Digitalization, resource mobilization and firm growth in emerging industries

Article

Published Version

Audretsch, D. B. and Belitski, M. (2024) Digitalization, resource mobilization and firm growth in emerging industries. British Journal of Management, 35 (2). pp. 613-628. ISSN 1467-8551 doi: 10.1111/1467-8551.12769 Available at https://centaur.reading.ac.uk/113729/

To link to this article DOI: http://dx.doi.org/10.1111/1467-8551.12769

Publisher: Wiley

BJM BRITISH JOURNAL of MANAGEMENT — BRITISH ACADEMY OF MANAGEMENT

Check for updates

British Journal of Management, Vol. 0, 1–18 (2023)
DOI: 10.1111/1467-8551.12769

Digitalization, Resource Mobilization and Firm Growth in Emerging Industries

David B. Audretsch[1] and Maksim Belitski[2,3,4]

[1]School of Public and Environmental Affairs, Indiana University Bloomington, 1315 E. 10th Avenue SPEA, Bloomington, IN, 47405, USA, [2]Henley Business School, University of Reading, Whiteknights Campus, Reading, RG6 6UD, UK, [3]College of Business, Loyola University of New Orleans, 6363 St. Charles Avenue, New Orleans, LA, 70118, USA, and [4]ICD Business School, 12 Rue Alexander Parodi, Paris, 75010, France
Corresponding author email: m.belitski@reading.ac.uk

While most firms do not grow, a small number of firms grow and enhance their equity and debt capital intensity. Researchers, managers and policymakers question the role that digital technologies play in propelling firm growth and resource mobilization. Using a longitudinal dataset from emerging industries in the United Kingdom during 2010–2019, we distinguish three types of firms and examine their growth and resource mobilization. First, we find that digitally advanced firms grow faster and enhance equity capital intensity while reducing debt capital intensity. Second, we find that the relationship between digitally advanced firms and firm growth is mediated by equity capital intensity. Third, firm size positively moderates the effect of digitally advanced firms on firm growth. Firm age does not moderate this relationship. Other firm-level characteristics, such as number of digital tools, firm productivity, accelerator experience and stage of growth, may either impede or facilitate a firm's growth and resource mobilization. This study helps policymakers and firm managers in emerging industries better understand the role of digitalization and resources in firm growth.

Introduction

Recently, the disruptions to business during the COVID-19 pandemic further highlighted the importance of digitalization for firm growth, cost efficiency, innovation and resilience (Björkdahl, 2020). It became urgent for firms to invest in digital technologies and to enter digital markets for future innovation and growth. This urgency prompted financial (Vismara, 2022), technological, economic and institutional changes, termed the 'new normal'. Industries, societies and entrepreneurs are not reverting to the previously less digital world (Ahlstrom *et al.*, 2020).

The broad impact of digital technologies on businesses and commerce is unprecedented in scale. The Digitally Driven report (Digitally Driven, 2021), based on a survey of over 5000 small and medium enterprise (SME) leaders across 30 European countries during 2020, showed that while 90% of businesses reported negative impacts from the pandemic, those that integrated digital technologies into their operations and adopted various digital business tools continued mobilizing resources, mitigating the negative effects of the pandemic. Put simply, sales and jobs were saved in the most digitally advanced businesses that demonstrated greater resilience and rapid growth (Digitally Driven, 2021).

Thus, policymakers are very keen to support and investors are keen to invest in businesses that utilize digital technologies and see them as an essential for their business model, innovation and new markets entry (Kowalkowski, Kindström and Gebauer, 2013). Digitally Driven (2021) uses two criteria to distinguish between digitally advanced versus digitally uncertain businesses. The first criterion is the use of digital tools, with digitally driven businesses utilizing on average 13 digital tools, including robotics and artificial intelligence, out of 20 tools named in the report versus, on average, one digital tool for digitally uncertain businesses and anything between two and 13 digital tools on average for digitally evolving businesses. The second criterion is how essential digital tools are for a business model, with all digitally advanced firms seeing the use of digital tools as essential, digitally evolving firms seeing the use of digital tools as desirable, while digitally uncertain businesses are the opposite (digital tools not being essential or desirable). The desirability of digital tools and their incorporation into a business model is directly linked to firm presence in digital markets and the use of digital tools for innovation, sales, customer engagement and data collection in these markets.

Digitally advanced businesses outperformed others across a range of operational and financial metrics during 2020–2021 as they utilize 'on average 3.3 times more digital tools than digitally uncertain businesses' (Digitally Driven, 2021: 9), on average '2.25 times more social media and video platforms, on average 8.7 times more customer insights tools and 5–14 times more online training platforms, business/data analytics tools and website e-commerce' (Digitally Driven, 2021: 25).

A broader adoption of digital tools and their integration into business models is not limited to traditional industries. It is especially relevant in emerging industries, where firms substantially rely on digital tools for resource attraction and growth.

While it's suggested that digitalization enhances cost efficiency, connectivity, innovation, new product development and operational efficiency, limited focus has been given to the role that the adoption and utilization of digital tools play in firm growth (Björkdahl, 2020; Coad, Daunfeldt and Halvarsson, 2018) and resource mobilization (Cumming, Meoli and Vismara, 2021; Fisch, Meoli and Vismara, 2022; Vanacker and Manigart, 2010).

Despite the extant research and progress in our understanding of firm growth (Belitski *et al.*, 2023; Coad, Daunfeldt and Halvarsson, 2018), we lack key insights into specific firm- and industry-level factors as relevant considerations (Nason and Wiklund, 2018) and what mechanisms moderate this relationship. More insight into emerging industries and firm idiosyncrasies such as firm age and firm size is also needed (Audretsch, Belitski and Caiazza, 2021; Olleros, 1986).

Drawing on the knowledge-based view (KBV) of a firm (Grant, 1996), the objective of this paper is to use the context of emerging industries to: (a) examine the direct effect of a firm's adoption of digital tools in mobilizing equity and debt resources and facilitating its growth; and (b) identify and measure the indirect effect (via resource mobilization) of firm digitalization on firm growth (Björkdahl, 2009, 2020).

We ask the following research question: What are the direct and indirect effects (mediated by resource mobilization) of an increase in firm digitalization on firm growth? To address this, we study growth in a sample of firms in emerging industries, rather than exclusively focusing on high-growth firms in sectors like manufacturing (Björkdahl, 2020). Employment and sales are the most commonly used growth indicators within the firm growth literature (Coad, Daunfeldt and Halvarsson, 2018; Delmar, 2006).

Drawing on the theoretical synthesis of Bertoni, Meoli and Vismara (2023), we make two contributions bringing together two literature strands on firm growth and resource mobilization. First, we distinguish firm growth from other by-products that emerge from investment in digital technology, such as the development of cost-efficient processes and service operations (Kowalkowski, Kindström and Gebauer, 2013), innovation, scalability and resilience (Björkdah, 2020) and resource allocation (Dethine, Enjolras and Monticolo, 2020; Martín-Peña, Sánchez-López and Díaz-Garrido, 2019). Building on the KBV of a firm (Cumming, Meoli and Vismara, 2021; Vismara, 2016), we argue that digitally advanced firms, compared to digitally evolving and uncertain firms, are able to increase the rate of firm growth by increasing both equity and debt capital intensity in a firm. We untangle and focus on resource mobilization and digital capabilities which help to explain whether firms can achieve higher levels of firm growth. Second, we explain the role of two boundary conditions (firm age and firm size) in moderating the effect between digitally advanced firms and resource mobilization (Bertoni *et al.*, 2022) and firm growth. In doing so, we provide insights into the underlying mechanisms and drivers of resource mobilization and growth using the micro-level data of 5023 firms in the United Kingdom, with 36,205 observations during 2010−2019 (Beauhurst, 2021).

Extending the KBV of a firm (Grant, 1996; Nason and Wiklund, 2018), we argue that the digital technologies and capabilities employed by digitally advanced firms confer a competitive advantage (Eisenhardt and Santos, 2002). We support this hypothesis using panel data for UK firms in emerging sectors. Our findings could offer invaluable insights to practitioners, academics and policymakers about the magnitude and dynamics of digitalization's impact on firm growth trajectories and resource mobilization.

This paper is structured as follows. The next section provides an overview of the emerging industries in the United Kingdom and develops the foundations for digitally advanced, evolving and uncertain firms. The third section debates and develops the research hypotheses. The fourth section describes the data, main variables and model used in the estimation. The fifth section presents the results, including robustness checks. The final section discusses and concludes.

Digitalization in emerging industries: Overview

Firms in emerging sectors have garnered significant attention from researchers and policymakers because they are highly innovative and exhibit rapid growth. This makes them exceptionally appealing to investors who view these firms as lucrative sources of profit, offering high returns on investment. Companies in emerging sectors lead the way in adopting digital technologies, experimenting with a multitude of digital tools and technologies. They introduce new products and services that are both technologically sophisticated and innovative, fundamentally transforming business operations and everyday life. According to the International Data Corporation (IDC), the overall investment in emerging sectors in the United Kingdom that utilize the latest technologies is anticipated to surge by 20% globally in 2023 (IDC, 2019).

Digitalization has profoundly influenced business models, impacting firms' capacities to innovate using digital tools (Kuusisto, 2017) and mobilize resources for accelerated growth (Bertoni *et al.*, 2022). Nambisan *et al.* (2017) posit that digital technologies, combined with new communication channels, have broadened the horizons for innovation and experimentation in ways that were unimaginable just a decade ago. Drawing on the theoretical framework on digitalization by Björkdah (2020) and a recent classification of businesses by Digitally Driven (2021), we distinguish between three types of firms: digitally advanced, digitally evolving and digitally uncertain. Given the microdata availability on digital tools adoption and following the guidelines of Digitally Driven (2021), we apply two criteria: number of digital tools[1] adopted and number of digital markets[2] where a firm is present. It is vital to recognize that the significance of digital tools in business models directly correlates with the digital markets in which firms operate and cater for, and vice versa (Nambisan *et al.*, 2017). Firms active in multiple digital markets are likely to regard digital tools as indispensable for their operations and business models (digitally advanced), in contrast to firms that are not present in digital markets and, therefore, do not view digital tools as crucial (digitally uncertain). Digitally evolving businesses essentially occupy a transitional phase between these two extremes.

We develop the typology of digitally advanced versus uncertain firms in Figure 1. This framework can be applied across various industries and markets, as the same digital tools – such as social media platforms or customer relationship management systems – are universally used across diverse markets, products and services.

[1] Beauhurst (2021) identifies the following digital technologies used by the firms: e-commerce and business website; Big Data; data analytics tools; email platforms; business website; customer insight tools; knowledge and data collaboration tool; digital ads; online marketplace tools such as Google play and Apple store; video-conferencing and digital working; digital payments; search engine optimization; social media and video platforms such as Pinterest, LinkedIn and Facebook; cloud technology; mobile tools; Internet of Things; robotics and artificial intelligence.

[2] Firms in emerging industries can be present in the following digital markets: mobile and mobility; IT and telecom; e-commerce; e-outlets; electronic digital banking; business and IT architecture; business banking; digital healthcare; design services; electrical parts and instruments; hardware; public relations; online games; IT support; website hosting; nanotechnology; semiconductors; collaboration tools and software; business analytics; business-to-customers web; business-to-business web; online publishing; research tools; medical devices; clinical diagnostics; medical instruments; processors; mobile and server hardware; networking; consumer electronics; other hardware; embedded software; middleware; desktop software; server software; SaaS; Internet platforms and other software.

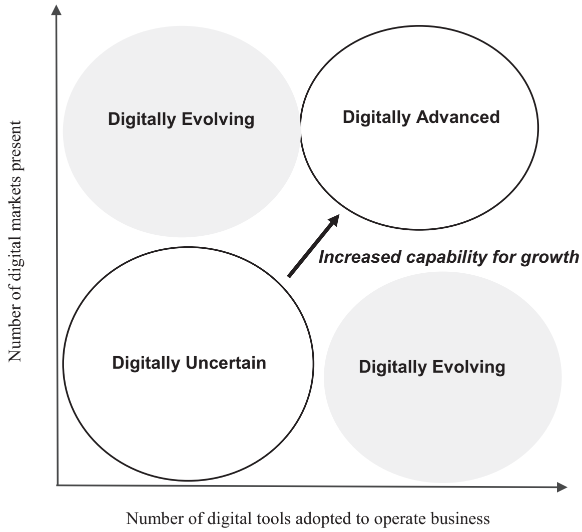

Figure 1. Firms typology by number of digital markets present and digital tools used. Source: Modified and adapted from Digitally Driven (2021)

Theoretical framework

Digitalization is important as it enables more integrated value chains, increases efficiency, reduces lead times and allows for better control over operations to increase growth (Björkdahl, 2020). Digitalization has become a vital resource for firms, with digitally advanced firms considering digital technologies and capabilities (Martín-Peña, Sánchez-López and Díaz-Garrido, 2019; Nason and Wiklund, 2018) their most important strategic resource.

There are several mechanisms which enable digitally advanced firms to grow rapidly and create value, specifically in emerging markets. First, digitally advanced firms enable better servitization, providing a valuable opportunity to improve firm business models. Digitalization transforms a firm's business model into a stronger digital business model (Martín-Peña, Sánchez-López and Díaz-Garrido, 2019) and changes the strategic alignment between its business and IT strategies, securing efficiency of operations and its alignment with the strategy for value creation (Belitski and Liversage, 2019).

Second, digitally advanced firms enable faster and more secure delivery of services and products, improving the service orientation of a firm based on the ability of digitally advanced firms to access, process, store and exchange data faster. This gives firms a competitive advantage in highly competitive markets (Martín-Peña, Sánchez-López and Díaz-Garrido, 2019). While digital technologies play a key role in the provision of product-service systems, digitally advanced firms have greater digital capabilities that enhance their ability to access and absorb external data and information, reducing transaction and managerial costs for such operations and data analysis (Lu, Song and Yu, 2022).

Third, digitally advanced firms enable data sharing within a firm and externally, especially using the cloud technology that allows data management within the firm and across partners, such as enterprise group units, suppliers, clients, competitors and universities (Li *et al.*, 2016). Digital technologies reduce intermediation costs (Li *et al.*, 2016) when incorporated into supply chain processes, increasing their efficiency (Karimi and Walter, 2015) and creating opportunities for growth (Björkdahl, 2009; Porter and Heppelmann, 2014).

Fourth, digitally advanced firms are capable of more efficient monitoring and integration of data across organizations. For example, the visualization of new product developments and prototypes shortens the time between product ideation, development and market commercialization, increasing growth. We hypothesize:

H1: In emerging industries, digitally advanced firms generate greater revenues than digitally evolving and digitally uncertain firms.

In recent years, resource mobilization has witnessed how digital technologies may channel resources to firm performance (Walthof-Borm, Schwienbacher and Vanacker, 2018). While digital technologies provide a potential resource for digitally advanced firms (Digitally Driven, 2021), the way digital technologies can be implemented and then attract resources within varying industrial contexts is subject to debate. The KBV that considers a firm's knowledge and capabilities for value creation can explain the mechanism which relates firm digitalization to firm growth via resource mobilization (Bertoni, Meoli and Vismara, 2023; Vismara, 2016).

One can argue that digitally advanced firms are more capable of introducing advanced services and outreaching potential investors to raise funding.

Resource mobilization is unlikely to occur if little investment is made in human capital and digital technologies related to engaging with potential investors or data management, processing and analysis (Nambisan *et al.*, 2017), making both knowledge and digital technologies interconnect. A vast body of literature has been produced at the intersection of finance and management, aiming to predict how digital technology and its adoption by a firm may predict the fundraising process or help to secure debt and equity capital (Vismara, 2019, 2022; Vismara, Benaroio and Carne, 2017). There is a strand of literature in finance which argues that debt financing is preferable to equity financing for growth, as it enables firms to retain more control over decision-making and strategy, as well as higher retained profits in case a profit is generated. The extant literature by Modigliani and Miller (1963) and Myers and Majluf (1984) focuses on the capital structure theorem with taxes. Their model suggests explanations for several aspects of corporate financing behaviour, including the tendency to rely on internal sources of funds and to prefer debt over equity financing. This is different for the emerging sectors, which distinguishes this study from prior research on resource mobilization. In emerging industries where the business model of each firm is still under development, returns from R&D investment take time, limiting the owner's ability to secure debt capital and making equity capital investment more achievable. The reasons are as follows.

First, several digital tools could be used for resource mobilization for higher performance (Cumming, Meoli and Vismara, 2021). For example, customer and investor insight tools (e.g. Google Trends, online surveys) will help firms to outreach and collect data from potential customers and investors. Digital payment tools (e.g. PayPal, G Pay, Venmo, Apple Pay, Shop Pay, Amazon Pay, etc.) ease selling and enable scale-up. The use of social media especially improves firms' brand awareness among investors, generates word of mouth and can positively influence investors' decisions. Firms can also gain direct access to resources, with reduced costs (e.g. peer-to-peer or business-to-business lending, instead of traditional bank loans), using digital technologies fundraising in 'real time' (Tajvidi and Karami, 2021).

Second, increased firm digitalization leads to greater screening of investors and enhances the quality of business monitoring in terms of operations, payments and finance. The adoption of multiple digital technologies will ensure that complex information-based lending procedures can be automated and investors can easily monitor the use of funds, providing an advantage even for smaller firms (Vismara, 2016, 2018).

Third, digital capabilities will signal positively to potential investors and stakeholders, as digital platforms and tools (Koch and Windsperger, 2017; Nambisan and Baron, 2021) are often seen as a sign of a firm's technological capabilities and maturity (Dethine, Enjolras and Monticolo, 2020). Contemporary studies have demonstrated that digitally advanced firms exhibit greater coordination and leadership within the company and with external partners (Digitally Driven, 2021) and raise more equity funding.

The entire firm growth is ultimately dependent on whether and to what extent firms can identify the need to adopt digital technologies (Audretsch and Belitski, 2021) and then how they use them to mobilize resources. Digitally advanced firms are better prepared than digitally uncertain and evolving firms to take advantage of a large amount of information from the environment and incorporate technology to increase resource availability and ultimately create value (Nambisan *et al.*, 2017). Thus, we hypothesize:

H2: In emerging industries, resource mobilization has a mediating effect on the ability of digitally advanced firms to generate greater revenues than digitally evolving and digitally uncertain firms.

Firms vary in their ability to realize value from the opportunities inherent in the resources and capabilities they possess. For example, firms at different stages of firm growth (Nambisan and Baron, 2021) have different ambitions and resources for growth that may affect their adoption of digital technologies and their resource mobilization. The vast majority of firms remain small, and many seek moderate growth (Belitski *et al.*, 2023). Drawing attention to the role that firm age and firm size may play in understanding the relationship between the adoption of digital technology and firm growth, Nason and Wiklund (2018) revealed that firm size negatively moderates the resource–growth relationship, such that the growth effect is weaker in small firms.

An increase in firm size signals that a firm has successfully passed a series of transformational periods, from the seed to the venture and maturity stages. Firms will require debt and equity capital at each growth stage to determine their minimal viable product and commercialize it in the market. Resources are limited and firms therefore employ few if any people, which limits firm growth. Once a firm has defined its product, it begins to penetrate the market and hire more employees. Adding employees to an existing firm will further enrich the quality of its products and services through synergies and create a critical mass of skills and capabilities to accelerate, which is particularly important in emerging industries where a critical mass of skills and capabilities should be reached. Increasing the variety of products adjusted for different markets due to the ability to recognize and implement market opportunities as employee size grows, boosting sales. We hypothesize:

H3: In emerging industries, firm size positively moderates the relationship between (a) digitally advanced firms and firm growth as well as (b) digitally advanced firms and resource mobilization.

Contemporary research has suggested that firm age plays an important role in firm growth (Haltiwanger, Jarmin and Miranda, 2013). However, unlike firm size, firm age was found to be negatively associated with growth (Haltiwanger, Jarmin and Miranda, 2013). For instance, Daunfeldt, Elert and Johansson (2014) found that firm growth is smaller in older firms than in younger firms. This happens because a firm's strategic focus shifts over time from exploration to exploitation (March, 1991), and from market opportunity seeking to competitive advantage seeking and choosing a specific business model that works. However, this is different in emerging sectors, where firm ages are on average low, meaning many firms are startups or at the beginning of venture growth. Emerging industries experiment with new products and services and constantly apply market opportunity-seeking strategies, unable to shift from exploration to exploitation. Younger firms tend to devote more time and effort to product innovation and invest more in R&D (Audretsch, Belitski and Caiazza, 2021).

There is a lower share of established firms in the industry compared to recently established early-stage growth firms, which aim to challenge the industry status quo or create entirely new industries. The relative share of firms that transition from exploration to exploitation (March, 1991) will be higher than the share of established firms going through this transition in emerging industries. This means that unlike Coad, Daunfeldt and Halvarsson (2018), who found that young firms are more likely to have two consecutive periods of positive growth and older firms have more erratic growth, given that many of the firms are young in emerging industries, an increase in firm age will balance exploration and exploitation strategies and is unlikely to facilitate firm growth and resource mobilization. We hypothesize:

H4: In emerging industries, firm age does not moderate the relationship between (a) digitally advanced firms and firm growth as well as (b) digitally advanced firms and resource mobilization.

The conceptual model of our hypothesis is illustrated in Figure 2.

Data and methods

Sample description

The sample is collected using the Beauhurst (2021) data service, which collects firm-level data on high-growth firms located in emerging sectors in the United Kingdom during 2010–2019. Beauhurst used an artificial intelligence algorithm to scrape firms' websites and social media, fundraising platforms, news, company annual reports and other announcements in search of data. Their tracking algorithm is based on the following seven selection criteria: equity or debt fundraising secured for the innovation activity; a company was either acquired or a company is a university (corporate) spinout; has completed one of the United Kingdom's top business accelerator programmes; has completed a management buy-in/buy-out; has been listed on one of the United Kingdom's high-growth lists (e.g. Fast Track 100 or Technology Fast 50 indicates that a company is gaining visibility and growing quickly); has received an innovation grant from a selected programme (e.g. Innovate UK); and has grown at least 10–20% annually over the last 3 years (scale-up). Compliance with at least one criterion would make a company trackable, which means it will get to our dataset. The data were downloaded in March 2020 and span the period January 2010 to January 2020, just before the COVID-19 pandemic. Having cleaned our sample of missing values and outliers in digitalization and resource mobilization, we matched 5023 firms and 36,205 observations during the 2010–2019 period. An average firm was observed for 7.2 years. The list of emerging sectors included in this study is

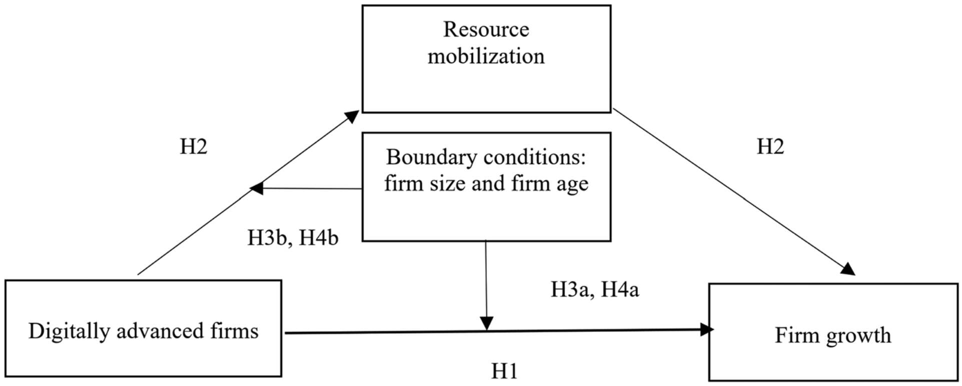

Figure 2. The conceptual model

available in Table 1, along with the industry, firm size, growth stage and region division.

Variables

Dependent variable. Firm growth is operationalized by determining the log-difference of firm sales, a common methodology employed when calculating growth rates based on firm sales or employment figures (Coad, 2009; Coad, Daunfeldt and Halvarsson, 2018; Tornqvist and Vartia and Vartia, 1985). Following the approach of Coad and Rao (2008), we retained firms in our sample that exhibit growth rates in the 95th percentile or higher. This inclusion is significant as we have a keen interest in high-growth firms. Additionally, while our data doesn't distinctly identify firms that have undergone mergers or acquisitions, we opt to include them in our analysis.

Independent variables. To understand the extent of digitalization in firms within emerging industries, we constructed three dependent variables. The first variable, termed 'Digitally Advanced Firms', is binary and equals 1 when a firm utilizes at least 10 digital technologies and is active in at least five digital markets in t−1, and 0 otherwise. The second variable, 'Digitally Evolving Firms', is also binary. It equals 1 when a firm employs between two and 10 digital technologies and is active in between one and five digital markets in t−1, and 0 otherwise. The third variable, 'Digitally Uncertain Firms', equals 1 when a firm employs at most one digital tool (excluding artificial intelligence and robotics) and is absent in digital markets, and 0 otherwise. Notably, if a firm uses the Amazon platform as a marketplace, it is categorized as 'digitally uncertain'.

Furthermore, we incorporated a binary variable titled 'digitally advanced firms' that equals 1 when a firm employs at least two digital technologies and operates in at least two digital markets, and 0 otherwise. Similarly, the variable 'digitally evolving firms' is set to 1 when a firm employs a minimum of one digital technology and operates in at least one digital market, and 0 otherwise. All other firms that do not meet these criteria are labelled as digitally uncertain, indicating that they neither use digital technologies nor are they present in digital markets, as delineated in Digitally Driven (2021).

In our dataset, digitally advanced firms represent 7% of the total, digitally evolving firms make up 28% and digitally uncertain firms account for 65%. It is worth noting that all variables used to determine a firm's digital prowess, its market presence and its engagement with digital technologies are evaluated on a year-by-year basis specific to each firm.

Digitally advanced firms are well prepared in the digital arena, using at least 10 digital technologies and being active in five or more digital markets. Conversely, digitally uncertain firms are not active in digital markets and don't leverage digital technologies, though they might use at least one digital tool (e.g. social media, Big Data, etc.).

To operationalize our independent variables related to resource mobilization and digitalization, we drew from the research of Nambisan *et al.* (2017). As proxies for resource mobilization by a firm, we employ the total debt to total assets and total equity to total assets ratios. The former is calculated by dividing a company's total debt by its

Table 1. Sample distribution across industry, region, firm size and stage of growth

Firm size	Firms	Share
Micro (1–9 FTEs)	2409	6.65
Small (10–49 FTEs)	8024	22.16
Medium (50–99 FTEs)	9858	27.23
Medium/large (100–249 FTEs)	10,154	28.05
Large (>250 FTEs)	5760	15.91
Total	**36,205**	**100**

Industry (by main product/service)	**Firms**	**Share**
Voiceover Internet Protocol	492	1.36
Cloud tech	800	2.21
Meta-materials	76	0.21
Precision medicine	626	1.73
Urban farming	163	0.45
Omnichannel	286	0.79
eHealth	2038	5.63
Regenerative medicine	395	1.09
Drones	648	1.79
Smart homes	416	1.15
Retail biometrics	65	0.18
Robotics	702	1.94
Precision agriculture	286	0.79
Digital (cyber) security	3067	8.47
Preventive care	308	0.85
Wearables	1503	4.15
FinTech	482	1.33
Internet of Things	2303	6.36
Big Data	1676	4.63
3D printing	76	0.21
Mobile commerce	427	1.18
Mobile services	1336	3.69
Open source	590	1.63
Sharing economy	930	2.57
Cryptocurrencies	264	0.73
Gamification	963	2.66
Educational technology	713	1.97
Social shopping	253	0.70
Advertising tech	449	1.24
Alternative finance	1481	4.09
Augmented reality	1854	5.12
Artificial intelligence	3715	10.26
Insurance tech	1282	3.54
Property tech	2411	6.66
Virtual reality	2346	6.48
Law tech	782	2.15
Total	**36,205**	**100**

Year observed	Firms	Share
2010	2436	6.73
2011	2696	7.45
2012	2993	8.27
2013	3299	9.11
2014	3634	10.04
2015	4031	11.13
2016	4241	11.71
2017	4270	11.79
2018	4321	11.93
2019	4284	11.83
Total	**36,205**	**100**

Growth stage	**Firms**	**Share**
Seed	18	0.05
Venture	502	1.39
Growth	4130	11.41
Established	29,158	80.54
Exited	2067	5.71
Zombie	330	0.91
Total	**36,205**	**100**

Region	**Firms**	**Share**
North of Scotland	436	1.21
East Midlands	2493	6.89
East of England	3549	9.81
East of Scotland	354	0.98
Highlands and Islands	140	0.39
London	7308	20.20
North East	999	2.76
North West	3613	9.99
Northern Ireland	1252	3.46
South East	5111	14.13
South West	2619	7.24
South of Scotland	73	0.11
Tayside	319	0.88
Wales	1050	2.90
West Midlands	2911	8.05
West of Scotland	809	2.24
Yorkshire and Humber	3169	8.76
Total	**36,205**	**100**

Source: Beauhurst (2021).

total assets, while the latter is obtained by dividing a company's total equity by its total assets.

Additionally, equity and total debt asset ratios may vary with firm age and firm size (Rossi and Vismara, 2018) as boundary conditions for firm growth and resource mobilization. This variation could influence firm growth, with potentially larger and more mature firms enjoying robust market positions and resource access (Delmar, McKelvie and Wennberg, 2013; Haltiwanger, Jarmin and Miranda, 2013). We proxy firm age as the number of years since the establishment in logarithms and use the number of employees (as a logarithm) to proxy firm size (Audretsch and Belitski, 2020; Belitski *et al.*, 2023).

Control variables. Drawing on prior research on firm growth (Coad, 2009; Coad and Rao, 2008) and the role of digitalization in building technological capabilities (Dethine, Enjolras and Monticolo, 2020; Kowalkowski, Kindström and Gebauer, 2013), we incorporated a control variable: the number of digital tools used by a firm. Guided by Digitally Driven (2021) and referencing the list of digital tools from Beauhurst (2021), these tools include e-commerce, business website, Big Data, data analytics tools, email platforms, customer insight tools, knowledge and data collaboration tools, digital ads, online marketplace tools (e.g. Google Play and Apple Store), videoconferencing, digital work tools, digital payments, search engine optimization, social media and video platforms (e.g. Pinterest, LinkedIn, Facebook), cloud technology, mobile tools, the Internet of Things, robotics and artificial intelligence. Notably, Beauhurst (2021) omits three digital tools: local listings, online training platforms and customer relationship management platforms. On average, firms in our sample use six technologies, with a standard deviation of 2.75 and a maximum uptake of 17 technologies.

Our subsequent control variable is labour productivity, employed as a proxy for firm efficiency. It's defined as the logarithmic ratio of sales to full-time employees. We incorporated a binary variable titled 'Accelerator', indicating whether a firm participated in a UK-registered accelerator programme for startups. We then utilized a series of binary variables related to various stages of firm growth, encompassing seed stage (pre-market, pre-profit), venture stage, early-growth stage, established stage and market exit stage, with the death stage serving as our reference category.

Furthermore, we applied year fixed effects (using 2010 as the benchmark year), 115 city/region fixed effects (with Aberdeen as the reference city) and two-digit SIC 2007 industry fixed effects, selecting e-health as the reference category. For the stages of firm growth, we used the exited firm stage as our reference category. An exhaustive list of the variables employed in this study can be found in Table 2, and a correlation matrix detailing the relationships between the principal variables is presented in Appendix A.

The model

Modelling the relationship between firm digitalization, resource mobilization and firm performance presents an interesting set of challenges. First, we assume here that firms in the process of resource mobilization simultaneously decide on firm growth strategy and which technological capabilities are available.

Second, there may be a reverse causality between resource mobilization and firm performance (Villanueva, Van de Ven and Sapienza, 2012). It may be that more dynamic and high-growth firms opt for more resources, and vice versa. We are unable to address the issue of simultaneity of decision-making, also known as reverse causality, using longitudinal data during 2010–2019 (Beauhurst, 2021), because the bias induced by permanent unobservable differences in resource mobilization and firm growth and simultaneity of decision-making between firm growth and resource mobilization may not be resolved using solely longitudinal data.

To address these challenges, we model all three indicators – firm performance, equity and debt resource mobilization – given their potential interdependency. An established method for modelling jointly determined indicators is the system of seemingly unrelated regression equations (SURE) introduced by Zellner (1962).

By adopting this system of equations, we achieve three primary objectives. First, we address potential endogeneity between firm growth and resource mobilization variables, allowing for joint estimation. Second, we enhance the efficiency of the estimates because the residuals exhibit interdependence due to the plausible endogeneity bias between resource mobilization and firm growth.

Table 2. Description of variables

Variable	Definition	Mean	SD	Min	Max
Firm growth	Firm growth is measured as the difference in logarithms of sales for t and t−1	0.11	0.52	−12.62	12.11
Equity to assets ratio	The total equity to total assets ratio is calculated by dividing a company's total amount of equity by the company's total amount of assets	0.23	0.36	0.00	1.00
Debt to assets ratio	The total debt to total assets ratio is calculated by dividing a company's total amount of debt by the company's total amount of assets. If a company has a total debt to total assets ratio of 0.4, 40% of its assets are financed by creditors and 60% by owners' (shareholders') equity	0.21	0.20	0.00	1.00
Digitally advanced firms	Binary variable equal to 1 if a firm uses at least 10 digital technologies and is present in at least five digital markets in t−1, and 0 otherwise	0.07	0.25	0.00	1.00
Digitally evolving firms	Binary variable equal to 1 if a firm uses between two and 10 digital technologies and is present in between one and five digital markets in t−1, and 0 otherwise	0.28	0.45	0.00	1.00
Digitally uncertain firms	Binary variable equal to 1 if a firm uses maximum one digital tool (which is not artificial intelligence or robotics) and is not present in digital markets, and 0 otherwise. Firm may use Amazon platform as a marketplace; in this case the firm is considered as digitally uncertain	0.65	0.47	0.00	1.00
Firm size	Full-time employees as a logarithm in t−1	3.78	1.68	0.00	11.94
Firm age	Years since establishment as a logarithm in t−1	1.91	1.37	0.00	4.79
Seed stage	Binary variable equal to 1 if firm is at the seed stage in t−1, and 0 otherwise	0.20	0.40	0.00	1.00
Venture stage	Binary variable equal to 1 if firm is at the venture stage in t−1, and 0 otherwise	0.14	0.35	0.00	1.00
Growth stage	Binary variable equal to 1 if firm is at the growth stage in t−1, and 0 otherwise	0.13	0.34	0.00	1.00
Established stage	Binary variable equal to 1 if firm is at the established stage in t−1, and 0 otherwise	0.38	0.48	0.00	1.00
Exited stage	Binary variable equal to 1 if firm is at the exit stage in t−1, and 0 otherwise	0.06	0.24	0.00	1.00
Accelerator experience	Binary variable equal to 1 if firm has participated in the accelerator programme in t−1, and 0 otherwise	0.17	0.38	0.00	1.00
Labour productivity	Firm sales to full-time employees ratio as a logarithm in t−1	11.92	1.98	0.00	15.36
Digital tools	Number of digital tools used by a firm in t−1 using data from Beauhurst (2021). Consists of a maximum of 17 digital tools: e-commerce and business website; Big Data; data analytics tools; email platforms; business website; customer insight tools; knowledge and data collaboration tool; digital ads; online marketplace tools such as Google Play and Apple Store; video-conferencing and digital working; digital payments; search engine optimization; social media and video platforms such as Pinterest, LinkedIn and Facebook; cloud technology; mobile tools; Internet of Things; robotics and artificial intelligence in t−1.	6.16	2.75	0.00	17.00

Source: Beauhurst (2021).

Third, we estimate the mediated effect of resource mobilization in the association between digitally advanced firms and firm growth.

We apply the SURE model, integrating both the ordinary least squares (for firm growth) and the Tobit method (for the total equity to total assets and total debt to total assets ratios) to examine the three outcomes of interest. Although all our dependent variables are continuous, the ratios of equity and debt to sales have a notable number of observations equating to zero. The mean total equity to total assets ratio in our dataset stands at 0.23, with the average total debt to total assets ratio being 0.21. We use a censored Tobit model, previously leveraged empirically, to navigate the challenges of censored data (Audretsch and Belitski, 2023).

We utilize the Stata 17 'cmp' module, which facilitates the estimation of SURE using the simulated likelihood method, for example the Geweke, Hajivassiliou and Keane (GHK) algorithm (Roodman, 2009).

Our SURE regression model, inclusive of industry, region and year fixed effects, is represented as a system of equations:

$$\begin{cases} \mathrm{Y_{it}} = \beta_{11} + \beta_{12}\mathrm{E_{it}} + \beta_{13}\mathrm{D_{it}} + \beta_{14}\mathrm{A_{it-1}} + \beta_{15}\mathrm{Size_{t-1}} + \beta_{16}\mathrm{Age_{it-1}} + \beta_{17}\mathrm{A_{it-1}} \times \mathrm{Age_{t-1}} + \beta_{18}\mathrm{A_{it-1}} \times \\ \mathrm{E_{it}} = \beta_{21} + \beta_{22}\mathrm{A_{it-1}} + \beta_{23}\mathrm{Size_{t-1}} + \beta_{24}\mathrm{Age_{it-1}} + \beta_{25}\mathrm{A_{it-1}} \times \mathrm{Age_{t-1}} + \beta_{26}\mathrm{A_{it-1}} \times \mathrm{Size_{t-1}} + \beta_{27}\mathrm{Z_{it-1}} + \varepsilon_{2t} \\ \mathrm{D_{it}} = \beta_{31} + \beta_{32}\mathrm{A_{it-1}} + \beta_{33}\mathrm{Size_{t-1}} + \beta_{34}\mathrm{Age_{it-1}} + \beta_{35}\mathrm{A_{it-1}} \times \mathrm{Age_{t-1}} + \beta_{36}\mathrm{A_{it-1}} \times \mathrm{Size_{t-1}} + \beta_{37}\mathrm{Z_{it-1}} + \varepsilon_{3t} \end{cases} \quad (1)$$

where $\mathrm{Y_{it}}$ represents sales growth of firm i in time t. The terms $\mathrm{E_{it}}$ and $\mathrm{D_{it}}$ in Equation (1) represent the equity to total assets ratio and the debt to total assets ratio of firm i in time t, introduced as dependent variables in the system of equations but also as an independent variable in the firm sales growth equation to account for the mediating effect of resource mobilization in its relationship between digitally advanced firms and their growth. $\mathrm{A_{it-1}}$ represents digitally advanced firms at time t−1 (with 'digitally uncertain' as the reference category); while $\mathrm{Size_{it-1}}$ and $\mathrm{Age_{it-1}}$ stand for firm i size and age at time t−1. At time t−1, $\mathrm{Z_{it-1}}$ is the vector of exogeneous variables related to the firm stage of growth controls, number of digital tools used by a firm, accelerator experience and other control variables of firm i at time t−1. $\mathrm{Z_{it-1}}$ are industry, region and time fixed effects, representing a system of equations; $\varepsilon_{\mathrm{it}}$ is the error term of firm i in each equation.

Results

Hypothesis testing

Table 3 provides estimates from the three distinct SURE models for each dependent variable, showcasing the mediating effect of equity and debt to assets ratios on firm growth. In specification 1 of Table 3, the direct and indirect impacts of digitalization – represented by the binary variable for digitally advanced firms – are examined in relation to firm sales growth and resource mobilization, thereby testing H1 and H2. Specification 2 in Table 3 delves into the interaction of firm digitalization with the twin boundary conditions of firm size and age, addressing H3 and H4.

Supporting H1, our results indicate that within emerging industries, digitally advanced firms achieve higher revenues compared to digitally evolving and digitally uncertain firms. Specifically, digitally advanced firms witness an average growth rate that is 1.29% higher than their digitally uncertain counterparts, as seen in specification 1 of Table 3. This effect escalates to 3.60% when adjusting for the firm age and firm size (specification 2, Table 3). Interestingly, there isn't a discernible difference between the sales growth impacts of digitally evolving firms and digitally uncertain ones, as evidenced by the insignificant coefficient in specifications 1 and 2 of Table 3.

H2 is only partly supported by our findings. Specification 1 of Table 3 reveals that digitally advanced firms maintain a 0.19 higher equity to total assets ratio when juxtaposed with digitally uncertain firms. This effect is consistent even when considering interactions with firm age and firm size in specification 2. An uptick in equity capital intensity by just one percentage point can amplify a firm's growth by between 1.78% ($\beta = 1.78$, $p < 0.05$) in specification 2 and 1.81% ($\beta = 1.81$,

Table 3. SURE estimation with firm growth, equity to assets and debt to assets ratios as dependent variables. All independent and control variables are 1-year lagged (t−1)

Specification	(1)			(2)		
Dependent variable	Firm growth (t)	Equity to assets ratio (t)	Debt to assets ratio (t)	Firm growth (t)	Equity to assets ratio (t)	Debt to assets ratio (t)
Equity to assets ratio (H2)	1.81**			1.78***		
	(0.73)			(0.66)		
Debt to assets ratio (H2)	0.463			0.68		
	(0.46)			(0.49)		
Seed stage	0.32	0.16***	−0.05**	0.33	0.14***	−0.05**
	(0.20)	(0.03)	(0.02)	(0.39)	(0.03)	(0.02)
Venture stage	0.23	0.13***	−0.02*	0.42	0.12***	−0.01
	(0.31)	(0.01)	(0.01)	(0.38)	(0.01)	(0.01)
Growth stage	0.34*	−0.04***	−0.02***	0.41**	−0.05***	−0.02***
	(0.20)	(0.01)	(0.01)	(0.19)	(0.01)	(0.01)
Established stage	0.82***	−0.06***	−0.02***	0.92***	−0.07***	−0.02***
	(0.23)	(0.01)	(0.01)	(0.23)	(0.01)	(0.01)
Accelerator experience	−0.76***	0.23***	−0.01	−0.82***	0.22***	−0.01
	(0.30)	(0.01)	(0.01)	(0.28)	(0.01)	(0.01)
Firm size	0.11	−0.01***	0.01***	0.01	−0.01***	0.01***
	(0.08)	(0.00)	(0.00)	(0.10)	(0.00)	(0.00)
Firm age	−0.08	−0.03***	−0.02***	0.06	−0.02***	−0.02***
	(0.12)	(0.00)	(0.00)	(0.12)	(0.00)	(0.00)
Labour productivity	0.12*	−0.02***	0.01***	0.07**	−0.02***	0.01***
	(0.05)	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)
Digitally advanced (H1, H2)	1.29***	0.19***	−0.01	3.60**	0.06**	0.11*
	(0.26)	(0.01)	(0.01)	(1.67)	(0.03)	(0.06)
Digitally evolving	−0.09	0.01***	−0.01***	1.13	0.10***	0.01
	(0.16)	(0.00)	(0.00)	(1.73)	(0.03)	(0.02)
Digital tools	0.05**	0.01***	0.01***	0.03**	0.01***	0.01***
	(0.02)	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)
Digitally advanced × Firm size (H3a, H3b)				0.44***	0.01	−0.01
				(0.18)	(0.01)	(0.01)
Digitally advanced × Firm age (H4a, H4b)				−0.10	−0.01	0.01
				(0.28)	(0.03)	(0.02)
Digitally evolving × Firm size				0.25	−0.01***	−0.01
				(0.17)	(0.00)	(0.00)
Digitally evolving × Firm age				−0.77***	−0.02***	0.01**
				(0.25)	(0.00)	(0.00)
Industry, year and region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.67	0.51***	0.29***	0.87	0.49***	0.28***
	(0.62)	(0.01)	(0.01)	(0.93)	(0.02)	(0.01)
atanhrho_12		−0.38***			−0.39***	
		(0.11)			(0.10)	
atanhrho_13		−0.13**			−0.15**	
		(0.07)			(0.07)	
atanhrho_23		0.18***			0.11***	
		(0.01)			(0.01)	
χ^2		7719.97			8601.79	
AIC		−79,359.87			−81,080.49	
Loglikelihood		39,936.20			40,100.28	

Note: We used year fixed effects (with 2010 as reference year), 115 city/region fixed effects (with Aberdeen as reference city), two-digit SIC 2007 industry fixed effects (e-health as reference category). For the firm growth stages, the reference category is exited firm stage. Significance level:
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$. All χ^2 test p-values < 0.01. Number of observations: 36,205 firm-year observations.
Source: Beauhurst (2021).

$p < 0.05$) in specification 1. However, the influence of debt capital intensity on firm growth remains non-significant, offering only partial support to H2, as seen in specifications 1 and 2. This discovery deviates from earlier studies that highlighted the significance of debt capital as a financing tool (referencing Myers and Majluf, 1984), suggesting potential avenues for further investigation.

Lastly, H3a is supported, suggesting that within emerging industries, firm size acts as a positive moderator between digitally advanced firms and their growth. A significant and positive coefficient ($\beta = 0.44$, $p < 0.001$) reveals that for digitally advanced firms, in contrast to digitally uncertain ones, a surge of 10% in firm size can cumulatively boost growth by 8.00% ($\beta = 3.60 + 4.40$, $p < 0.001$), as shown in specification 2 of Table 3.

H3b states that within emerging industries, firm size has a positive moderating effect on the relationship between digitally advanced firms and resource mobilization. However, this hypothesis is not supported. The interaction coefficients between digitally advanced firms and firm size, when examining equity and debt capital intensity as dependent outcomes, are not significant (as seen in specification 2, Table 3). Specifically, a rise in firm size positively impacts debt capital intensity ($\beta = 0.01$, $p < 0.001$) and inversely affects equity capital intensity ($\beta = -0.01$, $p < 0.001$) in specifications 1 and 2 of Table 3. This indicates that as firms expand, they gravitate more towards debt financing, subsequently reducing equity capital and diluting ownership.

H4a, positing that in emerging industries the age of a firm does not influence the relationship between being a digitally advanced firm and its growth, is supported. This is evidenced by the insignificant interaction coefficient ($\beta = -0.10$, $p > 0.10$) seen in specification 2 of Table 3. Essentially, regardless of whether they are newly established or have been in the market for a longer duration, digitally advanced firms experience similar rates of sales growth.

Similarly, H4b, which asserts that in emerging industries the age of a firm doesn't alter the relationship between digitally advanced status and resource mobilization, is also supported. This is indicated by the non-significant interaction coefficient ($\beta = -0.01$, $p > 0.10$) in specification 2 of Table 3. In simpler terms, both nascent and seasoned digitally advanced firms maintain equivalent levels of equity and debt resources.

In relation to firm growth within emerging industries, our results highlight specific patterns. Firms that are in their early stages of growth manifest a more pronounced equity capital intensity compared to those that have left the market. Specifically, firms in the seed stage exhibit, on average, a 16% higher equity capital intensity ($\beta = 0.16$, $p < 0.001$) as shown in specification 1 of Table 3, and firms in the venture stage show a 13% increase ($\beta = 0.13$, $p < 0.001$). Conversely, seed-stage firms present an average decrease of 5% in equity capital intensity ($\beta = -0.05$, $p < 0.01$) and venture-stage firms indicate a 2% decrease ($\beta = -0.02$, $p < 0.05$). When considering firms in both growth and established stages, there is a decline in equity capital intensity ranging from 4% to 6% ($\beta = -0.04$ to -0.06, $p < 0.001$) and a 2% reduction in debt capital intensity ($\beta = -0.02$, $p < 0.001$), in comparison to firms that have exited the market.

Furthermore, firms that participated in the UK accelerator programme tend to exhibit, on average, reduced growth rates, ranging from 76% to 82% ($\beta = -0.76$ to -0.82, $p < 0.001$), as evidenced in specifications 1 and 2 of Table 3. However, these same firms display an increased average in equity capital intensity, ranging from 22% to 23% ($\beta = 0.22$–0.23, $p < 0.001$). Lastly, our data demonstrates that labour productivity has a favourable influence on both firm growth and debt capital intensity. Yet, it appears to inversely affect equity capital intensity, as shown in specifications 1 and 2 of Table 3.

Further robustness check

For our first robustness test, we recalculated Equation (1) using a 2-year lag for all the independent and control variables, presented in Appendix B. This approach offers an intertemporal examination of the effects, illustrating the duration of the impact. The findings largely align with the results from specifications 1 and 2 of Table 3.

However, when we introduce a 2-year lag, the impact of digitally advanced firms outperforming digitally uncertain firms in revenue generation diminishes ($\beta = 1.45$, $p < 0.05$). This result does not back up H1, as detailed in Appendix B. Such an outcome suggests that the benefits of adopting digital tools and venturing into new digital markets are primarily manifest in the short term concerning sales growth.

H2 is partly supported. The effect of digitally advanced firms on firm growth equity capital intensity is significant ($\beta = 0.04$, $p < 0.05$) (Appendix B) and for debt capital intensity ($\beta = 0.18$, $p < 0.05$) (Appendix B). The effect of equity to total assets ratio on firm growth is significant ($\beta = 1.69$, $p < 0.05$) (Appendix B), but insignificant for debt to total assets ratio, partly supporting H2.

The moderation effect firm size in the relationship between digitally advanced firms and firm growth is positive and significant when controlling for the 2-year lag ($\beta = 0.32$, $p < 0.01$) (Appendix B), supporting H3a. H3b is not supported as firm size does not moderate the relationship between digitally advanced firms and resource mobilization (Appendix B). Firm age does not moderate the relationship between digitally advanced firms and firm growth ($\beta = 0.01$, $p > 0.10$) (Appendix B), supporting H4a. The interaction is insignificant for resource mobilization, supporting H4b (Appendix B).

To assess the relative fit of statistical models using 1-year versus 2-year lags, we employ the Akaike information criterion (AIC). The AIC serves as a reliable criterion, where a lower AIC value (or a more negative value in cases where the numbers are negative) signifies a superior model fit. This metric takes into account both the model's goodness of fit and its complexity.

From our analysis, the AIC values for the model utilizing 1-year lags, as displayed in Table 3, range between −79,359.87 and −81,080.49. Meanwhile, the AIC value for the model employing 2-year lags, presented in Appendix B, stands at −70,595.08. Given this comparison, the model incorporating 1-year lags offers a more appropriate fit than its counterpart with 2-year lags.

Our second robustness check includes performing fixed and random effects panel data estimation for the firm growth equation and random effects Tobit using longitudinal data for equity and debt capital intensity equations. Tobit estimation fits the random effects model. There is no command for a parametric conditional fixed effects model, as there does not exist a sufficient statistic allowing the fixed effects to be conditioned out of the likelihood. While Honoré (1992) has developed a semiparametric estimator for fixed-effect Tobit models, the unconditional fixed-effects Tobit models cannot be used for our left-censored dependent variable. All equations for firm growth, equity and dept capital intensity were estimated separately and not simultaneously (Baltagi, Bresson and Pirotte, 2003). In order to choose between fixed and random effects in the firm growth model, we performed a Hausman test with the null that the difference in coefficients is not systematic.

Drawing on Wooldridge (2003) and Baltagi and Baltagi (2008), we first applied the recommended option 'sigmamore', which is used when comparing fixed effects and random effects linear regression, because they are much less likely to produce a non-positive-definite differenced covariance matrix (although the tests are asymptotically equivalent whether or not one of the options is specified); we reject the null at the 1% significance level.

Second, we performed a Breusch and Pagan Lagrangian multiplier test for random effects after estimating Equation (1) using random effects estimation. We reject the null hypothesis (Var(u) = 0) using this test and conclude that the random effects are significant in the model and the use of the random effects model is appropriate (Baltagi and Baltagi, 2008) ($\bar{\chi}^2 = 5.16$, $p < 0.01$). The Breusch–Pagan Lagrange multiplier test is applied after estimating the random effects model. Third, we test whether joint firm fixed effects are non-zero, with F-statistics of 3.20 and 3.40, respectively. This means that firm-level fixed effects are non-zero and fixed effect estimation is preferred. Finally, we report the θ indicator, which if close to 1 requires the use of fixed effects in the estimation and if close to 0, random effects (Baltagi and Baltagi, 2008). The value of the θ indicator varies between 0.44 and 0.47. While it is important to make a definitive choice and the fixed estimation is preferred, we report a range of coefficients as the sign is not different, and the main difference comes from the size of the effect between two models.

In emerging sectors, digitally advanced enterprises exhibit, on average, a firm growth that is 1.14–1.65 percentage points higher than their digitally uncertain counterparts ($\beta = 1.14$, $p < 0.01$, specification 2, Appendix C and $\beta = 1.65$, $p < 0.01$, specification 4, Appendix C), supporting H1. While we are unable to test the mediating effect of resource mobilization in the relationship between digitally advanced firms and firm growth as in Table 3, we find that digitally advanced firms increase their equity capital intensity between 0.19 and 0.29 ($\beta = 0.19$–0.29, $p < 0.05$, specifications 5 and 6, Appendix C) and debt capital intensity between 0.11 and 0.12 ($\beta = 0.11$–0.12, $p < 0.01$, specifications 7 and 8, Appendix C). This is different from the SURE estimation in Table 3.

Firm size positively moderates the effect of digitally advanced firms on firm growth ($\beta = 0.02$–0.06, $p < 0.05$, specifications 2 and 4, Appendix C), supporting H3a. Firm size positively moderates the effect of digitally advanced firms on equity capital intensity ($\beta = 0.01$, $p < 0.05$, specification 6, Appendix C), supporting H3b with no effect on debt capital intensity. Finally, H4a is supported as the interaction coefficients are insignificant for random effects estimation ($\beta = -0.07$, $p > 0.10$, specification 2, Appendix C) and for fixed effects estimation ($\beta = -0.10$, $p > 0.10$, specification 4, Appendix C), confirming the SURE results. H4b is supported as the interaction coefficients are insignificant ($\beta = 0.03$, $p > 0.10$, specification 2, Appendix C and $\beta = 0.01$, $p > 0.10$, specification 4, Appendix C).

Discussion and conclusion

The extant literature has suggested that only a small fraction of firms experience growth (Daunfeldt, Elert and Johansson, 2014) and are able to mobilize resources (Walthof-Borm, Schwienbacher and Vanacker, 2018), and those who grow create most new jobs and use new digital technologies (Levallet and Chan, 2018; Mi, Shang and Zeng, 2022).

In this study, we analysed factors that facilitate and impede firm growth and resource mobilization. Specifically, drawing on the KBV of a firm (Grant, 1996), we examined the role that digital tool adoption plays in resource mobilization and firm growth in the context of emerging industries, as well as demonstrating how two boundary conditions (firm age and firm size) moderate this relationship.

Previous studies have predominantly focused on the resource-based view of firm growth (Coad, Daunfeldt and Halvarsson, 2018) in traditional industries and without taking into consideration the role that digital tools play in resource mobilization (Nambisan *et al.*, 2017; Vanacker and Manigart, 2010). Policy implications from these studies are limited in understanding firm growth in emerging industries and how new products are created. Thus, it is valuable to study how digitally advanced firms achieve greater equity and debt capital intensity for firm growth compared to digitally evolving and digitally uncertain firms using longitudinal data for 10 years and for emerging industries. Our results on the role of equity capital for firm growth and for digitally advanced firms contrast the well-known literature on debt capital preferences as a source of finance (Myers and Majluf, 1984), and relate to the fact that firms in emerging sectors rely on equity capital to a greater extent than debt capital (Bertoni, Meoli and Vismara, 2023; Butticè and Vismara, 2022) due to the nature of the industry.

Our findings demonstrated that firm growth depends on the persistence of digital transformation, such as becoming a digitally advanced firm. It is affected by the extent of digitalization and resource mobilization (Nambisan and Baron, 2021; Nambisan *et al.*, 2017; Vismara, 2016, 2018) and the effect is conditional on firm age and firm size, which together play a crucial role in the extent of firm growth. In this aspect, our findings are distinct from prior research on the role of debt and equity capital (Colombo, Meoli and Vismara, 2019, 2023) when applied to emerging industries. Digitally advanced firms are able to signal that they are more prestigious firms to invest in (Colombo, Meoli and Vismara, 2019) if the technologies and products they work on are prestigious and highly visible in digital markets, achieving a higher equity to total capital ratio than debt to total capital ratio.

While the absence of data on firm age and firm size in previous studies has resulted in the under-representation of young firms in many available longitudinal datasets, we overcome these shortcomings by using a full sample of active firms in emerging industries and high-growth firms tracked in the United Kingdom during 2010–2019. Interestingly, larger digitally advanced firms have higher average growth, while older digitally advanced firms are as likely to grow as younger firms. However, we still know very little about how growth in digitally advanced firms compared to digitally evolving and uncertain firms is associated with the change in the use of digital tools.

While our study extensively probes the impact of digitalization on firm performance and delves into the resource composition of firms, there remains an under-explored area concerning how other alternative resources – such as crowdfunding (Ahlstrom, Cumming and Vismara, 2018; Vismara, 2022; Vismara, Benaroio and Carne, 2017) and innovations like blockchain and initial coin offerings (Fisch, Meoli and Vismara, 2022; Rawhouser, Vismara and Kshetri, 2023) – concurrently influence firm growth. Future studies could enrich this domain by exploring the intricate interplay of various internal and external knowledge and financial sources. This exploration could be coupled with regional and industry-specific dynamics to understand how these factors jointly impact firm growth and resource mobilization across diverse markets, particularly within established and traditional sectors.

Our first limitation is the availability of data in Beauhurst (2021), as the entire sample of emerging industries limited our selection of firm, industry and regional factors. Replicating the study of these factors in different countries beyond the United Kingdom and in other institutional contexts will illuminate the generalizability of our results across geographical and economic contexts. Our second limitation is the development of digitally advanced, evolving and uncertain firm taxonomies that are not associated with the performance of technology, but rather the quantity of technologies used and the number of digital products and services that firms supply to markets.

Further research should focus on the qualitative multi-level drivers of the interplay between the choice of resources, such as equity versus debt versus alternative capital, and the role of different digital technologies, as each of them may have a different speed of growth and scalability. In addition, understanding the role of productivity in moderating the relationship between digitalization and resource mobilization is important, as most productive firms may be able to raise more resources and of higher quality.

References

Ahlstrom, D., J. L. Arregle, M. A. Hitt, G. Qian, X. Ma and D. Faems (2020). 'Managing technological, sociopolitical, and institutional change in the new normal', *Journal of Management Studies*, **57**, pp. 411–437.

Ahlstrom, D., D. J. Cumming and S. Vismara (2018). 'New methods of entrepreneurial firm financing: fintech, crowdfunding and corporate governance implications', *Corporate Governance: An International Review*, **26**, pp. 310–313.

Audretsch, D. B. and M. Belitski (2020). 'The role of R&D and knowledge spillovers in innovation and productivity', *European Economic Review*, **123**, art. 103391.

Audretsch, D. B. and M. Belitski (2021). 'Knowledge complexity and firm performance: evidence from the European SMEs', *Journal of Knowledge Management*, **25**, pp. 693–713.

Audretsch, D. B. and M. Belitski (2023). 'Evaluating internal and external knowledge sources in firm innovation and productivity: an industry perspective', *R&D Management*, **53**, pp. 168–192.

Audretsch, D. B., M. Belitski and R. Caiazza (2021). 'Start-ups, innovation and knowledge spillovers', *The Journal of Technology Transfer*, **46**, pp. 1995–2016.

Baltagi, B. H. and B. H. Baltagi (2008). *Econometric Analysis of Panel Data*, Vol. **4**. Chichester: Wiley.

Baltagi, B. H., G. Bresson and A. Pirotte (2003). 'Fixed effects, random effects or Hausman–Taylor? A pretest estimator', *Economics Letters*, **79**, pp. 361–369.

Björkdahl, J. (2009). 'Technology cross-fertilization and the business model: the case of integrating ICTs in mechanical engineering products', *Research Policy*, **38**, pp. 1468–1477.

Beauhurst (2021). 'Discover the UK most fast-growing companies'. Available at https://www.beauhurst.com/ [accessed 19 September 2021].

Belitski, M. and B. Liversage (2019). 'e-Leadership in small and medium-sized enterprises in the developing world', *Technology Innovation Management Review*, **9**, pp. 64–74.

Belitski, M., T. Stettler, W. Wales and J. Martin (2023). 'Speed and scaling: an investigation of accelerated firm growth', *Journal of Management Studies*, **60**, pp. 639–687.

Butticè, V. and S. Vismara (2022). 'Inclusive digital finance: the industry of equity crowdfunding', *The Journal of Technology Transfer*, **47**, pp. 1224–1241.

Bertoni, F., M. Meoli and S. Vismara (2023). 'Too much of a good thing? Board independence and the value of initial public offerings', *British Journal of Management*, **34**, pp. 942–972.

Bertoni, F., S. Bonini, V. Capizzi, M. G. Colombo and S. Manigart (2022). 'Digitization in the market for entrepreneurial finance: innovative business models and new financing channels', *Entrepreneurship Theory and Practice*, **46**, pp. 1120–1135.

Björkdahl, J. (2020). 'Strategies for digitalization in manufacturing firms', *California Management Review*, **62**, pp. 17–36.

Coad, A. (2009). *The Growth of Firms: A Survey of Theories and Empirical Evidence*. Cheltenham: Edward Elgar.

Coad, A., S. O. Daunfeldt and D. Halvarsson (2018). 'Bursting into life: firm growth and growth persistence by age', *Small Business Economics*, **50**, pp. 55–75.

Coad, A. and R. Rao (2008). 'Innovation and firm growth in high-tech sectors: a quantile regression approach', *Research Policy*, **37**, pp. 633–648.

Colombo, M. G., M. Meoli and S. Vismara (2019). 'Signaling in science-based IPOs: the combined effect of affiliation with prestigious universities, underwriters, and venture capitalists', *Journal of Business Venturing*, **34**, pp. 141–177.

Colombo, M. G., B. Montanaro and S. Vismara (2023). 'What drives the valuation of entrepreneurial ventures? A map to navigate the literature and research directions', *Small Business Economics*, **61**, pp. 59–84.

Cumming, D., M. Meoli and S. Vismara (2021). 'Does equity crowdfunding democratize entrepreneurial finance?', *Small Business Economics*, **56**, pp. 533–552.

Daunfeldt, S. O., N. Elert and D. Johansson (2014). 'The economic contribution of high-growth firms: do policy implications depend on the choice of growth indicator?', *Journal of Industry, Competition and Trade*, **14**, pp. 337–365.

Delmar, F. (2006). 'Measuring growth: methodological considerations and empirical results', *Entrepreneurship and the Growth of Firms*, **1**, pp. 62–84.

Delmar, F., A. McKelvie and K. Wennberg (2013). 'Untangling the relationships among growth, profitability and survival in new firms', *Technovation*, **33**, pp. 276–291.

Dethine, B., M. Enjolras and D. Monticolo (2020). 'Digitalization and SMEs' export management: impacts on resources and capabilities', *Technology Innovation Management Review*, **10**, pp. 18–34.

Digitally Driven (2021). European Small Businesses Find a Digital Safety Net During Covid-19: Report. Available at https://digitallydriven.connectedcouncil.org/europe/ [accessed 1 March 2022].

Eisenhardt, K. M. and F. M. Santos (2002). 'Knowledge-based view: a new theory of strategy', *Handbook of Strategy and Management*, **1**, pp. 139–164.

Fisch, C., M. Meoli and S. Vismara (2022). 'Does blockchain technology democratize entrepreneurial finance? An empirical comparison of ICOs, venture capital, and REITs', *Economics of Innovation and New Technology*, **31**, pp. 70–89.

Grant, R. M. (1996). 'Toward a knowledge-based theory of the firm', *Strategic Management Journal*, **17**, pp. 109–122.

Haltiwanger, J., R. S. Jarmin and J. Miranda (2013). 'Who creates jobs? Small versus large versus young', *Review of Economics and Statistics*, **95**, pp. 347–361.

Honoré, B. E. (1992). 'Trimmed LAD and least squares estimation of truncated and censored regression models with fixed effects', *Econometrica: journal of the Econometric Society*, **60**, pp. 533–565.

IDC (2019). International Data Corporation. Worldwide Artificial Intelligence Spending Guide. Available at: https://www.idc.com/getdoc.jsp?containerId=IDC_P33198. Accessed 11 September 2023.

Karimi, J. and Z. Walter (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**, pp. 39–81.

Koch, T. and J. Windsperger (2017). 'Seeing through the network: competitive advantage in the digital economy', *Journal of Organization Design*, **6**, pp. 1–30.

Kowalkowski, C., D. Kindström and H. Gebauer (2013). 'ICT as a catalyst for service business orientation', *Journal of Business & Industrial Marketing*, **28**, pp. 506–513.

Kuusisto, M. (2017). 'Organizational effects of digitalization: a literature review', *International Journal of Organization Theory and Behavior*, **20**, pp. 341–362.

Levallet, N. and Y. E. Chan (2018). 'Role of digital capabilities in unleashing the power of managerial improvisation', *MIS Quarterly Executive*, **17**, pp. 4–21.

Li, W., K. Liu, M. Belitski, A. Ghobadian and N. O'Regan (2016). 'e-Leadership through strategic alignment: an empirical study of small- and medium-sized enterprises in the digital age', *Journal of Information Technology*, **31**, pp. 185–206.

March, J. G. (1991). 'Exploration and exploitation in organizational learning', *Organization Science*, **2**, pp. 71–87.

Lu, Q., L. Song and K. Yu (2022). 'The effects of operational and digitalization capabilities on SMSs' supply chain financing under supply risk.' *International Journal of Logistics Research and Applications*, https://doi.org/10.1080/13675567.2022.2104232.

Martín-Peña, M. L., J. M. Sánchez-López and E. Díaz-Garrido (2019). 'Servitization and digitalization in manufacturing: the influence on firm performance', *Journal of Business & Industrial Marketing*, **35**, pp. 564–574.

Modigliani, F. and M. H. Miller (1963). 'Corporate income taxes and the cost of capital: a correction', *The American Economic Review*, **53**, pp. 433–443.

Mi, Z., Y. Shang and G. Zeng (2022). 'The impact of knowledge base on technological innovation of emerging industries from the perspective of related variety: a case study of China's fuel cell industry', *Growth and Change*, **53**, pp. 57–75.

Myers, S. C. and N. S. Majluf (1984). 'Corporate financing and investment decisions when firms have information that investors do not have', *Journal of Financial Economics*, **13**, pp. 187–221.

Nambisan, S. and R. A. Baron (2021). 'On the costs of digital entrepreneurship: role conflict, stress, and venture performance in digital platform-based ecosystems', *Journal of Business Research*, **125**, pp. 520–532.

Nambisan, S., K. Lyytinen, A. Majchrzak and M. Song (2017). 'Digital innovation management: reinventing innovation management research in a digital world', *MIS Quarterly*, **41**, pp. 223–238.

Nason, R. S. and J. Wiklund (2018). 'An assessment of resource-based theorizing on firm growth and suggestions for the future', *Journal of Management*, **44**, pp. 32–60.

Olleros, F. J. (1986). 'Emerging industries and the burnout of pioneers', *Journal of Product Innovation Management*, **3**, pp. 5–18.

Porter, M. E. and J. E. Heppelmann (2014). 'How smart, connected products are transforming competition', *Harvard Business Review*, **92**, pp. 64–88.

Rawhouser, H., S. Vismara and N. Kshetri (2023). 'Blockchain and vulnerable entrepreneurial ecosystems', *Entrepreneurship & Regional Development*, https://doi.org/10.1080/08985626.2022.2162979.

Roodman, D. (2009). 'How to do xtabond2: an introduction to difference and system GMM in Stata', *The Stata Journal*, **9**, pp. 86–136.

Rossi, A. and S. Vismara (2018). 'What do crowdfunding platforms do? A comparison between investment-based platforms in Europe', *Eurasian Business Review*, **8**, pp. 93–118.

Tajvidi, R. and A. Karami (2021). 'The effect of social media on firm performance', *Computers in Human Behavior*, **115**, art. 105174.

Tornqvist, L., P. Vartia and Y. O. Vartia (1985). 'How should relative changes be measured?', *American Statistician*, **39**, pp. 43–46.

Vanacker, T. and S. Manigart (2010). 'Pecking order and debt capacity considerations for high-growth companies seeking financing', *Small Business Economics*, **35**, pp. 53–69.

Villanueva, J., A. H. Van de Ven and H. J. Sapienza (2012). 'Resource mobilization in entrepreneurial firms', *Journal of Business Venturing*, **27**, pp. 19–30.

Vismara, S. (2016). 'Equity retention and social network theory in equity crowdfunding', *Small Business Economics*, **46**, pp. 579–590.

Vismara, S. (2018). 'Information cascades among investors in equity crowdfunding', *Entrepreneurship Theory and Practice*, **42**, pp. 467–497.

Vismara, S. (2019). 'Sustainability in equity crowdfunding', *Technological Forecasting and Social Change*, **141**, pp. 98–106.
Vismara, S. (2022). 'Expanding corporate finance perspectives to equity crowdfunding', *The Journal of Technology Transfer*, **47**, pp. 1629–1639.
Vismara, S., D. Benaroio and F. Carne (2017). *Gender in Entrepreneurial Finance: Matching Investors and Entrepreneurs in Equity Crowdfunding*. Cheltenham: Edward Elgar.
Walthof-Borm, X., A. Schwienbacher and T. Vanacker (2018). 'Equity crowdfunding: first resort or last resort?', *Journal of Business Venturing*, **33**, pp. 513–533.
Wooldridge, J. M. (2003). 'Cluster-sample methods in applied econometrics', *American Economic Review*, **93**, pp. 133–138.
Zellner, A. (1962). 'An efficient method of estimating seemingly unrelated regressions and tests for aggregation bias', *Journal of the American Statistical Association*, **57**, pp. 348–368.

David Auretsch is a Distinguished Professor and the Ameritech Chair of Economic Development at Indiana University, where he also serves as Director of the Institute for Development Strategies. He is an Honorary Professor of Industrial Economics and Entrepreneurship at the WHU-Otto Beisheim School of Management in Germany and a Research Fellow of the Centre for Economic Policy Research in London.

Maksim Belitski is Professor in Entrepreneurship and Innovation at Henley Business School and a Research Fellow at the Institute for Development Strategies, Indiana University, USA, Chair in Entrepreneurship at Loyola University, New Orleans and a Visiting Professor at ICD Business School, IGS Groupe in Paris. Maksim has worked with local UK businesses across sectors, with an emphasis on IT, finance, creative sectors and university–private–public collaborations.

Supporting Information

Additional supporting information can be found online in the Supporting Information section at the end of the article.