport equipment follows by a clear margin and represents the only non-service focused sector among the three most digitalized industries. At the lower end, firms in agriculture, forestry, and fishing show the lowest observed scores (0.045). However, as the sample only contains two firms in this industry, generalizability may be limited. Firms engaging in real estate activities (0.133) and construction business (0.182) perform slightly better and complement the bottom three industry sectors.

Table 3: Digital readiness across industries

Class	Sectors (NACE2)	Digital readiness index[1] Mean	Std. dev.	Firms
1	Agriculture, forestry, and fishing (01-03)	0.045	0.021	2
2	Mining, quarrying, and other industries (05-09; 35-39)	0.247	0.190	332
3	Manufacture of food products, beverages, tobacco products, textiles, apparel, leather, and related products (10-15)	0.230	0.178	278
4	Manufacture of wood and paper products and printing (16-18)	0.320	0.201	168
5	Manufacture of coke, and refined petroleum products, chemicals, chemical products, pharmaceuticals, medicinal chemical, and botanical products (19-21)	0.298	0.198	96
6	Manufacture of rubber and plastic products, mineral products, basic metals and fabricated metal products, except machinery and equipment (22-25)	0.283	0.191	423
7	Manufacture of computer, electronic, optical products, and electrical equipment (26-27)	0.369	0.187	265
8	Manufacture of machinery and equipment n.e.c. (28)	0.359	0.191	173
9	Manufacture of transport equipment (29-30)	0.379	0.232	66
10	Other manufacturing, and repair and installation of machinery and equipment (31-33)	0.307	0.224	212
11	Construction (41-43)	0.182	0.178	36
12	Wholesale and retail trade, transportation and storage, accommodation and food service activities (45-47; 49-53;55-56)	0.279	0.216	421
13	Information and communication (58-63)	0.517	0.221	281
14	Financial and insurance activities (64-66)	0.430	0.227	123
15	Real estate activities (68)	0.133	0.097	5
16	Professional, scientific, technical, administration and support service activities (69-75; 77-82)	0.331	0.219	877
17	Public administration, defense, education, human health, and social work activities (84-88)	-	-	0
18	Other services (89-99)	0.343	0.31	3
	Average/total	0.322	0.218	3.761

Note: [1] Scale is normalized to values between 0 and 1, with 0=no digital readiness and 1=full digital readiness.

The sector differences in Table 3 largely reflect findings in previous studies on digitalization (Berghaus et al. 2016; BMWi 2017b). However, research presents ambiguous findings on the levels of firm digitalization and the status within manufacturing-related industries in particular. Whereas some studies highlight relative shortcomings within these sectors (e.g., Digital Intelligence Institute 2015; Capgemini Consulting 2017), others support the patterns presented in this analysis and emphasize above average levels of firm digitalization in manufacturing-related sectors (IW Consult 2018). In the end, these discrepancies may simply occur due to differences in the measurement approach, industry classifications, or survey designs. Therefore, comparability between digitalization indicators and measurements might be limited.

Previous studies also indicate that differences in the level of digitalization are influenced by firm size (Berghaus et al. 2017; IW Consult 2018). The presented findings mainly support this assumption. Table 4 on the following page shows that firms with less than 20 employees have the lowest average digital readiness score with 0.272. The average score steadily increases with firm size and reaches an average maximum of 0.510 for firms with more than 1,000 employees. High upfront investment costs for digital infrastructure, technologies and software may partially explain this observation. Large firms may simply have more financial resources that allow them to invest in digitalization and, consequently, improve their digital readiness score.

Table 4: Digital readiness and firm size

	Digital readiness index[1]		
Size classes	Mean	Std. dev.	Firms
Fewer than 20 employees	0.272	0.217	1,815
20-49 employees	0.320	0.217	778
50-99 employees	0.349	0.202	457
100-249 employees	0.384	0.21	368
250-499 employees	0.394	0.186	159
500-999 employees	0.454	0.171	99
1,000 and more employees	0.510	0.19	85
Average/total	0.322	0.218	3,761

Note: [1] Scale is normalized to values between 0 and 1, with 0=no digital readiness and 1=complete digital readiness.

In terms of firm age, studies find that start-up companies are amongst the most digitalized firms despite often being relatively small in size (e.g., Berghaus et al. 2017; IW Consult 2018). My findings support such a relationship and shows that the youngest firms achieve the highest average digital readiness scores. As illustrated in Table 5, firms that are younger than 8 years old show the highest average score of 0.349. With an increase in age, the scores continuously decrease and reach a low of 0.307 for firms that are older than 40 years. Two reasons may explain this relationship. First, start-up companies tend to utilize and emphasize digitally geared business models. Second, young firms rarely face organizational inertia that may impede digitalization efforts in more established firms (e.g., Berghaus et al. 2017; IW Consult 2018). However, the overall differences are rather small compared to the effect of firm size. This indicates that firm age may not be such a crucial factor when it comes to digital readiness in my sample.

Table 5: Digital readiness and firm age

Firm age groups	Digital readiness index[1]		
	Mean	Std. dev.	Firms
Younger than 8 years	0.349	0.227	265
8-15 years	0.342	0.228	632
16-25 years	0.323	0.219	1,186
26-40 years	0.312	0.211	846
More than 40 years	0.307	0.211	824
Average/total	0.322	0.218	3,753

Note: [1] Scale is normalized to values between 0 and 1, with 0=no digital readiness and 1=complete digital readiness.

Overall, the analyses provide consistent patterns for firm-level digitalization based on the digital readiness index and match previous findings on the impact of structural firm characteristics on digitalization levels. This supports the validity of the index as a reliable indicator for firm digital readiness.

4.3 Outcome Variables and Summary Statistics

In general, there is broad consensus that innovation is vital for a firm's long-term performance and competitiveness (e.g., Tushman & O'Reilly III 1996; Jansen et al. 2006; Christensen et al. 2015; OECD 2018b). Previous studies show that a higher level of digitalization positively correlates with the innovation activities of firms (Sambamurthy et al. 2003; Kleis et al. 2012; IW Consult 2016, 2018). Investments in digital technologies can enable firms to develop new processes, products and services, and may even lead to business model innovations. Studies also present evidence for a positive impact of digitalization on economic performance indicators. In particular, higher levels of digitalization within firms may significantly increase work productivity (Brynjolfsson et al. 2011; IW Consult 2018) and are associated with higher levels of revenue growth (Schröder et al. 2015).

The MIP survey 2018 provides information on the levels of three main innovation indicators for the reference year 2017. In particular, firms are asked to state the share of revenues in 2017 derived from innovations that were introduced in the years 2015, 2016 and 2017. Moreover, firms are specifically requested to state the share of revenues from market novelties, which serves as an indicator for radical innovation capabilities of a firm. The survey also contains information on the share of revenues from more incremental innovations introduced in the same period. This includes innovations that are primarily based on existing products and services but still represent significant improvements. Compared to an investigation of innovation capabilities based on patent filings, these variables allow to measure the success of firm innovations in the market. To investigate the effect of digital readiness on the economic performance of firms, I use MIP data on firm revenues and employees. This allows to calculate productivity per employee which serves as an indicator for firm efficiency. To reduce skewness and ease interpretability, its log-transformed variable is used as dependent variable. Finally, I use information on firm revenues to calculate the revenue growth rate (in %) from 2016 to 2017.

Table 6: Summary statistics of input and outcome variables

Variable	Description	Min.	Max.	Median	Mean	Obs.
Independent						
Hidden champion	Dummy variable which takes the value 1 if a firm is a Hidden Champion and 0 for non-HCs	0	1	0	0.031	3,761
Digital readiness (2016)	Normalized index with scores between 0 (no digital readiness at all) and 1 (highest possible digital readiness score)	0	1	0.303	0.322	3,761
Dependent						
Innovation performance indicators (2017)						
Share of revenues from all innovations	(%) Share of revenues in 2017 from products or services that are new to the firm or new to the market and were introduced between 2015-2017	0	100	0	6.370	2,141
Share of revenues from incremental innovations	(%) Share of revenues in 2017 from products or services that are new to the firm and were introduced between 2015-2017	0	100	0	4.882	2,119
Share of revenues from radical innovations	(%) Share of revenues in 2017 from products or services that are new to the market and were introduced between 2015-2017	0	100	0	1.265	2,133
Financial performance indicators (2017)						
Productivity	Logarithm of a firm's productivity measured as revenues per full-time employee 2017	8.958	14.197	11.608	11.663	2,169
Revenue growth	(%) Change in revenues from 2016 to 2017	-100	137.32	1.818	2.601	1,748

Note: The difference in observations results from incomplete survey data.

The summary statistic for the share of revenues from all types of innovations in Table 6 shows an average share of revenues of 6.37% and reveals that some firms generate up to 100% of their revenues from products and services that are younger than three years. The median value of zero indicates, that most firms do not generate any revenues from innovation. This suggests that, at least in this period, they did not introduce any product innovations to the market. Furthermore, the low average share of revenues from radical innovations (1.265%) compared to the average share of revenues from incremental innovations (4.882%) implies that the total share of revenues from innovations is mainly driven by improvements of existing solutions rather than by radically new products or services.[24] The difference in observations between the three innovation indicators is the result of partially incomplete survey information regarding

[24] Research emphasizes that incremental innovation activities are much more predictable and less risky than radical innovation efforts. Thus, they account for the most part of all innovation activities (e.g., Leifer et al. 2000).

firm innovation activities. The average revenue growth rate from 2016 to 2017 of all sample firms is 2.6%. Almost 1% of firms report a total loss of their revenues from 2016 to 2017. This does not necessarily imply that these firms went bankrupt but could also indicate high dependency on project-driven businesses. Due to irregular panel participation and panel mortality, only about 30% of the firms that participated in at least one of the three survey waves 2016 to 2018 responded in all three survey waves. This significantly reduces the number of observations that can be used for the empirical analysis and explains the differences in observation sizes.

4.4 Instrumental Variable Estimation (2SLS)

Endogeneity concerns in the context of digitalization-related measurements are a major challenge for empirical investigations on their performance effects. For example, one could argue that differences in innovation performance is the result of different strategic and cultural alignments. If firms intentionally focus on innovation strength, they may be more likely to invest in new technologies that can lay the foundations for future innovation success. In such cases, superior innovation performance could cause higher levels of firm digitalization. A similar issue applies to growth and productivity effects. Superior economic performance often results in better resources which can be used for investments in digitalization. In all these cases, the coefficient reflecting the impact of the digital readiness index in the ordinary least squares (OLS) would be inconsistent and positively biased. Therefore, the correlations between digital readiness and the outcome variable in the OLS are likely to be biased and do not allow for causal interpretation.

To address these endogeneity concerns, I follow Brynjolfsson (2011) and apply a two-stage least square analysis (2SLS) with broadband availability as instrumental variable (IV). The official statistics database of the German states (INKAR)[25] constantly gathers information about the percentage of German households in each county with at least 50MBits Internet access. By matching the information on Internet access with the addresses of the firms in the MIP, I receive an indicator of *'broadband access'* for each firm based on the administrative district level. With regard to the necessary requirements as suggested by Angrist and Pischke (2008), access to broadband Internet[26] is a valid instrument. First, broadband availability needs fulfill the rele-

[25] For additional information about the database visit www.inkar.de.

[26] One could argue that this indicator may not perfectly describe the actual broadband access for every firm. In particular, larger firms may enforce contracts to ensure broadband access in otherwise isolated areas. Despite

vance assumption and have explanatory power for firm digital readiness. It seems highly plausible that access to broadband Internet is a prerequisite for digital readiness. Almost any digital application and technology is dependent on a (fast) connection to the Internet and firms without access to broadband Internet face serious challenges in establishing digital readiness. A high correlation (.1056) between both variables confirms this notion. Second, the exclusion restriction requires that broadband availability should only affect firm performance via digital readiness. It seems implausible that access to broadband affects any performance indicator other than through increased firm-level digitalization. Access to the Internet alone does not provide added value to firms and performance effects can only be obtained by improved digital capabilities. Third, the exchangeability assumption needs to be met, requiring that broadband access and outcome variables do not share common causes. Although the instrument may be related to regional economic performance as well-performing regions may attract more investments from infrastructure providers, it can be assumed that broadband access is exogenous to a single firm's performance. Moreover, data suggest that the instrument seems to be primarily influenced by population density (BBSR 2012).

In summary, this provides strong indication that even the by definition untestable exchangeability assumption and exclusion restriction (Becker 2016) hold and, thus, support for the validity of the broadband as an instrument for digital readiness. The following system of equations summarizes the empirical strategy of my IV estimations:

First stage: $\textit{Digital readiness}_{i,2016} = a_0 + a_1\, \textit{Broadband}_{i,2016} + a_2\, HC_i + (a_3\, X_i) + u_i$

Second stage: $\textit{Outcome}_{i,2017} = b_0 + b_1\, \textit{Digital}\ \widehat{\textit{readiness}}_{i,2016} + b_2\, HC_i + (b_3\, X_{i)} + v_i,$

With $\textit{Digital readiness}_{i,2016}$ measuring firm i's digital readiness score and $\textit{Broadband}_{i,2016}$ indicating the number of households with broadband Internet access in firm i's administrative district in 2016. HC_i is a constant dummy variable classifying each firm i into either HC or non-HC. $\textit{Outcome}_{i,2017}$ refers to firm i's innovation and financial performance in the year 2017. The equations include a set of regional control variables X_i that are used for robustness tests in Chapter 5.4.

these potential issues, the broadband access indicator should still provide a suitable measure for the availability of fast Internet for the on average rather small firms in the sample.

Testing IV requirements

Econometrics highlights several testing approaches to evaluate an instrument's validity based on the relevance assumption. First, the first-stage estimators reveal potential correlation between the IV and the endogenous regressor. Second, the Kleibergen and Paap (KP) rk LM statistic (Kleibergen & Paap 2006) tests if the excluded instruments are relevant (i.e., if they are correlated with the endogenous regressor). Third, the KP Wald F statistic indicates the strength of the correlation (Kleibergen & Paap 2006), with test statistics above 10 usually considered as minimum requirement for strong IVs (e.g., Stock et al. 2002; Angrist & Pischke 2008). If the IV fails any of these criteria, it is considered being *'weak'* and, accordingly, may yield even more biased estimates than the ordinary OLS (Wooldridge 2013).

The results (cf., Tables 7 and 8) show a highly significant first-stage coefficient for the broadband access on digital readiness. Moreover, both the underidentification test (KP rk LM) and the weak identification test (KP Wald F) indicate a strong instrument. In particular, for all first-stage regressions, the respective KP Wald F statistics are well above the threshold value of 10. The underidentification tests of all models can be rejected at the 1% level. Conditional on the exclusion restriction and exchangeability assumption, these findings suggest that broadband access is a valid instrument and the 2SLS should yield consistent and less biased estimates as compared to the OLS.

5 Results and Discussion

This section provides the results of the empirical analysis. First, the effect of digital readiness on firm innovation and economic performance is discussed. Second, I provide a comparison of digital readiness scores between HCs and non-HCs with similar structural characteristics. The section concludes with a discussion of several robustness tests.

5.1 Digital Readiness and Innovation Performance Indicators

Overall, the findings in Table 7 provide strong evidence for a statistically significant and substantial positive impact of the digital readiness index score on innovation. For the baseline model, both OLS (1a) and 2SLS (1b) show large and positive coefficients for the digital readiness index variable on the revenue from all innovations in 2017. The results of the IV estimation in model (1b) indicate that a 10 percentage points increase in digital readiness increases the share of revenues from innovations by 5.43%. Even though the IV coefficient has the same sign as the OLS coefficient, the effect size of the 2SLS has more than doubled. Accordingly, the OLS regression does not show a positive bias, but in fact understates the actual effect of digital readiness. There are two probable reasons that may explain why the IV estimates are significantly larger than the effect indicated by OLS.

The digital readiness score might suffer from measurement error which would bias the OLS towards zero. Since the digital readiness score is based on a self-evaluation, measurement error cannot be excluded. Moreover, the survey does not allow for *'don't know'*- answers which may induce respondents to make non-accurate statements about their digital readiness, either by accident or simply because they cannot relate to a particular question. This likely leads to OLS coefficients that understate the effect of digital readiness. Assuming that the IV is uncorrelated with the measurement error, 2SLS will yield larger coefficients in such cases. Although unlikely, an omitted variable that is negatively correlated with both digital readiness and the outcome variables could also lead to a downward bias of OLS estimates. Since 2SLS regressions are specifically used to solve these issues, it appears possible that IV estimates suggest larger effects (Card 2001; Wooldridge 2013; Becker 2016).

Yet, differences in the described effects seem most likely to cause this discrepancy. Whereas OLS regression aims at the average treatment effect (ATE) that describes the effect of a one-unit increase of digital readiness on the outcome for all firms in the sample, 2SLS regressions yield a local average treatment effect (LATE) for firms whose digital readiness was actually affected by the instrument only. In the case at hand, diminishing returns of digital readiness on (innovation) performance may partially explain the negative bias of OLS estimates. An increase at the bottom of the digital readiness index may have a larger effect on performance than the same increase at higher digital readiness scores. This seems reasonable considering that already basic digital technologies and tools enable firms to significantly decrease turnaround times and reduce the cost of information-intensive processes up to 90% (Markovitch & Willmott 2014; Isaksson et al. 2018). Accordingly, it is plausible to assume that broadband Internet access has an effect on digital readiness scores especially for those firms that show relatively low levels of digitalization and where a one-unit increase has a large effect on performance. This return might be very different from the effect of a one-unit increase of digital readiness for firms that already show higher levels of digitalization (Card 2001; Becker 2016).

Even though these claims cannot be tested, they provide a plausible explanation for the findings.[27] Models (2a) and (2b) include a HC dummy variable, showing that effect sizes remain stable and significant. The 2SLS in model (2b) reports only a slight decrease to 5.28 percentage points more innovation-based revenues for every 10-percentage point increase in digital readiness. Moreover, model estimates do not indicate a statistically significant effect of being a HC on innovation outcomes. This may suggest that HCs indeed do not show higher levels of revenues from innovations compared to control group firms when digital readiness is held constant. Yet, the more plausible reason is that my relatively small number of HC observations imply a small sample bias, leading to low statistical power for the estimates. Support for this view comes from an analysis of the effect of digital readiness for the subsamples of control group firms and HC firms.[28] The results indicate that the coefficient in the full sample is mainly driven by the effect of digital readiness on innovation for control group firms. I do not find a statistically significant effect of digital readiness within the HC subsample which may explain why a test of equality of coefficients[29] between the two subsamples cannot be rejected.

Table 7 further provides information on the impact of digital readiness on innovation types and their respective revenue share. In particular, models (3a) and (3b) show its impact on the share of revenues from incremental innovations. Whereas the OLS (3a) indicates a statistically significant coefficient of the digital readiness variable, the positive effect disappears in the 2SLS model (3b). Hence, the model is unable to provide evidence for a significant effect of digital readiness on incremental innovation output of a firm. Besides of a small sample bias, it may be the case that digital applications and technologies do not improve incremental innovation capabilities of firms but especially foster their ability to generate radically new innovations.

The results of models (4a) and (4b) provide support for this assumption. Both OLS and IV estimates show a positive and significant effect of digital readiness on the share of revenues from radical innovations. Confirming previous findings in models (1b) and (2b), the OLS again underestimates the effect of digital readiness. This positive impact of digital readiness on radical innovation capabilities is an important finding in the context of preparedness towards digital

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[27] Although unlikely (see exchangeability assumption in the previous section), an omitted variable that is negatively correlated with both digital readiness and the outcome variables could also lead to a downward bias of OLS estimates. Since 2SLS regressions are specifically used to solve these issues, it appears possible that IV estimates suggest larger effects.

[28] See Table C.5 in the appendix for the OLS and 2SLS regressions of the effect of digital readiness on revenue from all types of innovation for the HC and control group firm subsamples.

[29] See Tables C.4 in the appendix for the results of the ‘Chow test’ (Chow 1960) of equality of coefficients between models.

transformation. It shows that by improving their digital capabilities, firms may be able to generate more radical (digital) innovations that rely less on already established expertise. The effects are also economically significant. For every 10 percentage point increase in digital readiness, firms can improve the share of revenues from radical innovations by 2.64 percentage points. Assuming that some of these (radical) innovation are digital-based or at least digitally enhanced, this could indicate that companies can substantially improve their digital preparedness by increasing investments in digital technologies and capabilities. Consistent with findings in models (2a) and (2b), I am unable to observe a significant HC effect on both the share of revenues from incremental innovations and radical innovations. Moreover, the results of an investigation of the subsamples yield similar insights, indicating that the sample size for the HC subsample impedes statistical significance. In both cases the test of equality of effect sizes of digital readiness between HCs and control group firms cannot be rejected.[30]

In summary, the large positive and significant effect of digital readiness on the share of revenues from innovation (1b) and radical innovation (3b) in particular confirms previous research (Bouwman et al. 2018) and shows that investments in digitalization lead to better innovation performance. Moreover, it provides support for my assumptions in the context of the digital readiness index. Digital connectedness to suppliers and customers as well as software-based communication platforms may improve collaboration and information exchange within a firm and to external (innovation) partners. Together with information processing capabilities, like big data analyses, this may foster the creation of new knowledge which is a crucial requirement for all innovation efforts. Even though my small HC sample size leads to low statistical power and impede an investigation on possible differences in effect sizes between HCs and control group firms, I find no reason to believe that the digital readiness effect size differs between HCs and structurally similar control group firms.

[30] See Tables C.5 and C.6 in the appendix for the OLS and 2SLS regressions of the effect of digital readiness on the share of revenues based on incremental innovation and radical innovation, respectively, for the HC and control group firm subsamples. The tables also provide the results of the ‘Chow test’ of equality of coefficients between models.

Table 7: OLS and 2SLS results for innovation performance indicators

Innovation performance indicators (in % of revenue 2017)								
	Revenue from all types of innovations				**Revenue from incremental innovations**		**Revenue from radical innovations**	
	OLS	IV estimates	OLS	IV estimates	OLS	IV estimates	OLS	IV estimates
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
Digital readiness	25.050***	54.264**	24.460***	52.761**	13.058***	27.389	11.066*	26.414***
	(5.656)	(21.762)	(5.862)	(22.288)	(5.018)	(21.531)	(5.906)	(8.656)
Hidden champion			2.318	1.276	2.852	2.311	0.125	-0.460
			(2.702)	(2.896)	(2.555)	(2.747)	(1.311)	(1.269)
Constant	3.957*	-7.063	3.043	-7.122	3.629**	-1.467	-0.873	-6.326**
	(2.206)	(8.097)	(1.910)	(7.956)	(1.689)	(7.541)	(1.429)	(2.715)
First-stage results								
		Digital readiness		Digital readiness		Digital readiness		Digital readiness
		(1b)		(2b)		(3b)		(4b)
Broadband Internet		0.255***		0.249***		0.247***		0.247***
		(0.048)		(0.051)		(0.052)		(0.052)
Hidden champion				0.022		0.024		0.025
				(0.025)		(0.025)		(0.025)
Constant		0.177***		0.172***		0.170***		0.170***
		(0.036)		(0.036)		(0.037)		(0.037)
Control group weights	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.065	-0.023	0.069	-0.013	0.032	0.005	0.080	-0.071
First-stage F statistic		28.464		23.589		22.200		22.231
Underidentification test		15.071		12.128		11.584		11.604
Observations	2,141	2,141	2,141	2,141	2,119	2,119	2,133	2,133

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table explores the effect of digital readiness and the HC dummy on financial performance indicators. The underidentification and weak identification (First-stage F statistic) tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al. 2010). Control group weights are derived from an entropy balancing method using Stata's ebalance command (Hainmueller & Xu 2013).

5.2 Digital Readiness and Economic Performance Indicators

Table 8 shows the results of the OLS and 2SLS regression for the impact of digital readiness on productivity (1a to 2b) and revenue growth rates (3a to 4b). For firm productivity, I find that in the baseline specification digital readiness increases the logarithm of productivity by 0.935 in the OLS (1a) and by 2.219 in the 2SLS instrumental variable regression (1b). In line with findings for innovation performance, the OLS underestimates the true effect of digital readiness on productivity. Again, the difference in effect sizes may be primarily attributed to the fact that OLS (ATE) and 2SLS (LATE) describe different effects. The magnitude of the productivity increase caused by digital readiness is remarkable. Already a 10 percentage points increase in digital readiness results in an almost 25% increase in productivity.[31] Similar to findings for innovation performance, the coefficient of digital readiness decreases if the model takes the HC effect into account. Model (2b) shows that it reduces the effect of a 10 percentage points increase on productivity to roughly 21%.[32] Contrary to my previous findings on innovation performance, the model shows a significant positive effect of the HC dummy. Holding digital readiness constant, HCs show a roughly 25% higher productivity compared to control group firms.[33] This is supported by previous studies that indicate similar HC advantages compared to non-HCs in terms of productivity (Simon 2012; Rammer & Spielkamp 2019).

An investigation of the effect for HC and control group firm subsamples reveals that the increase in productivity caused by higher levels of digital readiness in the full sample (2b) seems to be mainly driven by the control group firm subsample.[34] Due to small sample sizes in the context of HCs, the model lacks statistical power to identify a significant effect size for the HC subsample. In line with the statement in the previous section, the structural similarity between HCs and control group firms indicates that a similar positive effect of digital readiness on productivity should also hold for HCs. Overall, the results support the assumption that investments in digitalization can increase firm productivity by improving its efficiency (Brynjolfsson et al. 2011; Barua et al. 2013; Saam et al. 2016; IW Consult 2018). On the one hand, it may

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[31] The coefficient of digital readiness in model (1b) is 2.219. As the variable ranges from 0 to 1, a 10 percentage points higher digital readiness increases the logarithm of productivity by 0.2219. Accordingly, the exponentiated value equals 1.2484 indicating a 24.8% increase in productivity.

[32] The coefficient of digital readiness in model (2b) is 1.946. As the variable ranges from 0 to 1, a 10 percentage points higher digital readiness increases the logarithm of productivity by 0.1946. Accordingly, the exponentiated value equals 1.2148 indicating a 21.5% increase in productivity.

[33] The coefficient of HC dummy in model (2b) is 0.223. Accordingly, its exponentiated value equals 1.250 indicating a 25% increase in productivity.

[34] See Table C.8 in the appendix for the OLS and 2SLS regressions of the effect of digital readiness on productivity for the control group firm and HC subsamples.

enable firms to decrease costs, for example by improving their internal and external digital connectedness. This supports firms to automate tasks, processes or parts of the production, resulting in significant time and production cost savings. Along similar lines, software-based communication and intranet-based platforms can reduce cost of communication and ease the information flow within firms as well as to their suppliers and customers. On the other hand, an increase in digital readiness may develop new revenue streams while holding inputs (relatively) constant. In particular, e-commerce and social media presence may improve customer reach and provide additional distribution channels for products/services. Moreover, advanced information processing capabilities and innovative solutions may allow firms to increase customer value and, thus, allow them to enforce higher prices.

The regression results for the impact of digital readiness on firm revenue growth rate from 2016 to 2017 (3a to 4b), however, do not yield statistically significant estimates. While I find a significant and strong effect in the OLS regressions in models (3a) and (4a), the respective IV estimations are unable to provide statistically significant evidence (cf. models 3b and 4b). While this could indicate that digital readiness indeed does not affect revenue growth, the more plausible reason is a lack of statistical power in the model. Contrary to the other outcome variables, revenue growth rate is based on information from two consecutive surveys and requires firms to provide revenue data for 2016 and 2017 to be included in the analysis. This significantly reduces the sample size. The results for the HC and control group subsamples illustrate similar outcomes and show a significant effect of digital readiness on revenue growth rate only for control group firm OLS estimates.[35]

[35] See Table C.9 in the appendix for the OLS and 2SLS regressions of the effect of digital readiness on revenue growth rate for the control group firm and HC subsamples.

Table 8: OLS and 2SLS results for productivity and revenue growth rate

Economic performance indicators 2017

	Productivity (log)				**Revenue growth rate 2016-2017** (in %)			
	OLS	IV estimates	OLS	IV estimates	OLS	IV estimates	OLS	IV estimates
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
Digital readiness	0.935***	2.219***	0.871***	1.946***	16.974**	9.670	16.848**	8.448
	(0.200)	(0.585)	(0.225)	(0.576)	(6.961)	(20.052)	(6.910)	(20.617)
Hidden champion			0.261***	0.223***			1.358	1.471
			(0.073)	(0.075)			(2.822)	(2.914)
Constant	11.687***	11.192***	11.583***	11.188***	0.217	2.973	-0.392	2.723
	(0.079)	(0.219)	(0.073)	(0.212)	(2.987)	(7.768)	(2.758)	(7.594)
First-stage results								
		Digital readiness		Digital readiness		Digital readiness		Digital readiness
		(1b)		(2b)		(3b)		(4b)
Broadband Internet		0.266***		0.260***		0.259***		0.259***
		(0.046)		(0.050)		(0.051)		(0.053)
Hidden champion				0.020				0.002
				(0.024)				(0.027)
Constant		0.177***		0.172***		0.175***		0.175***
		(0.035)		(0.035)		(0.038)		(0.037)
CG weights	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.087	-0.077	0.133	0.019	0.021	0.027	0.020	0.021
First-stage F statistic		32.983		27.242		25.864		23.930
Underidentification test		16.884		13.490		13.039		11.678
Observations	2,169	2,169	2,169	2,169	1,748	1,748	1,748	1,748

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table explores the effect of digital readiness and the HC dummy on financial performance indicators. The underidentification and weak identification (First-stage F statistic) tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al. 2010). Control group weights are derived from an entropy balancing method using Stata's ebalance command (Hainmueller & Xu 2013).

5.3 Comparison of Digital Readiness Index Levels

A comparison of means for digital readiness in Table 9 shows that HCs have a significantly higher average digital readiness index score than non-HCs (1a) and control group firms (1b). With an average digital readiness of 0.425 HCs demonstrate a 10.6 percentage points higher mean score than non-HCs in the sample (0.319). Compared to control group firms, which achieve higher average digital readiness (0.354) than unweighted non-HCs, they still exhibit a statistically significant 7.1 percentage points higher readiness.

The reduction in the HC advantage can be explained by structural differences between non-HCs and control group firms. Control group firms are specifically designed to match HCs in terms of size, age, and industry class and thus tend to be larger and more concentrated in manufacturing-related industries compared to non-HCs. As both characteristics already have a positive impact on the average digital readiness score[36], a reduction in the HC-specific advantage seems plausible. This observation holds even if regional controls[37], which may affect the average firm digital readiness, are included (2a and 2b). However, the slight decrease of the HC advantage to 6.9 percentage points (2b) may reflect the fact that HCs are more likely to be located in regions where digitalization is already more advanced. All in all, the findings provide support for the assumption that HCs prioritize and invest in new technologies earlier than their industry peers (Simon 2012, 2019).

Table 9: Comparison of digital readiness index levels

Digital readiness index levels

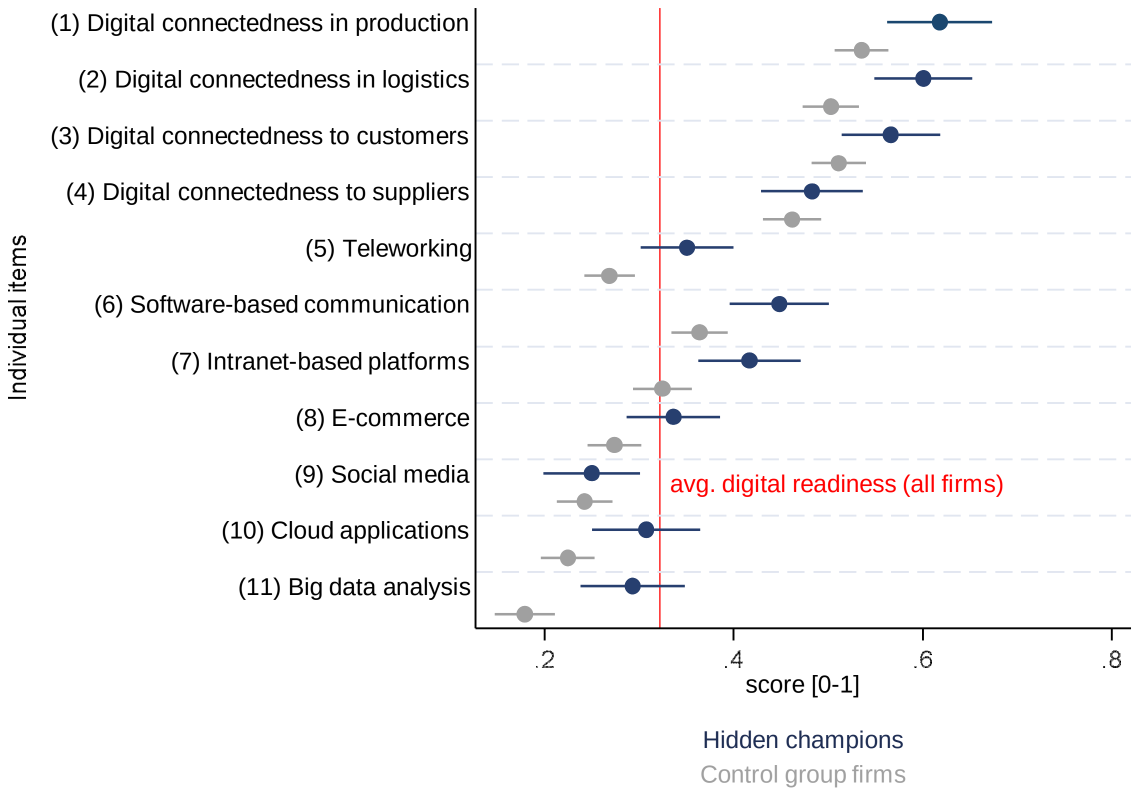
	Digital readiness index score [0-1]			
	(1a)	(1b)	(2a)	(2b)
Hidden champions	0.106***	0.071***	0.111***	0.069***
	(0.018)	(0.021)	(0.018)	(0.021)
Constant	0.319***	0.354***	0.312***	0.326***
	(0.004)	(0.011)	(0.009)	(0.026)
Control group weights	No	Yes	No	Yes
Regional controls	No	No	Yes	Yes
R-squared	0.007	0.031	0.021	0.036
Observations	3,743	3,743	3,743	3,743

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Notes: Regional controls include population density, jobs per 1,000 residents, and region type and are all measured at the administrative district level. Control group weights are derived from an entropy balancing method using Stata's ebalance command (Hainmueller & Xu 2013).

[36] This information is provided in the description of the digital readiness index in Chapter 4.2.
[37] See Table C.14 in the appendix for an overview and description of the included regional control variables.

Figure 4 shows that HCs outperform control group firms at every individual component of the digital readiness index[38]. Except for digital connectedness with suppliers (4) and the use of social media (9), the differences in effect sizes are also statistically significant. This indicates that HCs do not focus digitalization efforts on particular areas but emphasize a wide range of digital technologies and applications. With an 11.4 percentage points higher score for HCs, big data analysis capabilities show the largest difference, suggesting that compared to control group firms, HCs seem to put more emphasis on rather sophisticated digital capabilities. Considering the importance of data in the digital economy as well as in the context of digital innovations, this leading edge may support them in creating a technological lead over their competitors.

Figure 4: Comparison of all digital readiness index items



Notes: This figure plots point estimates for the individual items on which the digital readiness index is based on. 95% confidence intervals are depicted as lines.

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[38] See Table C.16 in the appendix for a detailed overview of the individual item scores for HCs, non-HCs, and control group firms.

Summary of the results

The results of the IV estimations provide evidence for a significant and positive effect of firm digital readiness on the market performance of innovations and firm productivity. Moreover, I find that HCs are significantly more productive compared to control group firms with similar levels of digital readiness. Low statistical power due to a relatively small HC-specific sample size (50-64), prevents the identification of statistically significant digital readiness effects for the HC subsample. However, I find no reason to believe that the digital readiness effect size differs between HCs and structurally similar control group firms. A comparison of digital readiness scores reveals a significantly higher digital readiness average for HCs which also outperform control group firms at every of the 11 surveyed indicators for digitalization. This digital lead may allow HCs to benefit from the positive effects of higher levels of digital readiness on innovation performance and productivity and more importantly, should also facilitate the development of digital innovations in the future.

Evaluating firm preparedness towards digital transformation is a complex endeavor and difficult to reduce to individual decisive factors. It depends on various additional factors, such as a firm's cultural, strategic and structural alignment, that are not captured by the presented digital readiness index. However, the regression results in combination with the theoretical foundation of the DCV that indicates superior innovation, leadership and organizational capabilities, provide strong support for my hypothesis. Therefore, it can be reasonably assumed that HCs are better prepared for the digital transformation than non-HCs, and firms of similar size, age and industry characteristics in particular.

5.4 Robustness Tests

To verify that the results in Tables 7 and 8 are not mainly driven by control group design, I run the regressions without entropy balance weights. These models basically describe the effect of digital readiness on the outcome variables for the original and unadjusted sample of HCs and non-HCs.

Corresponding to findings in Tables 7 and 8, I find no indication for instrument weakness and that the OLS underestimates the effect of digital readiness on the outcomes. The results (cf. Tables C.10 – C.14 in the appendix) of the 2SLS regressions indicate a decrease in effect size for the digital readiness index for all outcome variables. Still, they remain highly significant and of substantial size. The decrease in digital readiness effect size may indicate that HCs and similar control group firms benefit disproportionally from digitalization. Since HCs and control group firms significantly differ from the unadjusted full sample, specifically in terms of industry distribution and firm size, this may indicate that the impact of digitalization is dependent on these parameters. In particular, firms which are relatively large and operate primarily in manufacturing-related industries seem to profit more from investments in digital capabilities than the average firm in the sample. Contrary to the previous models, I find significant positive HC-specific effects for the share of revenues from all innovations as well as from incremental innovations in the unweighted sample. This confirms previous studies that show superior HC capabilities in terms of continuous product and service portfolio improvements (Simon 2012; Rammer & Spielkamp 2019). The results support a positive effect of digital readiness on all outcome variables. At the same time, the findings emphasize the importance of a valid control group approach for determining HC-specific effects.

To investigate a potential impact of region-specific characteristics on the effect of digital readiness on the outcome variables, I include a set of regional control variables.[39] The respective regression models specifically observe the effect of population density, jobs to resident ratio, and the region type, all measured at the administrative district level. A direct comparison with the regressions in Tables 7 and 8 shows slightly decreased but still substantial digital readiness effects on the outcome variables with significance levels remaining stable (cf. Tables C.10 – C.14 in the appendix). While the results suggest that regional factors can influence the impact of digital readiness, they again confirm the positive impact of digital readiness described in the previous subsections.

6 Conclusion

In this study, I investigate how digitalization affects firm performance and specifically focus on the digital preparedness of HCs compared to non-HC firms of similar age, size, and within the same industry class. Supported by empirical evidence, organizational theory emphasizes that especially in highly dynamic environments, DCs can improve long-term competitiveness by enabling firms to sense threats, seize opportunities, and reconfigure their resource base. Previous studies regularly refer to innovation competence, entrepreneurial leadership, and organizational agility as key determinants for strong DCs. Consistent with previous HC research, I

[39] See Table C.15 in the appendix for an overview and description of the included regional control variables.

show that these features are particularly pronounced in HCs which indicates superior DCs that may help HCs to be better prepared for the digital transformation.

To study this, I draw on data from the MIP survey of 2016, 2017 and 2018. This enables the development of a digital readiness index that measures the prevalence of 11 digital applications as well as to classify firms in HCs and non-HCs. Due to endogeneity concerns, I analyze the effect of digital readiness on firm performance using an IV-setup. My findings show a significant and substantial positive effect of digital readiness on the innovation performance and productivity, confirming results in previous studies. Moreover, I find that HCs demonstrate significantly higher levels of firm-level digitalization than non-HCs as well as control group firms with similar demographic characteristics. In combination with the positive performance effects of increased levels of digital readiness, this strongly supports the assumption that HCs are indeed better prepared for the digital transformation than non-HC firms.

My findings contribute to research on HCs as well as SMEs in general. Existing studies on HCs often lack empirical evidence, rely on case studies or are limited in terms of information value due to small sample sizes. To the best of my knowledge, there is only one empirical study (cf. Freimark et al. 2018) that specifically investigates digitalization in the context of HCs. In more general terms, the results contribute to research about the effect of firm-level digitalization levels on performance. The positive effect of increased levels of digital readiness suggests that investments in digital technologies and capabilities can allow firms to significantly improve their innovation performance and productivity. From a practitioner's point of view, these findings may help to reduce reluctance concerning digitalization efforts due to uncertain and difficult to assess outcomes. Moreover, it specifically links the strategic focus of HCs on superior innovation competence, entrepreneurial leadership styles, and organizational agility to enhanced preparedness towards digital transformation. This may provide guidance to firm leaders on how to adjust their organization so that it can better cope with the challenges of the digital age and improve competitiveness.

This study is subject to several limitations.[40] First, the digital readiness index may provide a biased picture of firm digitalization as respondents may differ when defining individual digital applications and assessing their prevalence within their organization. Although my control

[40] A general limitation of the IV-setup is that if the untestable exchangeability and exclusion restrictions do not hold, the estimations of the 2SLS would not be consistent. Moreover, the LATE measures the effect of digital readiness on performance for an unknown subgroup which may limit generalizability of the results (Becker 2016).

group approach mitigates the effect of differences in firm size, age, and industry affiliation, the position of respondents within the organization may systematically affect the digital readiness scores. Second, the index is limited in terms of scope. It only covers 11 rather specific digital capabilities and technologies and does not include other critical aspects such as a firm's digital alignment in terms of culture, organization and business model. Third, data on firm digitalization is limited to a single survey year which may not satisfy the dynamic nature of developments in the context of digital transformation. Fourth, my small sample of HC observations does not provide enough statistical power to investigate a HC-specific effect of digital readiness on the outcome variables. Thus, my conclusions rely on the assumption that the average effect size does not differ between HCs and control group firms.

Future research may want to address some of these limitations, for example, by conducting regular surveys to measure digital capabilities of firms which would enable a panel-based analysis of performance effects. This could increase robustness of the results, enable fixed-effects methods, and reveal trends in firm digitalization levels. Researchers could also specifically investigate if the digital gap between HCs and other firms is changing over time and whether the digital transformation affects the composition of HCs. Due to the global scale of the phenomenon and its cross-national implications, it makes sense to transfer the analysis in broader context and compare the digital capabilities of Germany's HCs with international firms. Future studies could try to apply existing approaches (e.g., Karimi & Walter 2015) and specifically measure the strength of dynamic capabilities of HCs. To increase generalizability of the IV estimates, researchers may also want to identify additional instruments and investigate how they affect the effect sizes of digital readiness on the outcome.

Appendix

A Supplementary Information

Appendix A.1: Mannheim Innovation Panel – survey 2016 extract

7 Usage of Digitalisation

7.1 To what extent does your enterprise currently use the following applications of digitalization in different business function areas, and will the usage of these application likely increase, decrease or stay the same in the next three to five years?

Please tick at least one box in each line!	*Current usage* High	Medium	Low	No	*In the next 3 to 5 years* Increase	Stay the same	Decrease
Production / service provision:							
- Digital interconnection within production / provision of services	☐1	☐2	☐3	☐4	☐1	☐2	☐3
- Digital interconnection between production / service provision and logistics	☐1	☐2	☐3	☐4	☐1	☐2	☐3
- Digital interconnection with customers	☐1	☐2	☐3	☐4	☐1	☐2	☐3
- Digital interconnection with suppliers	☐1	☐2	☐3	☐4	☐1	☐2	☐3
Internal organization / communication:							
- Teleworking	☐1	☐2	☐3	☐4	☐1	☐2	☐3
- Software-based communication (Skype etc.)	☐1	☐2	☐3	☐4	☐1	☐2	☐3
- Intranet-based platforms (Wikis etc.)	☐1	☐2	☐3	☐4	☐1	☐2	☐3
Sales / external communication:							
- E-Commerce	☐1	☐2	☐3	☐4	☐1	☐2	☐3
- Social media (Facebook, Twitter etc.)	☐1	☐2	☐3	☐4	☐1	☐2	☐3
Information processing:							
- Cloud computing / cloud applications	☐1	☐2	☐3	☐4	☐1	☐2	☐3
- Big data analysis	☐1	☐2	☐3	☐4	☐1	☐2	☐3

7.2 In what areas does your enterprise currently experience the greatest difficulties when trying to use the opportunities of digitalization?

Bitte machen Sie in jede Zeile ein Kreuz!	*Difficulties when using digitalization* High	Medium	Low	No
Financing	☐1	☐2	☐3	☐4
Shortage of skilled IT personnel	☐1	☐2	☐3	☐4
Shortage of IT knowledge of own staff	☐1	☐2	☐3	☐4
Uncertainty about future development in sales markets	☐1	☐2	☐3	☐4
Uncertainty about future technological development in the area of digitalization	☐1	☐2	☐3	☐4
Uncertainty about future technical standards	☐1	☐2	☐3	☐4
Technical infrastructure (data transfer rate etc.)	☐1	☐2	☐3	☐4
Adaptation or conversion of existing IT systems	☐1	☐2	☐3	☐4
Interfaces / data exchange with business and co-operation partners	☐1	☐2	☐3	☐4
Data protection	☐1	☐2	☐3	☐4
Data security	☐1	☐2	☐3	☐4

Thank you very much for your valuable assistance!

If you have any questions, or would like a copy of the survey findings ("Sector Report on Innovation"), please complete your contact information below:

Name of respondent	Enterprise address or stamp
Position in the enterprise	
Telephone	
E-Mail	

B Supplementary Figures

Figure B.1: Density comparison over industry classes

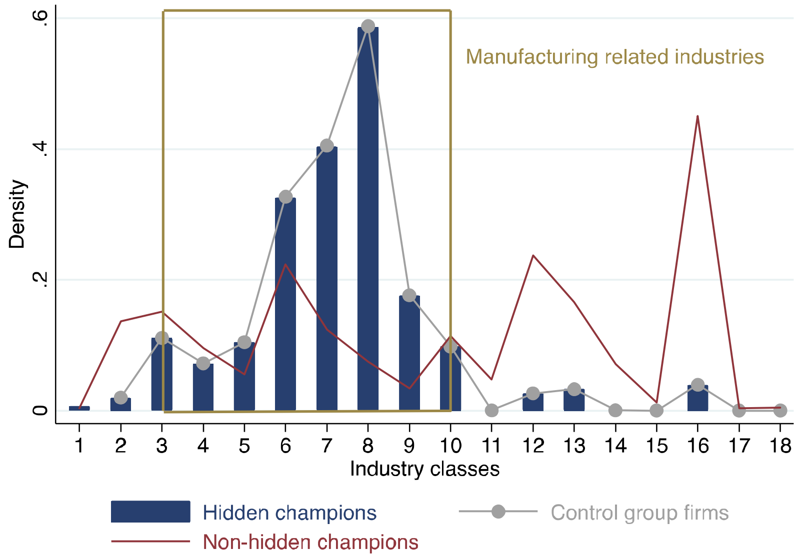
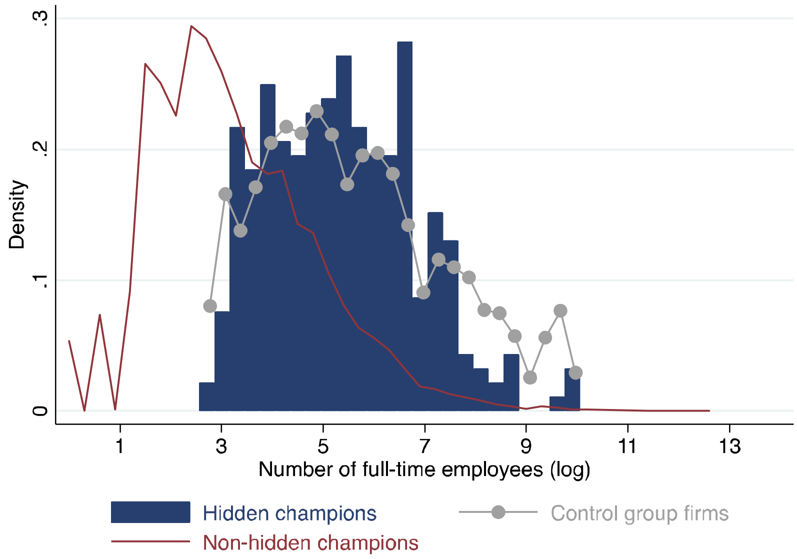
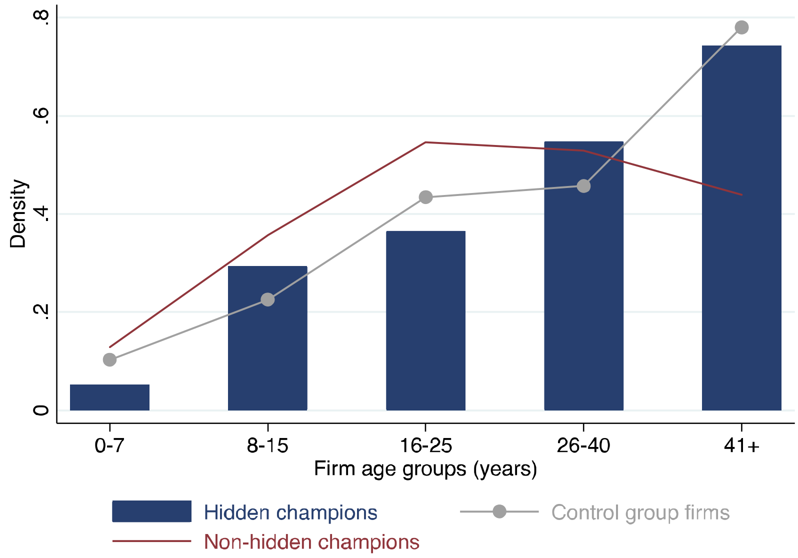


Figure B.2: Density comparison over size classes



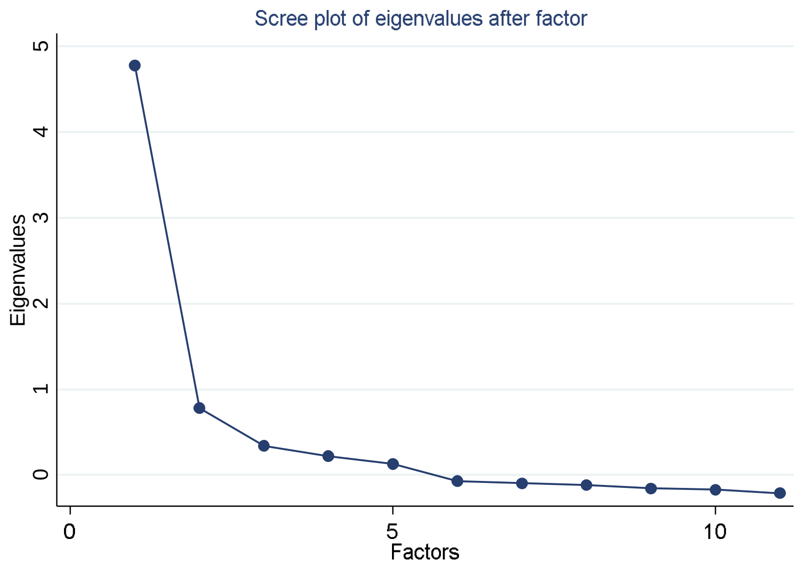
Notes: For illustration purposes the figure shows the logarithm of employees. However, the entropy balance control group approach uses the actual number of employees. This explains the remaining differences between HCs and control group firms.

Figure B.3: Density comparison over age groups



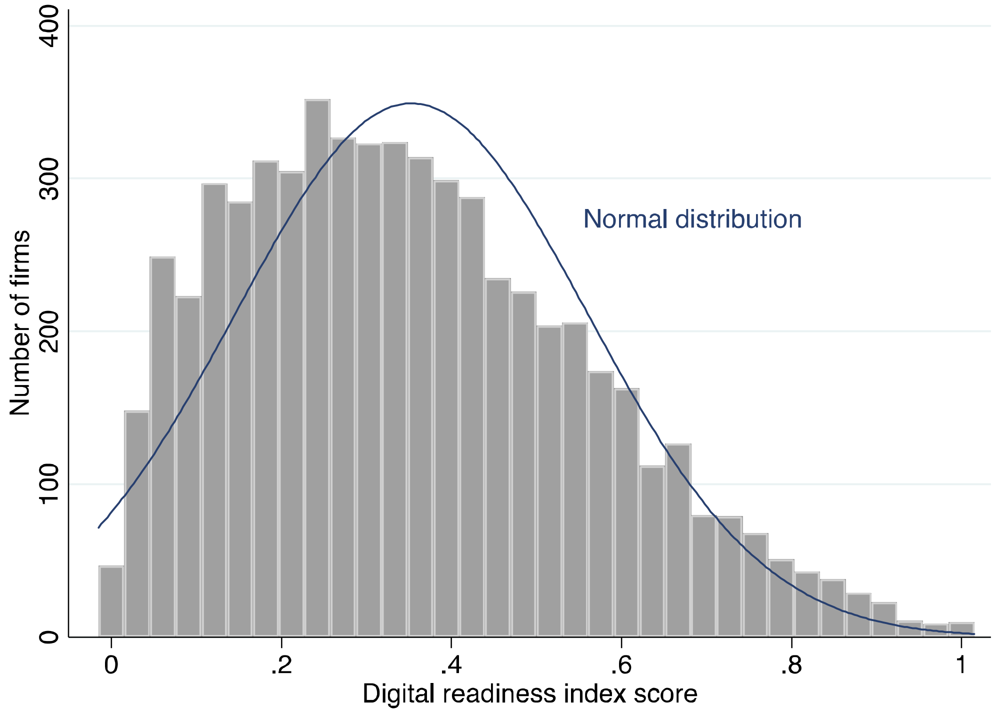
Notes: For illustration purposes the figure shows age groups. However, the entropy balance control group approach uses the exact firm age. This explains the remaining differences between HCs and control group firms.

Figure B.4: Scree plot of eigenvalues



Note: This figure shows eigenvalues over factors and according to the '*elbow*' criterion suggests one retained factor.

Figure B.5: Distribution of digital readiness index scores



Note: This graph shows the distribution of digital readiness values and the hypothetical normal distribution.

C Supplementary Tables

Table C.1: Industry class description and NACE2 equivalent

Industry class	Description	Share of HCs	NACE2 equivalent
1	Agriculture, forestry, and fishing	-	01-03
2	Mining, quarrying, and other industries	-	05-09; 35-39
3	Manufacture of food products, beverages, tabacco products, textiles, apparel, leather, and related products	4.31%	10-15
4	Manufacture of wood and paper products and printing	5.17%	16-18
5	Manufacture of coke, and refined petroleum products, chemicals, chemical products, pharmaceuticals, medicinal chemical, and botanical products	5.17%	19-21
6	Manufacture of rubber and plastic products, mineral products, basic metals and fabricated metal products, except machinery and equipment	11.21%	22-25
7	Manufacture of computer, electronic, optical products, and electrical equipment	21.55%	26-27
8	Manufacture of machinery and equipment n.e.c.	31.90%	28
9	Manufacture of transport euqipment	11.21%	29-30
10	Other manufacturing, and repair and installation of machinery and equipment	6.03%	31-33
11	Construction	-	41-43
12	Wholesale and retail trade, transportation and storage, accommodation and food service activities	1.72%	45-47; 49-53; 55-56
13	Information and communication	-	58-63
14	Financial and insurance activities	-	64-66
15	Real estate activities	-	68
16	Professional, scientific, technical, administration and support service activities	1.72%	69-75; 77-82
17	Public administration, defence, education, human health, and social work activities	-	84-88
18	Other services	-	89-99

Table C.2: Entropy balance table for HCs, non-HCs and control group firms

	Means			Variance			Skewness			Std. diff.	
		Controls			Controls			Controls			
Covariate	HCs	Pre	Post	HC	Pre	Post	HC	Pre	Post	Pre	Post
Employees 2015	821.870	260.088	821.929	8,178,812.63	32,240,469.88	8,179,518.02	6.931	50.537	6.932	0.196	0.000
Year of foundation	1968.733	1981.589	1968.873	1541.171	1360.866	1541.262	-1.870	-4.977	-1.880	-0.327	-0.004
Industry classes											
(3) Manufacture of food products, beverages, tobacco products, textiles, apparel, leather, and related products	0.043	0.075	0.043	0.042	0.069	0.042	4.499	3.225	4.482	-0.157	-0.001
(4) Manufacture of wood and paper products and printing	0.052	0.045	0.052	0.049	0.043	0.049	4.048	4.416	4.033	0.032	-0.002
(5) Manufacture of coke, and refined petroleum products, chemicals, chemical products, pharmaceuticals, medicinal chemical, and botanical products	0.052	0.025	0.052	0.049	0.024	0.049	4.048	6.119	4.033	0.121	-0.002
(6) Manufacture of rubber and plastic products, mineral products, basic metals and fabricated metal products, except machinery and equipment	0.112	0.112	0.113	0.100	0.100	0.101	2.460	2.453	2.438	-0.001	-0.004
(7) Manufacture of computer, electronic, optical products, and electrical equipment	0.216	0.066	0.218	0.171	0.062	0.170	1.384	3.496	1.367	0.362	-0.006
(8) Manufacture of machinery and equipment n.e.c.	0.319	0.037	0.322	0.219	0.036	0.218	0.777	4.877	0.764	0.602	-0.006
(9) Manufacture of transport equipment	0.112	0.015	0.113	0.100	0.014	0.101	2.460	8.102	2.438	0.308	-0.004
(10) Other manufacturing, and repair and installation of machinery and equipment	0.060	0.056	0.061	0.057	0.053	0.057	3.693	3.847	3.678	0.017	-0.002
(16) Professional, scientific, technical, administration and support service activities	0.017	0.240	0.017	0.017	0.182	0.017	7.417	1.217	7.390	-1.704	-0.001

Treated units: 116 Total of weights: 116

Control units: 3,637 Total of weights: 116

Notes: This table shows the covariate distribution as well as the standardized differences between the covariates before and after entropy balancing is applied using Stata's ebalance command (Hainmueller & Xu 2013). Only industry classes that contain hidden champions are included in the balancing, all firms in other industries are excluded from balancing.

Table C.3: Digital readiness – alpha scores and KMO values

Variable	Range	Sign.	Average interim covariance	Cronbach's alpha	Kaiser-Meyer-Olkin	Observations
Joint digital readiness index	0-1[1]	+	0.382	0.889	0.883	3,761
Production and/or provision of services						
(1) Digital connectedness within production and/or provision of services	0-3[2]	+	0.369	0.878	0.847	3,775
(2) Digital connectedness between production and/or provision of services and logistics	0-3	+	0.373	0.881	0.843	3,775
(3) Digital connectedness with customers	0-3	+	0.374	0.878	0.850	3,773
(4) Digital connectedness with suppliers	0-3	+	0.386	0.882	0.833	3,771
Internal organization and communication						
(5) Teleworking	0-3	+	0.385	0.880	0.925	3,773
(6) Software-based communication (Skype etc.)	0-3	+	0.372	0.876	0.896	3,773
(7) Intranet-based platforms (Wikis etc.)	0-3	+	0.374	0.877	0.917	3,774
Sales and external communications						
(8) E-commerce	0-3	+	0.387	0.880	0.921	3,774
(9) Social media (Facebook, Twitter etc.)	0-3	+	0.396	0.883	0.910	3,775
Information processing						
(10) Cloud applications	0-3	+	0.388	0.881	0.890	3,775
(11) Analysis of Big Data	0-3	+	0.395	0.880	0.893	3,776

Notes: [1] Scale is normalized to values between 0 and 1, with 0=no digital readiness and 1=complete digital readiness. [2] Scale ranges from 0 to 3, with 0=no usage, 1=low usage, 2=medium usage, 3=high use of the respective technology in the firm. Results for alpha values as reported by Stata's alpha command. Results for KMO values as reported by the postestimation command kmo in Stata.

Table C.4: Digital readiness – factor analysis results

Factor analysis / correlation	Number of observations: 3,761			
Method: Principal factors	Retained factors: 1			
Rotation: (unrotated)[1]	Number of params: 11			
Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor 1	4,757	3,975	0.879	0.879
Factor 2	0.782	0.444	0.144	1,024
Factor 3	0.337	0.098	0.062	1,086
Factor 4	0.238	0.123	0.044	1,130
Factor 5	0.115	0.193	0.021	1,151
Factor 6	0.078	0.008	0.014	1,137
Factor 7	-0.087	0.028	0.016	1,121
Factor 8	-0.116	0.039	0.021	1,099
Factor 9	-0.155	0.015	0.028	1,070
Factor 10	-0.171	0.039	0.031	1,039
Factor 11	-0.211	.	0.039	1,000

Variable	Factor 1	Uniqueness
(1) Digital connectedness within production and/or provision of services	0.673	0.368
(2) Digital connectedness between production and/or provision of services and logistics	0.639	0.403
(3) Digital connectedness with customers	0.675	0.364
(4) Digital connectedness with suppliers	0.608	0.420
(5) Teleworking	0.655	0.486
(6) Software-based communication (Skype etc.)	0.726	0.363
(7) Intranet-based platforms (Wikis etc.)	0.704	0.420
(8) E-commerce	0.636	0.513
(9) Social media (Facebook, Twitter etc.)	0.594	0.537
(10) Cloud applications	0.644	0.456
(11) Analysis of Big Data	0.664	0.434

Notes: [1]Since there is only 1 retained factor with an Eigenvalue > 1 left, the results for the factor values equal those of the (varimax) rotated solution. Results as reported by Stata's factor command. The factor loadings are computed using the squared multiple correlations as estimates of the commonality.

Table C.5: Share of revenues from all types of innovations – subsamples

Dependent variable: Share of revenues from all types of innovations 2017 (in %)
OLS vs. IV estimates - sub samples

Subgroup	Control group firms		Hidden champions	
	(OLS)	(IV estimates)	(OLS)	(IV estimates)
Digital readiness	27.378***	49.023**	17.446	37.983
	(5.379)	(21.441)	(12.576)	(33.584)
Constant	-2.993	-10.782	8.514	1.931
	(2.026)	(7.528)	(6.947)	(11.581)
First-stage results				
		Digital readiness		Digital readiness
Broadband Internet		0.165***		0.515***
		(0.049)		(0.097)
Constant		0.252***		-0.018
		(0.039)		(0.071)
Control group weights	Yes	Yes	Yes	Yes
Regional controls	Yes	Yes	Yes	Yes
R-squared	0.131	0.067	0.032	0.004
First-stage F statistic		11.520		28.020
Underidentification test		9.617		7.996
Mean of dep. variable	11.828		15.046	
-Chow test- results				
F statistic			0.535	0.077
p-value			0.465	0.782
Observations	2,075	2,075	60	60

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Notes: Regional controls include population density, jobs per 1,000 residents, and region type and are all measured at the administrative district level. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al. 2010). The Chow test is the test of equality between the digital readiness coefficients of the respective sub sample results for OLS & IV estimation (Chow 1960) as reported by Stata's suest command. Control group weights are derived from an entropy balancing method using Stata's ebalance command (Hainmueller & Xu 2013).

Table C.6: Share of revenues from incremental innovations – subsamples

Dependent variable: Share of revenues from incremental innovations 2017 (in %)
OLS vs. IV estimates - sub samples

Subgroup	**Control group firms**		**Hidden champions**	
	(OLS)	(IV estimates)	(OLS)	(IV estimates)
Digital readiness	11.446**	22.550	16.652	32.150
	(4.590)	(19.045)	(11.615)	(33.511)
Constant	0.641	-3.312	5.190	0.405
	(1.824)	(6.545)	(5.680)	(11.008)
First-stage results				
		Digital readiness		Digital readiness
Broadband Internet		0.152***		0.506***
		(0.049)		(0.098)
Constant		0.257***		-0.017
		(0.040)		(0.072)
Control group weights	Yes	Yes	Yes	Yes
Regional controls	Yes	Yes	Yes	Yes
R-squared	0.040	0.016	0.033	0.015
First-stage F statistic		9.536		26.433
Underidentification test		8.266		7.964
Mean of dep. variable	8.273		11.618	
-Chow test- results				
F statistic			0.038	0.000
p-value			0.845	0.990
Observations	2,056	2,056	57	57

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Notes: Regional controls include population density, jobs per 1,000 residents, and region type and are all measured at the administrative district level. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata’s ivreg2 command (Baum et al. 2010). The Chow test is the test of equality between the digital readiness coefficients of the respective sub sample results for OLS & IV estimation (Chow 1960) as reported by Stata’s suest command. Control group weights are derived from an entropy balancing method using Stata’s ebalance command (Hainmueller & Xu 2013).

Table C.7: Share of revenues from radical innovations – subsamples

Dependent variable: Share of revenues from radical innovations 2017 (in %)
OLS vs. IV estimates - sub samples

Subgroup	**Control group firms**		**Hidden champions**	
	(OLS)	(IV estimates)	(OLS)	(IV estimates)
Digital readiness	14.299*	25.743*	3.237	9.867
	(7.620)	(14.797)	(3.966)	(7.863)
Constant	-3.454*	-7.519	3.853	1.806
	(1.925)	(4.896)	(3.247)	(1.767)
First-stage results				
		Digital readiness		Digital readiness
Broadband Internet		0.152***		0.506***
		(0.049)		(0.098)
Constant		0.256***		-0.017
		(0.040)		(0.072)
Control group weights	Yes	Yes	Yes	Yes
Regional controls	Yes	Yes	Yes	Yes
R-squared	0.152	0.078	0.184	0.151
First-stage F statistic		9.580		26.433
Underidentification test		8.308		7.964
Mean of dep. variable	3.058		3.605	
-Chow test- results				
F statistic			1.074	0.270
p-value			0.300	0.604
Observations	2,070	2,070	57	57

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Notes: Regional controls include population density, jobs per 1,000 residents, and region type and are all measured at the administrative district level. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al. 2010). The Chow test is the test of equality between the digital readiness coefficients of the respective sub sample results for OLS & IV estimation (Chow 1960) as reported by Stata's suest command. Control group weights are derived from an entropy balancing method using Stata's ebalance command (Hainmueller & Xu 2013).

Table C.8: Firm productivity – subsamples

Dependent variable: Productivity 2017 (log)
OLS vs. IV estimates - sub samples

Subgroup	**Control group firms**		**Hidden champions**	
	(OLS)	(IV estimates)	(OLS)	(IV estimates)
Digital readiness	1.097***	2.668***	0.239	0.533
	(0.237)	(0.915)	(0.358)	(0.851)
Constant	11.592***	11.025***	11.680***	11.581***
	(0.089)	(0.336)	(0.217)	(0.355)
First-stage results				
		Digital readiness		Digital readiness
Broadband Internet		0.177***		0.519***
		(0.048)		(0.095)
Constant		0.247***		-0.004
		(0.037)		(0.071)
Control group weights	Yes	Yes	Yes	Yes
Regional controls	Yes	Yes	Yes	Yes
R-squared	0.135	-0.120	0.147	0.139
First-stage F statistic		13.569		30.034
Underidentification test		11.324		7.805
Mean of dep. variable	11.903		12.196	
-Chow test- results				
F statistic			4.162	3.395
p-value			0.041	0.066
Observations	2,101	2,101	64	64

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Notes: Regional controls include population density, jobs per 1,000 residents, and region type and are all measured at the administrative district level. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al. 2010). The Chow test is the test of equality between the digital readiness coefficients of the respective sub sample results for OLS & IV estimation (Chow 1960) as reported by Stata's suest command. Control group weights are derived from an entropy balancing method using Stata's ebalance command (Hainmueller & Xu 2013).

Table C.9: Revenue growth rate – subsamples

Dependent variable: Revenue growth rate 2016-2017 (in %)
OLS vs. IV estimates - sub samples

Subgroup	Control group firms		Hidden champions	
	(OLS)	(IV estimates)	(OLS)	(IV estimates)
Digital readiness	11.155***	22.717	32.531	19.405
	(4.056)	(21.128)	(20.548)	(29.591)
Constant	-0.104	-4.298	-2.740	1.578
	(2.017)	(7.777)	(9.233)	(11.242)
First-stage results				
		Digital readiness		Digital readiness
Broadband Internet		0.195***		0.542***
		(0.052)		(0.091)
Constant		0.236***		-0.017
		(0.044)		(0.069)
Control group weights	Yes	Yes	Yes	Yes
Regional controls	Yes	Yes	Yes	Yes
R-squared	0.018	0.004	0.077	0.067
First-stage F statistic		13.975		35.418
Underidentification test		11.112		7.708
Mean of dep. variable	5.857		7.440	
-Chow test- results				
F statistic			0.968	0.086
p-value			0.325	0.770
Observations	1,692	1,692	50	50

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Notes: Regional controls include population density, jobs per 1,000 residents, and region type and are all measured at the administrative district level. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al. 2010). The Chow test is the test of equality between the digital readiness coefficients of the respective sub sample results for OLS & IV estimation (Chow 1960) as reported by Stata's suest command. Control group weights are derived from an entropy balancing method using Stata's ebalance command (Hainmueller & Xu 2013).

Table C.10: Share of revenues from innovations – robustness tests

Dependent variable: Share of revenues from all types of innovations 2017 (in %)
OLS vs. IV estimates

	OLS (1a)	IV estimates (1b)	OLS (2a)	IV estimates (2b)
Hidden champion	7.576***	5.224*	2.193	1.531
	(2.479)	(2.875)	(2.755)	(2.802)
Digital readiness	15.678***	43.351***	23.428***	42.220*
	(1.834)	(15.785)	(5.660)	(21.941)
Constant	1.262**	-7.343	0.749	-5.428
	(0.527)	(4.861)	(2.748)	(7.515)
First-stage results				
		Digital readiness		Digital readiness
Broadband Internet		0.085***		0.282***
		(0.019)		(0.055)
Hidden champion		0.081***		0.024
		(0.020)		(0.024)
Constant		0.247***		0.150***
		(0.015)		(0.045)
Control group weights	No	No	Yes	Yes
Regional controls	No	No	Yes	Yes
R-squared	0.053	-0.086	0.079	0.043
First-stage F statistic		19.585		26.547
Underidentification test		19.206		14.217
Observations	2,135	2,135	2,135	2,135

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Notes: Regional controls include population density, jobs per 1,000 residents, and region type and are all measured at the administrative district level. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al. 2010). Control group weights are derived from an entropy balancing method using Stata's ebalance command (Hainmueller & Xu 2013).

Table C.11: Share of revenues from incr. innovations – robustness tests

Dependent variable: Share of revenues from incremental innovations 2017 (in %)
OLS vs. IV estimates

	OLS	IV estimates	OLS	IV estimates
	(1a)	(1b)	(2a)	(2b)
Hidden champion	5.943**	4.729*	2.824	2.226
	(2.390)	(2.629)	(2.650)	(2.729)
Digital readiness	11.594***	26.095**	12.605***	28.835
	(1.530)	(12.843)	(4.883)	(22.240)
Constant	1.114***	-3.377	1.419	-3.819
	(0.431)	(3.955)	(2.191)	(7.405)
First-stage results				
		Digital readiness		Digital readiness
Broadband Internet		0.085***		0.273***
		(0.019)		(0.057)
Hidden champion		0.080***		0.027
		(0.021)		(0.024)
Constant		0.245***		0.151***
		(0.015)		(0.046)
Control group weights	No	No	Yes	Yes
Regional controls	No	No	Yes	Yes
R-squared	0.041	-0.012	0.038	0.004
First-stage F statistic		19.480		23.100
Underidentification test		19.123		12.850
Observations	2,113	2,113	2,113	2,113

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Notes: Regional controls include population density, jobs per 1,000 residents, and region type and are all measured at the administrative district level. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al. 2010). Control group weights are derived from an entropy balancing method using Stata's ebalance command (Hainmueller & Xu 2013).

Table C.12: Share of revenues from radical innovations – robustness tests

Dependent variable: Share of revenues from radical innovations 2017 (in %)
OLS vs. IV estimates

	OLS (1a)	IV estimates (1b)	OLS (2a)	IV estimates (2b)
Hidden champion	2.117***	1.237	0.132	-0.046
	(0.776)	(0.937)	(1.232)	(1.163)
Digital readiness	3.356***	13.910**	10.334*	15.115**
	(0.801)	(5.925)	(5.452)	(7.349)
Constant	0.168	-3.104*	-0.690	-2.230
	(0.238)	(1.792)	(1.493)	(1.767)
First-stage results				
		Digital readiness		Digital readiness
Broadband Internet		0.085***		0.273***
		(0.019)		(0.057)
Hidden champion		0.079***		0.027
		(0.021)		(0.024)
Constant		0.245***		0.150***
		(0.015)		(0.046)
Control group weights	No	No	Yes	Yes
Regional controls	No	No	Yes	Yes
R-squared	0.017	-0.115	0.086	0.107
First-stage F statistic		19.972		23.130
Underidentification test		19.635		12.875
Observations	2,127	2,127	2,127	2,127

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Notes: Regional controls include population density, jobs per 1,000 residents, and region type and are all measured at the administrative district level. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al. 2010). Control group weights are derived from an entropy balancing method using Stata's ebalance command (Hainmueller & Xu 2013).

Table C.13: Firm productivity – robustness tests

Dependent variable: Productivity 2017 (log)
OLS vs. IV estimates

	OLS	IV estimates	OLS	IV estimates
	(1a)	(1b)	(2a)	(2b)
Hidden champion	0.508***	0.415***	0.249***	0.229***
	(0.064)	(0.100)	(0.071)	(0.072)
Digital readiness	0.482***	1.545*	0.833***	1.421**
	(0.081)	(0.851)	(0.217)	(0.612)
Constant	11.493***	11.158***	11.497***	11.299***
	(0.031)	(0.269)	(0.102)	(0.225)
First-stage results				
		Digital readiness		Digital readiness
Broadband Internet		0.086***		0.289***
		(0.019)		(0.054)
Hidden champion		0.083***		0.022
		(0.020)		(0.024)
Constant		0.250***		0.156***
		(0.015)		(0.043)
Control group weights	No	No	Yes	Yes
Regional controls	No	No	Yes	Yes
R-squared	0.029	-0.050	0.146	0.112
First-stage F statistic		20.539		28.828
Underidentification test		20.246		15.347
Observations	2,165	2,165	2,165	2,165

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Notes: Regional controls include population density, jobs per 1,000 residents, and region type and are all measured at the administrative district level. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al. 2010). Control group weights are derived from an entropy balancing method using Stata's ebalance command (Hainmueller & Xu 2013).

Table C.14: Revenue growth rate – robustness tests

Dependent variable: Revenue growth rate 2016-2017 (in %)
OLS vs. IV estimates

	OLS	IV estimates	OLS	IV estimates
	(1a)	(1b)	(2a)	(2b)
Hidden champion	4.430	2.014	1.579	1.550
	(2.762)	(3.724)	(2.939)	(2.949)
Digital readiness	5.745*	38.647	17.111**	19.430
	(3.125)	(35.514)	(6.832)	(18.538)
Constant	0.803	-9.424	-1.232	-2.029
	(1.165)	(11.058)	(3.381)	(6.766)
First-stage results				
		Digital readiness		Digital readiness
Broadband Internet		0.081***		0.309***
		(0.021)		(0.055)
Hidden champion		0.070***		0.005
		(0.021)		(0.026)
Constant		0.249***		0.147***
		(0.017)		(0.046)
Control group weights	No	No	Yes	Yes
Regional controls	No	No	Yes	Yes
R-squared	0.003	-0.074	0.033	0.032
First-stage F statistic		15.345		31.793
Underidentification test		14.965		15.319
Observations	1,742	1,742	1,742	1,742

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Notes: Regional controls include population density, jobs per 1,000 residents, and region type and are all measured at the administrative district level. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al. 2010). Control group weights are derived from an entropy balancing method using Stata's ebalance command (Hainmueller & Xu 2013).

Table C.15: Description of regional control variables and instrument

Regional controls	Description	Min.	Max.	Mean	Obs.
Population density 2016	Population density per km^2 for every of the 402 German administrative districts	18	4,713	1,113	3,753
Job densitiy 2016	Number of jobs (+residents) per km2 for every of the 402 German admininstrative districts	16.700	5,961	385.812	3,753
Region type 2016	Settlement-based region type fro every of the 402 German administrative districts. Categorical variable with 1 = urban regions, 2 = regions with signs of urbanization, 3 = rural regions	1.00	3.00	1.742	3,751
Instrument variable					
Broadband access (2016)	Percentage of households in administrative district with at least 50MBits Internet access	1	100	71.775	3,753

Note: For more information about the variables see www.inkar.de

Table C.16: Digital readiness item scores – entropy balance results

		Hidden champions		Controls before entropy balancing (non-HCs)			Controls after entropy balancing (CG firms)		
Variable / item	Range of scale	Mean	Std. dev.	Mean	Std. dev	Diff.	Mean	Std. dev.	Diff.
Measure: Digital readiness index	0-1[1]	0.425	0.189	0.319	0.218	0.106 ***	0.353	0.210	0.072 ***
Production and/or provision of services									
(1) Digital interconnectivity within production and/or provision of services	0-1	0.618	0.302	0.519	0.357	0.099 ***	0.525	0.324	0.093 ***
(2) Digital interconnectivity between production and/or provision of services and logistics	0-1	0.601	0.282	0.423	0.360	0.178 ***	0.503	0.322	0.098 ***
(3) Digital interconnectivity with customers	0-1	0.566	0.282	0.488	0.336	0.078 **	0.511	0.310	0.055 *
(4) Digital interconnectivity with suppliers	0-1	0.483	0.293	0.416	0.323	0.067 **	0.462	0.302	0.021
Internal organization and communication									
(5) Teleworking	0-1	0.351	0.267	0.239	0.304	0.112 ***	0.269	0.285	0.082 ***
(6) Software-based communication (Skype etc.)	0-1	0.448	0.285	0.294	0.322	0.154 ***	0.364	0.320	0.084 ***
(7) Intranet-based platforms (Wikis etc.)	0-1	0.417	0.294	0.276	0.324	0.141 ***	0.324	0.313	0.093 ***
Sales and external communications									
(8) E-commerce	0-1	0.336	0.269	0.244	0.300	0.092 ***	0.274	0.294	0.062 **
(9) Social media (Facebook, Twitter etc.)	0-1	0.250	0.278	0.219	0.286	0.031	0.242	0.287	0.008
Information processing									
(10) Cloud applications	0-1	0.307	0.311	0.226	0.300	0.081 ***	0.225	0.278	0.082 **
(11) Analysis of Big Data	0-1	0.293	0.299	0.153	0.257	0.140 ***	0.179	0.265	0.114 ***

Notes: [1] Scale is normalized to values between 0 and 1, with 0=no digital readiness and 1=complete digital readiness.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ (based on heteroskedasticity robust estimation).

References

Angrist, J.D. & Pischke, J.-S. (2008). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press.

Augier, M. & Teece, D.J. (2009). Dynamic Capabilities and the Role of Managers in Business Strategy and Economic Performance. *Organization Science*, *20*(2), 410–421.

Baregheh, A., Rowley, J., & Sambrook, S. (2009). Towards a Multidisciplinary Definition of Innovation. *Management Decision*, *47*(8), 1323–1339.

Barua, M.K., Sharma, A.K., & Sharma, D. (2013). Efficiency and Productivity of Banking Sector: A Critical Analysis of Literature and Design of Conceptual Model. *Qualitative Research in Financial Markets*, *5*(2), 195–224.

Baum, C.F., Schaffer, M.E., & Stillman, S. (2010). IVREG2: Stata Module for Extended Instrumental Variables/2SLS and GMM Estimation. *Statistical Software Components*.

BBSR (2012). Schnelles Internet – Breitbandkluft in Deutschland. Retrieved July 1, 2020, from: https://www.bbsr.bund.de/BBSR/DE/Raumentwicklung/RaumentwicklungDeutschland/Projekte/Archiv/Breitband/breitband_node.html.

Becker, S.O. (2016). Using Instrumental Variables to Establish Causality. *IZA World of Labor*.

Berghaus, S., Back, A., & Kaltenrieder, B. (2016). *Digital Maturity and Transformation Report 2016*. St. Gallen: Universität St. Gallen, Crosswalk.

Berghaus, S., Back, A., & Kaltenrieder, B. (2017). *Digital Transformation and Maturity Report 2017*. St. Gallen: Universität St. Gallen, Crosswalk.

Bharadwaj, A., El Sawy, O.A., Pavlou, P.A., & Venkatraman, N. (2013). Digital Business Strategy: Toward a Next Generation of Insights. *MIS Quarterly*, 471–482.

Bitkom (2020). Deutsche Wirtschaft läuft der Digitalisierung weiter hinterher. Retrieved January 6, 2020, from: https://www.bitkom.org/Presse/Presseinformation/Deutsche-Wirtschaft-laeuft-der-Digitalisierung-weiter-hinterher.

BMWi (2017a). *Industrie 4.0 Fortschrittsbericht, April 2017*. Berlin: Bundesministerium für Wirtschaft und Energie.

BMWi (2017b). *Monitoring-Report Wirtschaft Digital 2017*. Berlin: Bundesministerium für Wirtschaft und Energie.

BMWi (2018). *Monitoring-Report Wirtschaft Digital 2018*. Berlin: Bundesministerium für Wirtschaft und Energie.

BMWi (2019). *Nationale Industriestrategie 2030*. Berlin: Bundesministerium für Wirtschaft und Energie.

Bouwman, H., Nikou, S., Molina-Castillo, F.J., & de Reuver, M. (2018). The Impact of Digitalization on Business Models. *Digital Policy, Regulation and Governance*, *20*(2), 105–124.

Brynjolfsson, E., Hitt, L.M., & Kim, H.H. (2011). *Strength in Numbers: How Does Data-Driven Decisionmaking Affect Firm Performance?*. Available at SSRN: https://ssrn.com/abstract=1819486.

Capgemini Consulting (2017). Culture First! Von den Vorreitern des digitalen Wandels lernen. Retrieved September 1, 2020, from: https://www.capgemini.com/consulting-de/wp-content/uploads/sites/32/2017/10/change-management-studie-2017-capgemini-consulting.pdf.

Capgemini Consulting & MIT Sloan Management (2017). Digital Transformation: A Roadmap for Billion-Dollar Organizations. Retrieved January 2, 2019, from: https://www.capgemini.com/wp-content/uploads/2017/07/Digital_Transformation__A_Road-Map_for_Billion-Dollar_Organizations.pdf.

Card, D. (2001). Estimating the Return to Schooling: Progress on Some Persistent Econometric Problems. *Econometrica*, *69*(5), 1127–1160.

Chow, G.C. (1960). Tests of Equality between Sets of Coefficients in Two Linear Regressions. *Econometrica*, 591–605.

Christensen, C.M., Raynor, M.E., McDonald Rory, & McDonald, R. (2015). What is Disruptive Innovation. *Harvard Business Review*, *93*(12), 44–53.

Cleff, T. (2015). *Deskriptive Statistik und Explorative Datenanalyse*. Wiesbaden: Springer Fachmedien.

Collis, D.J. (1994). Research Note: How Valuable are Organizational Capabilities? *Strategic Management Journal*, *15*(1), 143–152.

Cortina, J.M. (1993). What is Coefficient Alpha? An Examination of Theory and Applications. *Journal of Applied Psychology*, *78*(1), 98.

Danneels, E. (2002). The Dynamics of Product Innovation and Firm Competences. *Strategic Management Journal*, *23*(12), 1095–1121.

Digital Intelligence Institute (2015). Branchenatlas Digitale Transformation. Retrieved May 25, 2018, from: https://www.contenit.de/fileadmin/files/PDF/Dokumente/Branchenatlas-Digitale-Transformation.pdf.

Din, F.-U., Dolles, H., & Middel, R. (2013). Strategies for Small and Medium-Sized Enterprises to Compete Successfully on the World Market: Cases of Swedish Hidden Champions. *Asian Business & Management*, *12*(5), 591–612.

Drnevich, P.L. & Kriauciunas, A.P. (2011). Clarifying the Conditions and Limits of the Contributions of Ordinary and Dynamic Capabilities to Relative Firm Performance. *Strategic Management Journal*, *32*, 254–279.

Dyer, L. & Shafer, R.A. (1998). From Human Resource Strategy to Organizational Effectiveness: Lessons from Research on Organizational Agility. *CAHRS Working Paper Series*, *98*(12), 1–35.

Eisenhardt, K.M. & Martin, J.A. (2000). Dynamic Capabilities: What are They? *Strategic Management Journal*, *21*(10-11), 1105–1121.

FAZ (2019). Anlagenbauer Eisenmann insolvent. *Frankfurter Allgemeine Zeitung*, July 30, 2019.

Freimark, A.J., Habel, J., Hülsbömer, S., Schmitz, B., & Teichmann, M. (2018). *Hidden Champions - Champions der digitalen Transformation?*. Munich: IDG Business Media GmbH.

Furrer, O., Thomas, H., & Goussevskaia, A. (2008). The Structure and Evolution of the Strategic Management Field: A Content Analysis of 26 Years of Strategic Management Research. *International Journal of Management Reviews*, *10*(1), 1–23.

Griffith, D.A. & Harvey, M.G. (2001). A Resource Perspective of Global Dynamic Capabilities. *Journal of International Business Studies*, *32*(3), 597–606.

Hainmueller, J. (2012). Entropy Balancing for Causal Effects: A Multivariate Reweighting Method to Produce Balanced Samples in Observational Studies. *Political Analysis*, *20*(1), 25–46.

Hainmueller, J. & Xu, Y. (2013). Ebalance: A Stata Package for Entropy Balancing. *Journal of Statistical Software*, *54*(7).

Hanelt, A., Piccinini, E., Gregory, R.W., Hildebrandt, B., & Kolbe, L.M. (2015). Digital Transformation of Primarily Physical Industries - Exploring the Impact of Digital Trends on Business Models of Automobile Manufacturers. *12th International Conference on Wirtschaftsinformatik*, 1313–1327.

Harhoff, D. (2008). Innovation, Entrepreneurship und Demographie. *Perspektiven Der Wirtschaftspolitik*, *9*(Special Issue), 46–72.

Haussmann, H. (2003). Spezifische Erfolgsfaktoren von Hidden-Champions im Internationalisierungsprozess. In D. Holtbrügge (Ed.), *Management Multinationaler Unternehmungen: Festschrift zum 60. Geburtstag von Martin K. Welge*, (pp. 105–120). Heidelberg: Physica-Verlag.

Helfat, C.E. (1997). Know-How and Asset Complementarity and Dynamic Capability Accumulation: the Case of R&D. *Strategic Management Journal*, *18*(5), 339–360.

Helfat, C.E., Finkelstein, S., Mitchell, W., Peteraf, M., Singh, H., Teece, D., & Winter, S.G. (2007). *Dynamic Capabilities: Understanding Strategic Change in Organizations*. London: Blackwell.

Helfat, C.E. & Raubitschek, R.S. (2018). Dynamic and Integrative Capabilities for Profiting from Innovation in Digital Platform-Based Ecosystems. *Research Policy*, *47*(8), 1391–1399.

Hess, T., Matt, C., Benlian, A., & Wiesböck, F. (2016). Options for Formulating a Digital Transformation Strategy. *MIS Quarterly Executive*, *15*(2), 123–139.

Hilz, C. (2013). Strategisches Management und Hidden Champions. In M. Landes & E. Steiner (Eds.), *Psychologie der Wirtschaft*, (pp. 579–587). Wiesbaden: Springer.

Isaksson, A.J., Harjunkoski, I., & Sand, G. (2018). The Impact of Digitalization on the Future of Control and Operations. *Computers and Chemical Engineering*, *114*, 122–129.

IW Consult (2018). *Digital - Atlas Deutschland 2018*. Köln: Institut der deutschen Wirtschaft.

IW Consult (2016). *Digitalisierung und Mittelstand*. Köln: Institut der deutschen Wirtschaft.

Jansen, J.J.P., Van Den Bosch, F.A.J., & Volberda, H.W. (2006). Exploratory Innovation, Exploitative Innovation, and Performance: Effects of Organizational Antecedents and Environmental Moderators. *Management Science*, *52*(11), 1661–1674.

Kane, G.C., Palmer, D., Nguyen-Phillips, A., Kiron, D., & Buckley, N. (2017). Achieving Digital Maturity. *MIT Sloan Management Review and Deloitte University Press*.

Karim, S. & Mitchell, W. (2000). Path-Dependent and Path-Breaking Change: Reconfiguring Business Resources Following Acquisitions in the US Medical Sector, 1978–1995. *Strategic Management Journal*, *21*(10-11), 1061–1081.

Karimi, J. & Walter, Z. (2015). The Role of Dynamic Capabilities in Responding to Digital Disruption: A Factor-Based Study of the Newspaper Industry. *Journal of Management Information Systems*, *32*(1), 39–81.

Katz, M.L. & Shapiro, C. (1994). Systems Competition and Network Effects. *Journal of Economic Perspectives*, *8*(2), 93–115.

Kleibergen, F. & Paap, R. (2006). Generalized Reduced Rank Tests Using the Singular Value Decomposition. *Journal of Econometrics*, *133*(1), 97–126.

Kleis, L., Chwelos, P., Ramirez, R. V., & Cockburn, I. (2012). Information Technology and Intangible Output: The Impact of IT Investment on Innovation Productivity. *Information Systems Research*, *23*(1), 42–59.

Lee, J., Lee, K., & Rho, S. (2002). An Evolutionary Perspective on Strategic Group Emergence: a Genetic Algorithm-Based Model. *Strategic Management Journal*, *23*(8), 727–746.

Leifer, R., McDermott, C.M., O'connor, G.C., Peters, L.S., Rice, M.P., & Veryzer Jr, R.W. (2000). *Radical Innovation: How Mature Companies Can Outsmart Upstarts*. Boston, MA: Harvard Business Press.

Lenka, S., Parida, V., Sjödin, D.R., & Wincent, J. (2016). Digitalization and Advanced Service Innovation. *Management of Innovation and Technology*, (3), 1–5.

Lichtblau, K., Stich, V., Bertenrath, R., Blum, M., Bleider, M., Millack, A., … Schröter, M. (2015). Industrie 4.0-Readiness. Retrieved May 1, 2018, from: http://www.impuls-stiftung.de/documents/3581372/4875835/Industrie+4.0+Readniness+IMPULS+Studie+Oktober+2015.pdf/447a6187-9759-4f25-b186-b0f5eac69974.

Makadok, R. (2001). Toward a Synthesis of the Resource-Based and Dynamic-Capability Views of Rent Creation. *Strategic Management Journal*, *22*(5), 387–401.

Manyika, J., Lund, S., Bughin, J., Woetyel, J., Stamelov, K., & Dhingra, D. (2016). Digital Globalization: The New Era of Global Flows. Retrieved January 29, 2019, from: https://www.mckinsey.com/business-functions/digital-mckinsey/our-insights/digital-globalization-the-new-era-of-global-flows.

Markovitch, S. & Willmott, P. (2014). Accelerating the Digitization of Business Processes. Retrieved January 29, 2019, from: https://www.mckinsey.com/business-functions/digital-mckinsey/our-insights/accelerating-the-digitization-of-business-processes.

Microsoft (2017). Digital Transformation Report. Retrieved August 28, 2019, from: https://qvartz.com/media/1501/digitaltransformationreport.pdf.

Mooi, E., Sarstedt, M., & Mooi-Reci, I. (2018). *Market Research - The Process, Data, and Methods Using Stata*. Singapore: Springer Nature.

Müller, S.C., Böhm, M., Schröer, M., & Bakhirev, A. (2016). Geschäftsmodelle in der digitalen Wirtschaft - Vollstudie. *Studien Zum Deutschen Innovationssystem*, (13), 1–148.

Normand, S.-L.T., Landrum, M.B., Guadagnoli, E., Ayanian, J.Z., Ryan, T.J., Cleary, P.D., & McNeil, B.J. (2001). Validating Recommendations for Coronary Angiography Following Acute Myocardial Infarction in the Elderly: A Matched Analysis Using Propensity Scores. *Journal of Clinical Epidemiology*, *54*(4), 387–398.

OECD (2018a). Defining Innovation. Retrieved January 3, 2019, from: https://www.oecd.org/site/innovationstrategy/defininginnovation.htm.

OECD (2018b). *Oslo Manual 2018 - Guidelines for Collecting, Reporting and Using Data on Innovation*, (4th ed.). Paris: OECD Publishing.

Peters, B. & Rammer, C. (2013). Innovation Panel Surveys in Germany. In F. Gault (Ed.), *Handbook of Innovation Indicators and Measurement*, (pp. 135–177). Cheltenham, UK and Northampton, USA: Edward Elgar Publishing.

Pitelis, C.N. & Teece, D.J. (2010). Cross-Border Market Co-Creation, Dynamic Capabilities and the Entrepreneurial Theory of the Multinational Enterprise. *Industrial and Corporate Change*, *19*(4), 1247–1270.

Pittrof, M. (2011). Kennzeichen der Unternehmenskultur bei Hidden Champions. In *Die Bedeutung der Unternehmenskultur als Erfolgsfaktor für Hidden Champions*, (pp. 37–70). Wiesbaden: Gabler.

Rammer, C. (2017). *ZEW - Innovationserhebung 2016*. Mannheim: Zentrum für Europäische Wirtschaftsforschung.

Rammer, C. & Spielkamp, A. (2019). German Hidden Champions: Competitive Strategies, Knowledge Management and Innovation in Globally Leading Niche Players. *Ekonomiaz: Revista Vasca de Economía*, *95*(01), 65–87.

Rammer, C. & Spielkamp, A. (2015). *Hidden Champions Driven by Innovation - Empirische Befunde auf Basis des Mannheimer Innovationspanels. ZEW Dokumentation Nr. 15-03*. Mannheim: Zentrum für Europäische Wirtschaftsforschung.

Reitzig, M. & Maciejovsky, B. (2015). Corporate Hierarchy and Vertical Information Flow Inside the Firm - a Behavioral View. *Strategic Management Journal*, *36*(13), 1979–1999.

Rogers, D.L. (2016). *The Digital Transformation Playbook: Rethink Your Business for the Digital Age*. New York City: Columbia University Press.

Rothaermel, F.T. & Hess, A.M. (2007). Building Dynamic Capabilities: Innovation Driven by Individual-, Firm-, and Network-Level Effects. *Organization Science*, *18*(6), 898–921.

Saam, M., Viete, S., & Schiel, S. (2016). *Digitalisierung im Mittelstand: Status Quo, aktuelle Entwicklungen und Herausforderungen*. Mannheim: Zentrum für Europäische Wirtschaftsforschung.

Sambamurthy, V., Bharadwaj, A., & Grover, V. (2003). Shaping Agility Through Digital Options: Reconceptualizing the Role of Information Technology in Contemporary Firms. *MIS Quarterly*, *27*(2), 237–263.

Schmieder, M. (2017). BenchMarking Center Europe: Hidden Champions. Retrieved August 28, 2019, from: https://www.benchmarking.center/images/download/studien/benchmarking/bmc_hidden_champions_2017.pdf.

Schmieder, M. (2018). Hidden Champions Benchmarking. In J.-P. Büchler (Ed.), *Fallstudienkompendium Hidden Champions*, (pp. 197–222). Wiesbaden: Springer Fachmedien.

Schröder, C., Schlepphorst, S., & Kay, R. (2015). IfM Bonn: Bedeutung der Digitalisierung im Mittelstand. *Institut Für Mittelstandsforschung, IfM-Materialien, No. 244*.

Simon, H. (2019). Die digitalen Hidden Champions. *Harvard Business Manager*, November 2019.

Simon, H. (2012). *Hidden Champions-Aufbruch nach Globalia: Die Erfolgsstrategien unbekannter Weltmarktführer*. Frankfurt am Main: Campus Verlag.

Simon, H. (2018). Hidden Champions - Innovative Speerspitze der Globalisierung. In J.-P. Büchler (Ed.), *Fallstudienkompendium Hidden Champions: Innovationen für den Weltmarkt*, (pp. 3–19). Wiesbaden: Springer Gabler.

Simon, H. (2009). *Hidden Champions of the Twenty-First Century: The Success Strategies of Unknown World Market Leaders*. New York: Springer Science & Business Media.

Statista (2020). Tech Companies Dominate S&P 500 Index. Retrieved July 1, 2020, from: https://www.statista.com/chart/20794/tech-companies-highly-valued-in-sp-500/.

Stock, J.H., Wright, J.H., & Yogo, M. (2002). A Survey of Weak Instruments and Weak Identification in Generalized Method of Moments. *Journal of Business & Economic Statistics*, *20*(4), 518–529.

Suh, Y. & Kim, M.-S. (2014). Internationally Leading SMEs vs. Internationalized SMEs: Evidence of Success Factors from South Korea. *International Business Review*, *23*(1), 115–129.

Teece, D., Peteraf, M., & Leih, S. (2016). Dynamic Capabilities and Organizational Agility: Risk, Uncertainty, and Strategy in the Innovation Economy. *California Management Review*, *58*(4), 13–35.

Teece, D. & Pisano, G. (1994). The Dynamic Capabilities of Firms: An Introduction. *Industrial and Corporate Change*, *3*(3), 537–556.

Teece, D.J. (2014). A Dynamic Capabilities-Based Entrepreneurial Theory of the Multinational Enterprise. *Journal of International Business Studies*, *45*(1), 8–37.

Teece, D.J. (2012). Dynamic Capabilities: Routines Versus Entrepreneurial Action. *Journal of Management Studies*, *49*(8), 1395–1401.

Teece, D.J. (2017). Dynamic Capabilities and (Digital) Platform Lifecycles. In J. Furman, A. Gawer, B. S. Silverman, & S. Stern (Eds.), *Advances in Strategic Management - Entrepreneurship, Innovation, and Platforms*, (Vol. 37, pp. 211–225). Emerald Publishing.

Teece, D.J. (2016). Dynamic Capabilities and Entrepreneurial Management in Large Organizations: Toward a Theory of the (Entrepreneurial) Firm. *European Economic Review*, *86*, 202–216.

Teece, D.J. (2007). Explicating Dynamic Capabilities: The Nature and Microfoundations of (Sustainable) Enterprise Performance. *Strategic Management Journal*, *28*(1), 1319–1350.

Teece, D.J., Pisano, G., & Shuen, A. (1997). Dynamic Capabilities and Strategic Management. *Strategic Management Journal*, *18*(7), 509–533.

Thangavelu, P. (2020). Companies That Failed to Innovate and Went Bankrupt. Retrieved July 1, 2020, from: https://www.investopedia.com/articles/investing/072115/companies-went-bankrupt-innovation-lag.asp.

The Economist (2014). Schumpeter - German Lessons. *The Economist*, July 12, 2014.

The Economist (2020). Special Report - The Data Economy. *The Economist*, February 22, 2020.

Tushman, M.L. & O'Reilly III, C.A. (1996). Ambidextrous organizations: Managing evolutionary and revolutionary change. *California Management Review*, *38*(4), 8–29.

Venohr, B. & Meyer, K.E. (2007). *The German Miracle Keeps Running: How Germany's Hidden Champions Stay Ahead in the Global Economy. Working Paper No. 30*. Berlin: Berlin School of Economics, Institute of Management.

Vogel, R. & Güttel, W.H. (2013). The Dynamic Capability View in Strategic Management: A Bibliometric Review. *International Journal of Management Reviews*, *15*, 426–446.

Voudouris, I., Lioukas, S., Makridakis, S., & Spanos, Y. (2000). Greek Hidden Champions:: Lessons from Small, Little-Known Firms in Greece. *European Management Journal*, *18*(6), 663–674.

Wang, C.L. & Ahmed, P.K. (2007). Dynamic Capabilities: A Review and Research Agenda. *International Journal of Management Reviews*, *9*(1), 31–51.

WEF (2020). Onward and Upward? The Transformative Power of Technology. Retrieved September 1, 2020, from: http://reports.weforum.org/digital-transformation/onward-and-upward-the-transformative-power-of-technology/.

Winter, S.G. (2003). Understanding Dynamic Capabilities. *Strategic Management Journal*, *24*(10), 991–995.

Wittenstein, D. (2019). Miracle or Myth? A Panel Analysis of Hidden Champion Performance. *Mimeo*.

WiWo & Neuland (2015). *Digital Transformation Report*. Köln: Wirtschaftswoche und Neuland GmbH.

Wooldridge, J.M. (2013). *Introductory Econometrics - A Modern Approach*, (5th ed.). Boston, MA: Cengage.

Yoo, Y., Boland Jr., R.J., Lyytinen, K., & Majchrzak, A. (2012). Organizing for Innovation in the Digitized World. *Organization Science*, *27*(5), 1398–1408.

Yoo, Y., Henfridsson, O., & Lyytinen, K. (2010). Research Commentary - The New Organizing Logic of Digital Innovation: An Agenda for Information Systems Research. *Information Systems Research*, *21*(4), 724–735.

Zahra, S.A., Sapienza, H.J., & Davidsson, P. (2006). Entrepreneurship and Dynamic Capabilities: A Review, Model and Research Agenda. *Journal of Management Studies*, *43*(4), 917–955.

ZEW (2019). Mannheim Innovation Panel - The Annual German Innovation Survey. Retrieved March 30, 2019, from: https://www.zew.de/WS109-1.

Zollo, M. & Winter, S.G. (2002). Deliberate Learning and the Evolution of Dynamic Capabilities. *Organization Science*, *13*(3), 339–351.

Zott, C. (2003). Dynamic Capabilities and the Emergence of Intraindustry Differential Firm Performance: Insights from a Simulation Study. *Strategic Management Journal*, *24*(2), 97–125.

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