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Competing for digital human capital: The retention effect of digital expertise in MNC subsidiaries

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Abstract
Employees with relevant knowledge and skills for digitalization have become increasingly important for the competitiveness of MNCs. However, the shortage of such digital human capital in many host countries is putting pressure on MNC subsidiaries to prevent these employees from leaving. We theorize that the retention of digital human capital in MNC subsidiaries does not merely depend on salaries but crucially on the learning opportunities that subsidiaries offer. By integrating mechanisms from the literature on subsidiary-specific advantages into theoretical models explaining voluntary mobility constraints of employees, we reason that the opportunities for acquiring new skills in subsidiaries with advanced digital expertise will reduce the odds of losing these valuable employees. We test our theoretical predictions for 11,598 employees with digital human capital working for 866 foreign MNC subsidiaries in Denmark observed between 2002 and 2012. We find that digital expertise helps retaining digital human capital. The effect is stronger if subsidiaries have an internationally diverse workforce and when they possess patented technologies. Both factors provide distinct learning opportunities from digital expertise. The effect is weaker if the subsidiary is located in regional clusters of digital expertise since alternative employers may offer similar learning opportunities.
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INTRODUCTION

Multinational corporations (MNCs) find themselves increasingly in a fierce competition to attract and retain host-country employees with critical knowledge and skills (Becker, Driffield, Lancheros, & Love, 2020; Lewin, Massini, & Peeters, 2009). Digital human capital – defined as the knowledge, skills, and abilities of individuals regarding digital technologies such as software coding, artificial intelligence (AI), or machine learning – is a current case in point. Digitalization and the ubiquitous use of digital technologies in organizations have become a widespread corporate trend (Nambisan, 2017; von Krogh, 2018). MNCs are heavily affected by these trends in terms of new opportunities for internationalization (Monaghan, Tippmann, & Coviello, 2020) or the importance of digital platforms (Li, Chen, Yi, Mao, & Liao, 2019; Nambisan, Zahra, & Luo, 2019). As a consequence, MNC employees who can realize the performance potentials from digitalization are of strategic importance (Banalieva & Dhanaraj, 2019). However, we lack a theoretical understanding about what keeps these crucial employees from leaving the MNC and working for other employers.

In this study, we focus on the retention of employees with digital human capital in foreign MNC subsidiaries. We argue that retaining this particular group of employees is not just a matter of salaries, but depends on whether MNC subsidiaries can offer unique learning opportunities. We integrate theoretical mechanisms from the literature on subsidiary-specific advantages in MNCs (Phene & Almeida, 2008; Rugman & Verbeke, 2001) into models explaining the retention of human capital based on firm-specific incentives (Call & Ployhart, 2021; Kryscynski, Coff, & Campbell, 2021). Following this theoretical logic, we hypothesize that the odds of losing digital human capital are lower for MNC subsidiaries with higher levels of digital expertise, i.e., the skills and assets for creating and advancing digital technologies, processes, or products which can be used throughout the MNC, and thereby provide valuable learning opportunities. What is more, we identify three boundary conditions for the strength of the retention effect: the attractive learning opportunities from an international diversity of the subsidiary's workforce, exclusive access to patented technologies, and the subsidiary's location in a regional cluster of digital expertise that provides many attractive outside options for employment.

Extant research acknowledges that foreign MNC subsidiaries can face "hot" host-country labor markets for skilled employees (Becker et al., 2020). However, the interaction of foreign MNC subsidiaries with host-country labor markets is oftentimes reduced to salary premia for their employees compared to domestic firms (e.g., van der Straaten, Pisani, & Kolk, 2020). Our understanding of the motivations for employees staying at or leaving MNC subsidiaries is limited to idiosyncratic situations such as employees becoming entrepreneurs (De Backer & Sleuwaegen, 2003) or MNC subsidiaries being closed down (Sofka, Preto, & Faria de, 2014).

General retention literature highlights the detrimental consequences for firm performance when skilled employees leave (Briscoe & Rogan, 2015; Campbell, Ganco, Franco, & Agarwal, 2012). However, firms have a higher chance of retaining their employees if they can offer incentives that are not monetary in nature but create specific utility for their employees that keeps them from considering other employers (Kryscynski et al., 2021), such as the social purpose of work (Burbano, 2016). Within our logic, this specific retention effect for employees with digital human capital is particularly likely to depend on learning opportunities. In fact, IT workers are even willing to accept lower salaries when their job allows them to have access to the latest systems in their work (Tambe, Ye, & Cappelli, 2020). Our theorizing uses these insights as a point of departure and expands them to the retention of digital human capital in MNC subsidiaries.

We test our hypotheses by using the unique empirical opportunity provided by population-level employer–employee register data in Denmark. The data allow us to identify employees with digital human capital, i.e., all individuals with a university degree related to digitalization, such as AI, machine learning, or informatics, working for foreign MNC subsidiaries in Denmark between 2002 and 2012. Our dataset consists of 11,598 unique employees with digital human capital who work for 866 foreign MNC subsidiaries with at least one such employee, resulting in a total of 37,731 individual-year observations. Based on this longitudinal dataset, we can observe when employees with digital human capital are changing employers, i.e., our dependent variable, and control for many relevant factors, most notably the employees' salaries. Our results support all hypotheses.

The contribution of our study is twofold. First, we advance theory on the effects of subsidiary-specific advantages (Blomkvist, Kappen, & Zander, 2010; Rugman & Verbeke, 2001) by explicating the retention effects that they have for strategic subsidiary employees. While the notion that subsidiary-specific advantages result in a concentration of valuable skills and assets that are not available in other host-country firms or subsidiaries is foundational for this particular type of specificity (Meyer, Li, & Schotter, 2020), its consequence for creating distinct work conditions which set the subsidiary apart as a host-country employer is not well understood. This limits the application of the theory in an area in which it would be highly relevant, i.e., the labor market competition in host countries (Becker et al., 2020). In other words, while MNC subsidiaries build up digital expertise in order to benefit from the opportunities that digitalization affords, its benefit for retaining key employees has largely been overlooked by the extant research. By integrating theoretical mechanisms from strategic human capital theory (e.g., Chadwick, 2017; Coff & Kryscynski, 2011), we theorize how digital expertise as a subsidiary-specific advantage has substantial retention effects on subsidiary employees with digital human capital based on distinct learning opportunities. Further, we delineate how other dimensions of subsidiary-specific advantages create boundary conditions for this retention effect. Hence, our theorizing offers a platform for disentangling the heterogeneity within subsidiary-specific advantages with regards to their labor market effects.

Second, access to skilled human capital is an important motive for the internationalization strategies of MNCs (Almeida & Phene, 2004; Lewin et al., 2009). However, our current theoretical understanding is much more focused on the attraction of strategic human capital (e.g., Distel et al., 2019) instead of the retention which is arguably equally important for MNCs. We introduce distinct learning opportunities as a mechanism that helps subsidiaries retain strategic human capital in a digital context. However, the opportunities of foreign MNC subsidiaries for offering unique employment incentives that domestic firms cannot offer should be broader and deserve dedicated theorizing. For example, important retention effects may stem from the global reputation of an MNC as a leading employer.

THEORY AND HYPOTHESES

Our theoretical reasoning aims at explaining the likelihood that employees with digital human capital will leave an MNC subsidiary. For this purpose, we first outline the strategic value of digital human capital for MNCs before we discuss the role that the presence of digital expertise in subsidiaries can play for employee retention and how they can create voluntary mobility constraints (Call & Ployhart, 2021; Kryscynski et al., 2021). Hypotheses could be developed for the likelihood of retaining employees as well as the likelihood of employees leaving. We will use the latter wording for consistency with the empirical testing of the hypotheses but acknowledge that the reverse of the hypothesized relationship would always predict the former within our reasoning.

Digital Human Capital and Its Strategic Value for MNCs

Human capital consists of the skills, knowledge, experiences, and other characteristics of individuals that can be useful for firms (Ployhart & Moliterno, 2011). Employing individuals with particular types of human capital is of strategic importance for firms when they can create unique value from a firm's resources, e.g., by developing superior products or services for customers (Chadwick, 2017). Human capital can have these strategic effects when it is scarce on labor markets and supply is inelastic (Coff, 1997). Examples for such strategic human capital include entrepreneurial management skills (Campbell, 2013; Distel et al., 2019) or stakeholder knowledge (Grimpe, Kaiser, & Sofka, 2019).

Digital human capital is strategic for many firms because of a broader digitalization trend. The term digitalization describes the use of digital technologies in organizations for multiple purposes and functions (Nambisan, 2017; von Krogh, 2018). Digitalization is enabled by the electronic interconnectedness that networks provide between organizations via the Internet or internally via intranets (Ritter & Pedersen, 2019), and it affects the business models of many firms by offering new ways of increasing efficiency or creating new products (Slywotzky et al., 2001). Digitalization manifests itself in three primary areas of firm operations. First, production and service systems become increasingly integrated across value chains, e.g., linking suppliers and/or customers based on automated information exchanges or interfaces (Brynjolfsson & McAfee, 2014; Faraj, Pachidi, & Sayegh, 2018). Second, digitalization changes the way in which firms collect, store and analyze data. They rely increasingly on big data analytics, cloud computing, or the Internet of Things (Schwab, 2017; Sturgeon, 2019). Some firms employ artificial intelligence systems which can analyze data and take over decision making for certain business transactions (von Krogh, 2018). Finally, digitalization changes the way in which firms communicate externally and internally by using Internet-based platforms and channels (BarNir, Gallaugher, & Auger, 2003; Gallaugher, 1997). Hence, digitalization requires the rethinking of a firm's business model and increases competitive pressures from emerging, digital competitors (Ritter & Pedersen, 2019). While hardware systems, software languages, digital tools, and platforms are available to all firms, the employees who can design, integrate, and exploit their opportunities for an organization are central for successful digitalization (Slywotzky et al., 2001).

Individuals who are trained or have experience with digitalizing business operations are scarce on many labor markets and supply is limited. Scarcity emerges from the demand for digital human capital consistently outpacing supply (Tambe et al., 2020). Given the characteristics of digitalization, the effects are not confined to a single industry, e.g., telecommunications, but provide opportunities for increased efficiency or product differentiation in many industries ranging from manufacturing and financial services to the public sector. Hence, demand for digital human capital is broad. Simple programming jobs can be outsourced to external providers but those are rarely of strategic importance for firms. Instead, developing, designing, implementing, and maintaining advanced digital solutions requires that employees with digital human capital are not just specialized in a single system but understand the often times tacit interactions with other systems (Boh, Slaughter, & Espinosa, 2007). Much of this complex knowledge is tacit in nature which renders the supply of digital human capital inelastic. Many IT projects fail to meet budget allocations or schedules because of a lack of such complex knowledge (Wastell, 1999). What is more, many digitalization projects change procedures and processes throughout an organization (BarNir et al., 2003). Digital human capital is valuable when organizational obstacles have to be considered or overcome, but such experiences are typically tacit in nature (Ang, Slaughter, & Yee Ng, 2002). Examples include changes in marketing budgets to digital platforms, new sales channels, or increasingly flexible production processes.

The demand for digital human capital on labor markets is high while supply is limited, and these trends have important effects on MNCs. Digitalization triggers major changes in the internationalization processes of firms (Monaghan et al., 2020) and digital platforms become increasingly important for MNCs (Chen, Shaheer, Yi, & Li, 2019; Li et al., 2019; Nambisan et al., 2019). Digital human capital plays an important role in these digitalization strategies (Coviello, Kano, & Liesch, 2017). Banalieva and Dhanaraj (2019) provide a list of examples for advanced skills that are relevant for international, digital firms (p. 1378): "abstract thinking such as writing complex code to build a platform and later integrate it with other applications; engaging in continuous and complex interaction with engineers, service development specialists, or branding teams; integrating insights from predictive analytics; negotiating contracts for vendors to join the platform; forecasting revenue growth with new digital technologies, etc." Hence, having employees with digital human capital in MNC subsidiaries who possess these skills and can perform these tasks is of strategic importance.

Foreign MNC subsidiaries compete with local firms on host-country labor markets. Often times they need to overcome the advantages of domestic firms for attracting employees. Prospective employees may not be aware of a foreign MNC subsidiary (Newburry, Gardberg, & Belkin, 2006), MNC-wide human resource procedures can differ from local practices (Mezias, 2002), or MNCs have distinct needs (Distel et al., 2019). As a result, many foreign MNC subsidiaries pay wage premia for attracting host-country employees (van der Straaten et al., 2020). MNCs find themselves increasingly exposed to host-country labor markets for skilled employees on which demand outpaces supply (Becker et al., 2020). However, extant theory about the decisions of subsidiary employees to switch employers is limited to a narrow set of situations such as employees becoming entrepreneurs (De Backer & Sleuwaegen, 2003) or MNC subsidiaries being closed down (Sofka et al., 2014). This shortcoming is particularly salient for employees of foreign MNC subsidiaries with digital human capital since these employees are (a) likely to be of strategic importance for the digitalization of MNCs and (b) likely to be in high demand on host-country labor markets.

Retention of Digital Human Capital and the Role of Digital Expertise as a Subsidiary-specific Advantage

Retaining employees with strategic human capital is crucial for firms since these individuals can always exercise their free will and move to another employer (Coff, 1997). Loosing important employees is consequential for firm performance. Firms that are unable to retain key employees struggle with the coordination of complex tasks (Briscoe & Rogan, 2015), see the productivity of the remaining workforce declining (Campbell et al., 2012) and failure rates increasing (Phillips, 2002). Hence, firms have strong incentives to retain strategic human capital. In general, firms could simply offer higher wages. However, this perspective underestimates that most employees do not just work for an employer because of the salary that they receive. Instead, many long-lasting employment relationships are determined by non-monetary and often times affective benefits that particular employers can offer (Chadwick, 2017; Grimpe et al., 2019).

Kryscynski et al. (2021) introduce the concept of firm-specific incentives that "provide more utility to employees in the focal firm than similar incentives available at alternative employers" (p. 5). Such incentives can come in various forms such as the reputation of a firm (Cable & Turban, 2003), the opportunity to work autonomously (Gambardella, Panico, & Valentini, 2015), for a social mission (Burbano, 2016) or with exceptional colleagues (Oettl, 2012). In the presence of these firm-specific incentives, employees stay with an employer even if they could earn higher wages working for another firm (Kryscynski et al., 2021). In other words, employees create voluntary mobility constraints for themselves (Call & Ployhart, 2021).

While prior research on the retention of digital human capital is scarce, literature studying R&D employees as comparable types of highly skilled knowledge workers provides insights into the motivations of such individuals to change employers. This stream of research finds that knowledge workers perceive their working environment as a critical factor when making the decision to stay at or leave an employer. Major changes to the work environment requiring restructuring and a reorientation of activities, such as mergers and acquisitions (M&As), often provide empirical settings for studying the retention effects of work environments (Ernst & Vitt, 2000; Ranft & Lord, 2002). Paruchuri, Nerkar and Hambrick (2006) estimate that about one-third of the scientists and engineers unintentionally leave an acquisition target around the time of the acquisition. These effects can occur irrespective of the personnel intentions of the acquirer (Kapoor & Lim, 2007) and depend on the employers' activities and routines (Grimpe, 2007).

Central to the creation of voluntary mobility constraints of employees is the presence of incentives that are specific to a particular employer and a fit with the preferences of the focal employee (Kryscynski et al., 2021). Specificity in work conditions is likely to emerge in MNC subsidiaries because they are part of a broader MNC network. MNCs can pool resources and capabilities in certain subsidiaries while drawing from the resulting products and services throughout the MNC (Rugman & Verbeke, 2001). As a result of this specialization, certain subsidiaries have specific capabilities (Birkinshaw, 1997; Phene & Almeida, 2008) or advantages (Moore, 2001; Rugman & Verbeke, 2001). These advantages set certain subsidiaries apart because they have access to strategic MNC assets that are not available to other host-country firms and at the same time access to host-country assets that are not available to other subsidiaries (Meyer et al., 2020). Subsidiaries acquire these specific advantages because of favorable host-country conditions, through the initiative of subsidiary management or via assignment from global headquarters (Birkinshaw & Hood, 1998). Subsidiary-specific advantages can be persistent because they benefit from entrepreneurial, autonomous decision making in subsidiaries (Birkinshaw, Hood, & Jonsson, 1998), path dependency (Blomkvist et al., 2010) and provide their subsidiary with favorable bargaining positions within the MNC network, e.g., based on unique knowledge (Mudambi & Navarra, 2004). While this stream of research focusses on the intra-MNC consequences of subsidiary-specific advantages, our emphasis is on their effect on host-country labor markets. Subsidiary-specific advantages are important because they can explain why certain skills and assets are concentrated in specific subsidiaries in a host country but hardly present in others. Naturally, these varying levels of concentrated skills and assets shape the work conditions at a foreign MNC subsidiary with (or without) subsidiary-specific advantages and consequently its attractiveness as an employer in the host country.

Our reasoning focuses on subsidiary-specific advantages in the domain of digital technologies which we describe for short as the digital expertise of a foreign MNC subsidiary. The nature of digital technologies favors the emergence of digital expertise as a subsidiary-specific advantage. Given the availability of global networks and shared platforms or standards, digital algorithms, apps, or databases can be developed in the subsidiary that is best suited for the development purpose but efficiently rolled out to the rest of the MNC (Banalieva & Dhanaraj, 2019). Examples for the emergence of digital expertise in specific subsidiaries include the Google Safety Engineering Center (GSEC) in Munich creating technologies for Google's privacy engineering, or the Volkswagen Group Electronics Research Laboratory (ERL) in Silicon Valley researching car connectivity. Hence, the degree of digital expertise sets some foreign MNC subsidiaries in a host country apart from others and creates subsidiary-specific incentives for their employees.

We reason that the degree of digital expertise in a foreign MNC subsidiary leads to important learning opportunities for subsidiary employees with digital human capital, which in turn create voluntary mobility constraints. Kryscynski, et al. (2021) point out that employees choose to stay with employers when the specific incentives of the firm match their preferences. Access to novel technologies can create important utility for knowledge workers and scientists (Stern, 2004). In such a context, both employers and employees with digital human capital are interested in maintaining a productive work environment in which digital expertise in subsidiaries provides new opportunities for these employees to acquire new knowledge and skills.

Learning opportunities from working for subsidiaries with advanced digital expertise turn into retention-relevant utility for employees for two primary reasons. First, human capital theory posits that employees value the acquisition of skills that they may be able to use in their later careers (Becker, 1964). Digital human capital is often times acquired and advanced on the job (Ang et al., 2002; Boh et al., 2007). Hence, being able to access and build new skills is important for a career in the ICT industry more generally, and – more than other groups of employees – IT workers are responsible for enhancing their skills (Bidwell & Briscoe, 2010; Roberts, Hann, & Slaughter, 2006). Consistent with prior research which finds that highly skilled workers exchange wages for acquiring valuable knowledge on the job (Franco & Filson, 2006; Møen, 2005; Stern, 2004), IT workers have been shown to accept lower salaries when they have access to the latest systems (Tambe et al., 2020). Subsidiaries with high levels of digital expertise can offer their employees with digital human capital learning opportunities that advance their future careers, while subsidiaries without digital expertise are comparatively less likely to do so.

Second, working for a subsidiary with many learning opportunities from advanced digital expertise changes the nature of work tasks. It can result in higher task variety which is a marker of job attractiveness (Heckman & Oldham, 1980). Within a digital context, existing standards, technologies or hardware emerge constantly, replace existing ones or provide new opportunities (Bapna, Langer, Mehra, Gopal, & Gupta, 2012). Subsidiaries with advanced digital expertise are increasingly likely to incorporate these new technologies continuously. Hence, task variety can increase with new tasks being created or when existing tasks are performed in a new way. Subsidiaries with low levels of digital expertise are comparatively more likely to offer their employees with digital human capital routinized tasks with little variation.

In sum, employees with digital human capital working for subsidiaries with digital expertise are comparatively more likely to benefit from the distinct learning opportunities and stay with the MNC subsidiary. Conversely, subsidiaries without digital expertise are unlikely to have a particular strength in retaining these employees. We propose:

> **Hypothesis 1:** Employees with digital human capital are less likely to leave foreign MNC subsidiaries with increasing degrees of digital expertise.

Boundary Conditions for Retention Effects Based on the Digital Expertise of a Subsidiary

We further explore how the retention effects laid out in Hypothesis 1 depend on other subsidiary dimensions which are characteristic for the emergence of subsidiary-specific advantages. More specifically, we explore interactions with three central dimensions: the international diversity of the workforce, the level of technological capabilities and the quality of the regional environment. First, the international diversity of the subsidiary workforce is a relevant dimension of subsidiary-specific advantages because MNCs often times rely on the cross-border transfers of MNC experts to foster knowledge exploration in subsidiaries (Berry, 2014; Harzing, Pudelko, & Reiche, 2016). This results in a distinctively international workforce in subsidiaries which can affect learning opportunities from digital expertise. Second, subsidiary-specific advantages depend not just on intra-MNC interaction but also on a subsidiary's ability to access valuable host-country assets and knowledge (Rugman & Verbeke, 2001). This ability is higher when subsidiaries have advanced technological capabilities which are often times documented by their patented technologies (Phene & Almeida, 2008). The presence of such advanced technological capabilities is likely to influence the learning opportunities from digital expertise and hence the retention effects. Finally, subsidiary-specific advantages depend often times on the opportunities for absorbing valuable assets and knowledge that the host country provides (Almeida & Phene, 2004). These opportunities are usually clustered in host-country regions and require geographical proximity to benefit from them (Alcacer & Chung, 2007; Shaver & Flyer, 2000). At the same time, geographical clusters can be relevant moderators for retention effects of digital expertise because they can provide geographically concentrated opportunities for job mobility (Lamin & Ramos, 2016).

Taken together, we explore how the three important dimensions of subsidiary-specific advantages affect the strength of the retention effects from digital expertise for a subsidiary's employees with digital human capital. We suspect that the interaction effects of an internationally diverse workforce and technological capabilities emerge from differences in the learning opportunities from digital expertise that a subsidiary can offer while regional clusters of digital expertise affect the availability of attractive outside options on regional job markets.

Starting with international diversity, we argue that the retention effects are stronger when the workforce of the subsidiary is internationally diverse. The international diversity of employees is a defining feature of foreign MNC subsidiaries (Collings, Scullion, & Dowling, 2009). It emerges from a combination of factors. First, MNCs can transfer expat employees within the MNC network as a means of knowledge transfer or exercising control (Belderbos & Heijltjes, 2005). Second, many MNCs have global talent management procedures in place which screen the potential of employees across subsidiaries and help promising candidates develop their careers including experiences in various host countries (Collings & Isichei, 2018; Sarabi, Froese, & Hamori, 2017). Third, hiring of MNC subsidiaries follows standardized procedures which can reduce job market entry barriers for foreign individuals in host countries (Lanciotti & Lluch, 2020). As a result, foreign MNC subsidiaries are particularly likely to provide a work environment in which employees with many different nationalities interact, i.e., they provide an internationally diverse workforce (Gong, 2003).

International diversity of an MNC subsidiary's workforce is not automatically a positive retention factor in itself. Differences in nationalities can be a source of bias in group decision making since some team members may not identify with colleagues from other countries (Jackson et al., 1995). As a result, nationality-based categorization can result in conflict and a lack of cohesion (Nielsen & Nielsen, 2013). Distel, et al. (2019) find for example that locally hired managers are more productive in foreign MNC subsidiaries with less diverse workforces. Then again, international diversity affects the learning opportunities for the employees of a foreign subsidiary which is the central aspect of our reasoning and the basis for a moderating effect.

International diversity increases the range of experiences and perspectives that individuals bring from their specific institutional environments to a subsidiary (Smith et al., 1994). Working with a diverse group of colleagues provides a distinct context in which individuals make new experiences and develop skills. This is due to the fact that internationally diverse teams are more likely to challenge existing convictions, envision novel solutions to existing problems, create innovations and/or facilitate organizational learning (Elron, 1997; Nielsen & Nielsen, 2013). These conditions provide attractive learning opportunities for employees with digital human capital. Digital expertise in subsidiaries with internationally diverse employees is likely to result in more creativity and innovative thinking. What is more, MNCs provide a social community that enables exchanges of tacit knowledge between subsidiaries and global headquarters based on shared norms and rules (Kogut & Zander, 1993). Employees can tap into these personal networks of international colleagues which can connect them to experts in other subsidiaries. This distinct learning environment in foreign MNC subsidiaries with digital expertise and internationally diverse colleagues is hard to replicate by other employers in the host country and should therefore increase retention effects. Conversely, foreign MNC subsidiaries lacking international diversity among colleagues are more likely to offer learning opportunities from digital expertise that employees with digital human capital could also find at domestic firms. We propose:

Hypothesis 2: Employees with digital human capital are less likely to leave foreign MNC subsidiaries with increasing degrees of digital expertise, and this effect is stronger if the workforce of the subsidiary is internationally diverse.

Further, we suggest that the retention effects from an MNC subsidiary's digital expertise are stronger when subsidiaries possess patented technologies. Patents reflect proprietary technologies in innovative and emerging areas that provide exclusive learning opportunities other companies are unable to offer (Tambe et al., 2020).

Patents are conferred by patent offices in order to protect the efforts of inventors and thus maintain incentives to engage in costly R&D activities (Cohen et al., 2000). They provide their owners (inventors or their "assignees") a time-limited right to exclude others from commercializing an invention. To qualify for patent protection, an invention must make a novel and non-obvious contribution over existing knowledge (the "prior art"), and only the novel features can be patented (Encaoua, Guellec, & Martinez, 2006). By disclosing an invention to the patent office, firms engage in a social contract that the invention should be adequately described and made public in exchange for receiving a patent right (Scotchmer & Green, 1990).

Patented technologies of an MNC subsidiary influence the learning opportunities for employees with digital human capital that arise from the digital expertise of a subsidiary in two ways. First, the value of human capital is often times tied to the distinct resources that the firm controls in which the human capital was developed (Helfat, 1994). For example, a programmer can develop valuable skills by creating an artificial intelligence algorithm that uses the patented sensors of an autonomous car but less valuable skills without access to the sensor technology. Patents are exclusionary rights (Cohen et al., 2000). While the content of granted patents is publicly available, owners of patented technology can exclude others from actually using the patented technology in their own products or services. In that sense, the patented technologies of one firm affect the technology development of other firms that become more likely to avoid these technologies due to the risk of infringement (Shapiro, 2001). Hence, patented technologies increase the odds that other employers with comparable digital expertise will not be able to offer superior learning opportunities. Conversely, a subsidiary that holds patented technologies will be able to increase the learning opportunities that arise from digital expertise for its employees with digital human capital.

Second, patents can have retention effects for employees with digital human capital even when they have not worked directly with patented technologies in the past but provide unique learning opportunities for the future. In this regard, patents do not just describe property rights but also document that a subsidiary is on the forefront of technological development as evidenced by the patent grant (Magelssen, 2020). Scientists and engineers are highly motivated by being able to work on complex and challenging tasks (Agarwal & Ohyama, 2013; Roach & Sauermann, 2010). Patents imply that subsidiaries have developed new technological capabilities that go beyond the "state of the art". These subsidiaries provide employees with potential learning opportunities for the future because digitalization and innovation are complementary activities (Wu, Hitt, & Lou, 2020). In other words, these employees can interact directly with leading product development engineers, receive immediate feedback from laboratories and users or become inspired for new digital solutions in innovative products. These potentials for direct interaction can enable exciting new discoveries or collaborations for employees with digital human capital. Therefore, an engagement in cutting-edge technology development allows them to update their knowledge, skills and experience in emerging technologies to a greater extent than if the subsidiary did not have the ambition to go beyond the "state of the art" (Bapna et al., 2012).

Taken together, MNC subsidiaries with an increasing number of patents provide employees with digital human capital with access to leading knowledge that can be used by other potential employers only to a limited extent. Hence, the presence of patented technologies increases the subsidiary-specific learning opportunities from digital expertise in MNC subsidiaries for employees with digital human capital, resulting in voluntary mobility constraints (Call & Ployhart, 2021). As a result, MNC subsidiaries with patented technologies are more likely to succeed in retaining these employees. Our third hypothesis therefore reads:

Hypothesis 3: Employees with digital human capital are less likely to leave foreign MNC subsidiaries with increasing degrees of digital expertise, and this effect is stronger if the subsidiary has more patents.

Finally, boundary conditions for the effects of digital expertise on the retention of employees with digital human capital do not just emerge from the heterogeneity among foreign MNC subsidiaries but also from the degree to which host-country labor markets can offer outside options with comparable learning opportunities. This boundary condition takes into account that foreign MNC subsidiaries compete with domestic firms on labor markets (De Backer & Sleuwaegen, 2003; van der Straaten et al., 2020). We conjecture that employees with digital human capital are more likely to leave subsidiaries with digital expertise when these are located in digital expertise clusters.

Clusters are typically characterized as regions with a particularly high concentration of technological activity and innovation in an industry (Alcácer & Zhao, 2012). In that sense, regions differ in the extent to which firms in a specific industry possess digital expertise. In some regions, particular industries are likely to be at the forefront of digitalization in a host country while others are comparatively lagging. Within our reasoning, the host-country environment of a subsidiary is digitally leading and hence increasingly resembles a digital expertise cluster when the domestic firms in the same industry and region possess more digital expertise than the industry average. Importantly, digital expertise clusters can exist in all industries and not just in the ICT industry since they are regional in nature. For example, clusters for renewable energy production may regionally overlap with digital expertise clusters or exist in separate regions of a host country.

We argue that regions which increasingly resemble digital expertise clusters provide more attractive outside job opportunities for MNC subsidiary employees with digital human capital. In fact, a key characteristic of clusters is that they provide attractive local labor markets, increasing the likelihood that skilled employees can move to other firms (Almeida & Kogut, 1999) or startups (Glaeser & Kerr, 2009) without large relocation costs. Moreover, the colocation of firms increases the likelihood for direct interaction of firms and their employees which makes the investments of firms in digital expertise increasingly visible and credible (Sofka, Faria de, & Shehu, 2018). Foreign MNC subsidiaries with digital expertise will thus find it more challenging to retain these employees when many host-country employers in the cluster provide similar learning opportunities.

Taken together, we argue that employees with digital human capital will consider the learning opportunities from a subsidiary's digital expertise relative to those at domestic firms in the same host-country industry and region which may be a digital expertise cluster or not. Accordingly, the retention effect of digital expertise on employees with digital human capital in foreign MNC subsidiaries is weaker if they are located in a region that increasingly resembles a digital expertise cluster and vice versa. We propose:

Hypothesis 4: Employees with digital human capital are less likely to leave foreign MNC subsidiaries with increasing degrees of digital expertise, and this effect is weaker if subsidiaries are located in a digital expertise cluster.

DATA AND METHODS

Data

We test our theoretical predictions using linked employer–employee register data for Denmark. These data that cover the entire population have frequently been used in the social sciences (e.g., Kaiser, Kongsted, Laursen, & Ejsing, 2015, 2018; Lyngsie & Foss, 2017). Our theoretical model predicts differences in the propensity of employees with digital human capital to leave an MNC subsidiary for alternative employment. Hence, we condition on individuals with an education related to digitalization who are presently employed by a foreign MNC subsidiary and who either stay with their employer or leave the MNC subsidiary. For identifying digital human capital, we focus on the education of individuals. Education is a central source of skills, knowledge or abilities, and diplomas are crucial sources of information on labor markets by which individuals can signal hard to observe qualities to potential employers (Spence, 1973). To identify relevant educations, we use a detailed four-digit classification of an individual's final education provided by Statistics Denmark. The classification contains information on both the level and the content of the educational program in which an individual has been enrolled and is available since 1980. Based on a literature survey and conversations with experts on the Danish register data, we generate a comprehensive list of keywords, which indicate that the individual has acquired knowledge, skills and experiences in digitalization, and/or digital technologies, such as machine learning, informatics, or robotics. Given that these keywords appear in the description of the educational program and typically in the degree that they convey, we are confident that digital aspects are a defining building block of the education. Based on this classification procedure, we identify all employees with degrees in digital educations in Denmark between 2002 and 2012.

We define foreign MNC subsidiaries based on data obtained from Experian A/S, a credit rating agency, following prior research (e.g., Kaiser & Kuhn, 2016; Sofka et al., 2021). The data also allow us to distinguish between "any" foreign ownership and majority ownership, an issue that we discuss in one of our robustness checks. We constrain the sample of foreign MNC subsidiaries to those employing at least one employee with digital human capital during the observation period since these are the only subsidiaries at risk of losing them. Subsequently, we obtain the population of individuals with digital human capital who are employed by a foreign MNC subsidiary. By restricting the sample in this way, we eliminate effects from non-random sorting of individuals into (i) taking an education related to digitalization and (ii) working for a foreign MNC subsidiary. We obtain an estimation sample of 11,598 unique employees with digital human capital working for 866 unique foreign MNC subsidiaries between 2002 and 2012, i.e., a total of 37,731 individual-year observations without missing values in key variables.

Measures

Dependent variable

The dependent variable in our regressions is an individual's propensity to leave the MNC subsidiary in the next time period, i.e., in the following year. Using a full year of employment with another firm allows us to eliminate potential biases from individuals switching employment temporarily, e.g., as part of a sabbatical. Employers are mandated by Danish law to report employee hirings and departures. Hence, the data coverage is comprehensive and reliable.

Explanatory variables

We follow earlier research and capture differences in a subsidiary's specific advantages or capabilities based on the knowledge intensity of its workforce (Distel et al., 2019; Sofka et al., 2014). More specifically, our definition of digital expertise is tied to the amount of digital knowledge that is present in a subsidiary, relative to the total workforce. To test Hypothesis 1, we therefore measure digital expertise as the number of individuals with a digitalization-related education scaled by the total number of employees at the MNC subsidiary.

In Hypothesis 2, we suggest that the relationship between a subsidiary's digital expertise and an individual's likelihood to leave is moderated by the international diversity of the subsidiary's workforce. We define this variable using a concentration measure, i.e., the Blau index (Blau, 1960), corrected by firm size as suggested by Kaiser and Müller (2015). The index takes the value 0 if all individuals in the workforce possess the same citizenship and the value 1 if all citizenships are different.

Hypothesis 3 refers to the moderation of our main relationship with an MNC subsidiary's patents. We measure the latter using the stock of patents applied for by the MNC subsidiary. The patent data stem from the European Patent Office's PATSTAT database that are merged to the respective patent assignee by Statistics Denmark (Kaiser & Kuhn, 2019). We use the employer of the patent inventor to identify patenting activity precisely in the subsidiary in which the patent was created instead of the assignee organization which might be the location of the MNCs IP management department or its global headquarters.

Hypothesis 4 argues that the retention effect of digital expertise is moderated by whether the subsidiary is located in a regional cluster of digital expertise. We use a continuous measure to identify the degree to which a region resembles such a cluster. Similar to Salomon and Jin (2008), we operationalize this variable as the average digital expertise in the subsidiary's industry and region minus the average digital expertise in the industry in Denmark. Hence, positive values indicate that the MNC subsidiary is in a region which is increasingly likely to be a cluster of digital expertise for the host-country industry while negative values indicate that this is unlikely to be the case.

Following the comprehensive survey by Griffeth, Hom and Gaertner (2000), we control for an extensive set of variables that have been used in previous studies on employee mobility as well as for other potentially confounding variables that our rich data set allows us to control for. Specifically, we control for an individual's education level by including a dummy variable indicating that the individual holds at least a master's degree from one of the identified education programs related to digitalization and digital technologies (Tambe et al., 2020). We also include dummy variables controlling for gender and Danish citizenship (Felps, Mitchell, Hekman, Lee, Holtom, & Harman, 2009; Mitchell, Holtom, Lee, Sablynski, & Erez, 2001; Tambe et al., 2020; Trevor, 2001). We account for tenure by including the number of years an individual has been with a specific employer (Felps et al., 2009; Trevor, 2001) as well as for work experience (in no. of years) in general (Tambe et al., 2020). Years of tenure accounts for "duration" dependence, the relationship between how long an individual has been in a certain "state" (with the same employer) and the probability of leaving that state.

Relative and hypothetical alternative salaries constitute major drivers of job mobility (Trevor, 2001). We calculate hypothetical alternative salaries by running an OLS regression on log annual income and a set of year, age group, sector and region dummies for digital human capital employed in *domestic* firms and use the (exponentiated) predictions of that model as our measure of alternative income. Apart from hypothetical income, we also control for an individual's relative income position within the firm by including dummy variables measuring the salary quantiles. Using quantile dummy variables has the advantage that they capture differences in the quality of employees within a firm even when the absolute salary levels vary between firms due to firm-specific, industry, or regional differences (Grimpe et al., 2019).

Moreover, local, industry-specific labor demand may influence the decision to leave the current employer (Griffeth et al., 2000), which is why we include the number of firms with at least one employee with digital human capital in the subsidiary's region and industry. We also account for the general R&D employee intensity and patenting activity, both by industry and region relative to the national average, in order to control for industry and location-specific variation across the country that may make a particular region an attractive place for MNC subsidiaries to be located in. While these variables cover different facets of an employee's outside options, we include the number of hierarchy levels at the workplace to proxy for promotional chances (Griffeth et al., 2000). This variable is defined as the count of each firm's unique "DISCO" codes, the Danish version of the International Standard Classification of Occupations, scaled by the total number of employees since larger firms possess more hierarchy levels.

Firms may also be characterized by a high turnover rate of their employees with digital human capital. To control for the organizational commitment (Mitchell et al., 2001; Ono, 2007), we therefore include the average number of years of tenure of an individual's digital co-workers at the MNC subsidiary, scaled by firm age, and the workplaces' "churn rate" which we operationalize by the ratio of workplace leavers to the total workforce over the past three years (i.e., years *t-1* to *t-3*). Relatedly, we account for absenteeism (Griffeth et al., 2000) by including the logarithm of the employers' mean sick leave pay (in DKK) in our models. Since the variable is no longer recorded after 2010 in the database, we extrapolate it at the firm-level for 2011 and 2012. Leaving out both years instead reduces the sample but does not change our results qualitatively or quantitatively.

Turnover may also be driven by an individual's position in the hierarchy (Felps et al., 2009; Tan & Rider, 2017). We therefore control for whether the individual has a management role or is a member of the top management team (TMT). We create this variable based on DICSO codes. In addition, we include the natural logarithm of the firm's size (in number of employees) as well as a dummy variable indicating that the subsidiary is exporting (Kaiser et al., 2018).

The richness of our data allows us to include additional measures for an individual's motivation to leave the present employer. These include the number of jobs an individual held in the past five years, which could be positively related to a person's propensity to leave. Additionally, we control for whether the focal employee had left the current employer previously and returned afterwards ("return employee") since this may indicate an unobserved bond with the current employer. Moreover, we measure whether the individual has been promoted in the past five years, which is both an inside and an outside signal of quality. In addition, we include the number of patents that an individual holds since those patents indicate human capital that may make individuals more attractive on the job market.

Additionally, we include a set of individual-level variables which are likely to constrain labor mobility. More precisely, we control for the individual being married (or not) and for the number of children. Commuting time may also affect an individual's propensity to leave which is why we include a dummy variable for living and working in the same municipality and an additional dummy variable for living and working in the greater Copenhagen area. Possessing real estate may also reduce mobility. Therefore, we include a dummy variable for real estate ownership and, if so, the real estate value. Lastly, we include a set of region and year dummy variables.

Estimation Approach

Our model predicts the propensity of employees with digital human capital to leave their current employment at a foreign MNC subsidiary. We observe these employees over a period of eleven years on an annual basis as our data are recorded on 30 November of each year. This implies that each duration of an employment spell in an MNC subsidiary is discrete and that we are hence dealing with repeated event history data. Such data are appropriately handled with models for discrete durations like a binary logit model and required to be coded as duration data (Winkelmann & Bös, 2006).

The panel structure of our data allows us to run random effects estimations besides the "pooled" model. We cannot run fixed effects estimations since they require that individuals leave their employer at least once. However, it turns out that the random effects estimates of our main coefficient of interest are substantially larger than the one generated by a "pooled" model which is why we use the random effects model in our robustness checks only and prefer the "pooled" model in our main analysis since it generates more conservative estimates. Given that we calculate hypothetical alternative income by an OLS regression, i.e., we operate with a "generated regressor", we need to bootstrap our standard errors since the corresponding variance-covariance matrices are no longer block-diagonal (Wooldridge, 2007).

Finally, digital expertise in subsidiaries is potentially endogenous. For this purpose, we employ a "control function" approach (Choi & McNamara, 2018; Heckman & Robb, 1985) of which Heckman's classic sample selection model constitutes a special case. The basic idea behind the control function approach is to account ("control") for possible endogeneity bias by adding the residual term of a first stage regression of the endogenous variable on the set of explanatory variables plus a set of instruments, or "exclusion restrictions". We use the rollout of high-speed Internet across Denmark as an exogenous instrument. The control function approach generates a point estimate on our measure for digital expertise that is considerably larger than in the main model. For this reason, we decide not to use the control function approach for the main models since they allow a more conservative estimate, biased towards zero. Nevertheless, we report details and results of the control function approach in the section describing consistency checks below.

We run five different pooled models, with the main model only containing the digital expertise and control variables, and four additional models where we consecutively add the international workforce diversity, number of patents, and digital expertise cluster variable interactions and finally all interactions at the same time.

Results

Our empirical analysis starts with descriptive statistics displayed in Table 1. The propensity of leaving the present employer is on average 12.5%. This comparatively high number provides a first indication for the high demand for employees with digital human capital on host-country labor markets. With respect to our hypothesis testing variables, we find that digital expertise (the number of employees with digital human capital as a share of the subsidiary's total workforce), is 0.128, which varies considerably across observations given a standard deviation of 0.114. There is little international diversity in the subsidiary's workforce as indicated by a Blau index value of 0.059. Moreover, the subsidiary's patent stock is on average 29.2, again with a large standard deviation. On average, employees with digital human capital work at subsidiaries in regions that do not resemble a digital expertise cluster as a value of -0.033 of our cluster measure indicates.

Next, we present descriptive statistics for select control variables. Here we find that 19.4% of all MNC subsidiaries have at least one patent and 71.8% are exporters. They are also quite sizable with an average number of employees of 2227. The average employee with digital human capital in our data looks back at 13.3 years of working experience and 3.8 years of tenure at their current employer. The mean hypothetical alternative income in domestic employment is 410,312 DKK (about 63,778 USD), which is considerably above the Danish mean income of 326,000 DKK. 14.7% of the individuals hold at least a master's degree while the average employee with digital human capital only holds 0.027 patents. The average number of promotions is 0.705 over the past 5 years during which individuals held on average 0.43 different jobs other than the present one. Very few employees with digital human capital (0.003) have returned to the MNC subsidiary after working elsewhere. Half of them are married, and they have on average one child.

Table 2 shows the pairwise correlations of the variables used in our main models. The correlations among the variables are modest, except of course for control variables that are directly dependent upon one another like years of tenure and the number of jobs in the past five years for which the

Table 1 Descriptive statistics (n = 37,731)

	Mean	SD		Mean	SD
Dependent variable			Years of tenure	3.8	3.4
Leaves MNC employer (d)	0.125	–	Return employee (d)	0.003	–
Hypotheses-related variables			Human capital variables		
Digital expertise	0.128	0.114	TMT member (d)	0.049	–
International diversity	0.059	0.101	Management team member (d)	0.541	–
No. of patents	29.2	126.9	At least MA (d)	0.147	–
Digital expertise cluster	− 0.033	0.066	Stock of person's patents	0.027	0.503
Firm-level variables			No. of other jobs past five years	0.430	0.241
At least one patent (d)	0.194	–	No. of times promoted past 5 years	0.705	0.16
Mean years of tenure at workplace/firm age	0.212	0.215	Person-level variables		
Hypothetical income in domestic firm (in DKK)	410312	73583	Married (d)	0.518	–
No. of employees	2227	3925	Danish (d)	0.971	–
Exporting (d)	0.718	–	Female (d)	0.183	–
Industry & regional R&D worker intensity	0.037	0.036	No. of children	0.945	1.05
Industry & regional patenting intensity	0.013	0.054	Same municipality work & home (d)	0.190	–
No. of firms digital prof. in industry & region	13.192	16.398	Same municipality work & home in CPH (d)	0.105	–
No. of hierarchy levels scaled by firm size	0.018	0.051	Income and wealth		
Mean sick leave pay (in DKK)	12062	12231	Bottom 25% income at workplace (d)	0.088	–
Churn rate	0.187	0.089	Bottom 50% income at workplace (d)	0.170	–
Human capital variables			Bottom 75% income at workplace (d)	0.283	–
Years of working experience	13.3	7.6	Real estate value (in DKK)	912518	898860
			Possesses real estate (d)	0.704	–

(d) dummy variable

pairwise correlation is – 0.609. Moreover, the mean variance inflation factor is 2.75 for our most general model and hence well below the critical value of 10 suggested by Belsley, et al. (1980).

Table 3 displays the binary logit regression results. Model 1 is the main model, which includes all main effect variables. As expected, we find a negative and statistically highly significant relationship between a subsidiary's digital expertise and an employee's likelihood to leave. The more digital expertise a subsidiary has, the less likely it becomes that employees with digital human capital will leave that subsidiary. Model 2 includes the interaction effect between digital expertise and the international diversity of the workforce. The coefficient is negative and statistically highly significant, indicating that employees with digital human capital are even less likely to leave a subsidiary with digital expertise when the international diversity of the workforce is high. Model 3 includes the interaction effect between digital expertise and the subsidiary's number of patents, showing a negative and statistically highly significant coefficient. This finding provides evidence of the benefits of patented technologies for reducing the likelihood to leave subsidiaries with digital expertise. Next, Model 4 includes the interaction between a subsidiary's digital expertise and the degree to which the region in which the subsidiary is located resembles a digital expertise cluster. We find a positive and statistically significant effect which suggests that digital human capital is more likely to leave a subsidiary when it is located in a digital expertise cluster that provides attractive alternative employment opportunities. Finally, Model 5 includes all variables. We find fully consistent results and hence cannot reject our four hypotheses.

The coefficient estimates do not easily translate into marginal effects of conditional probabilities since this is generally not the case for logit models (unlike OLS models), i.e., they are functions of the four variables of interest. In order to make our coefficient estimates economically meaningful, we calculate the probabilities for leaving conditional on the different combinations of the four main variables. Since we cannot consider our four main explanatory variables at the same time, we let digital expertise vary between its observed range 0.1 and 0.85 and consider the 10% smallest ("low") and 10% highest ("high") values of the other three variables, one variable after the other. We display the predicted conditional probabilities in Figure 1 along with the corresponding 90% confidence

Table 2 Pairwise correlations (n = 37,731)

		(1)	(2)	(3)	(4)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(18)
(1)	ln(digital expertise)	1.00															
(2)	International diversity	0.04	1.00														
(3)	ln(no. of patents)	− 0.23	0.06	1.00													
(4)	Digital expertise cluster	− 0.22	0.03	0.06	1.00												
(6)	At least one patent (d)	− 0.24	0.06	0.80	0.11	1.00											
(7)	Mean years of tenure at workplace/firm age	− 0.02	0.18	− 0.11	− 0.03	− 0.01	1.00										
(8)	ln(hypothetical income in domestic firm (DKK))	0.31	− 0.18	− 0.23	0.02	− 0.12	0.17	1.00									
(9)	No. of employees	− 0.41	− 0.11	0.03	− 0.06	0.17	− 0.08	0.06	1.00								
(10)	Exporting (d)	0.01	− 0.17	0.20	0.03	0.15	− 0.13	− 0.16	− 0.04	1.00							
(11)	Industry & regional R&D worker intensity	0.39	− 0.35	− 0.33	− 0.06	− 0.29	− 0.05	0.41	0.25	− 0.20	1.00						
(12)	Industry & regional R&D patenting intensity	− 0.17	0.08	0.54	− 0.04	0.35	− 0.07	− 0.17	0.17	0.12	− 0.14	1.00					
(13)	No. of firms digital prof. in industry & region	0.49	0.26	− 0.36	0.04	− 0.33	0.10	0.26	− 0.24	− 0.20	0.40	− 0.22	1.00				
(14)	No. of hierarchy levels scaled by firm size	0.23	0.03	− 0.04	0.04	− 0.10	0.13	− 0.01	− 0.54	− 0.01	− 0.06	− 0.06	0.13	1.00			
(15)	ln(mean sick leave pay (in DKK))	0.13	− 0.06	− 0.02	0.05	0.01	0.03	0.11	− 0.02	0.07	0.04	− 0.03	0.04	0.03	1.00		
(16)	Churn rate	0.01	0.03	− 0.01	0.05	− 0.02	− 0.13	− 0.08	− 0.25	− 0.02	− 0.19	− 0.03	0.00	0.12	− 0.05	1.00	
(18)	Years of working experience	− 0.02	− 0.07	− 0.12	− 0.10	− 0.08	0.10	0.49	0.16	− 0.04	0.13	− 0.04	0.00	− 0.08	0.05	− 0.11	1.00
(19)	Years of tenure	− 0.03	0.00	0.03	− 0.02	0.10	0.18	0.29	0.11	0.05	0.02	0.08	− 0.01	− 0.03	0.09	− 0.05	0.41
(20)	Return employee (d)	− 0.01	0.01	0.00	0.00	0.00	0.00	0.02	0.02	− 0.02	0.01	0.00	0.01	− 0.01	0.00	0.01	0.02
(21)	TMT member (d)	− 0.06	0.00	− 0.02	− 0.03	− 0.01	− 0.01	0.01	− 0.02	0.01	− 0.03	− 0.02	− 0.04	− 0.04	0.00	0.02	0.10
(22)	Management team member (d)	0.18	0.13	0.05	0.07	0.02	0.06	0.17	− 0.07	− 0.12	0.05	− 0.01	0.17	− 0.07	0.03	− 0.07	0.00
(23)	At least MA (d)	0.10	0.02	0.04	0.02	0.05	0.00	0.07	− 0.05	0.01	0.02	− 0.02	0.09	− 0.01	0.02	− 0.01	− 0.05
(24)	Stock of person's patents	0.00	0.00	0.04	− 0.01	0.04	0.02	0.01	− 0.01	0.02	− 0.02	0.00	− 0.01	0.00	0.01	− 0.02	− 0.01
(25)	No. of jobs in past five years	0.00	0.01	0.01	0.03	− 0.03	− 0.15	− 0.27	− 0.10	− 0.02	− 0.05	− 0.02	− 0.01	0.06	− 0.12	0.08	− 0.37
(26)	Has been promoted past 5 years (d)	0.02	− 0.04	− 0.01	0.00	− 0.05	− 0.08	− 0.08	0.00	− 0.03	0.05	− 0.01	− 0.04	0.02	− 0.07	0.07	− 0.11
(27)	Married (d)	0.00	− 0.02	− 0.02	− 0.03	− 0.01	0.03	0.25	0.07	− 0.02	0.06	− 0.02	0.02	− 0.03	0.04	− 0.07	0.32
(28)	Danish (d)	− 0.02	− 0.01	− 0.02	− 0.32	− 0.03	0.01	0.04	0.03	− 0.02	0.02	0.01	− 0.02	− 0.02	− 0.01	− 0.02	0.15
(29)	Female (d)	− 0.08	0.02	− 0.04	0.00	− 0.04	0.05	0.08	0.08	− 0.06	0.02	0.00	− 0.01	− 0.05	0.03	− 0.03	0.10
(30)	No. of children	0.01	− 0.02	− 0.02	− 0.03	− 0.01	0.02	0.24	0.05	− 0.02	0.03	− 0.01	0.00	− 0.04	0.05	− 0.04	0.21
(31)	Same municipality work & home (d)	− 0.04	0.14	0.11	0.03	0.06	0.06	− 0.11	− 0.08	0.06	− 0.17	0.11	− 0.07	0.06	0.00	− 0.01	− 0.12
(32)	Same municipality work & home in CPH (d)	− 0.01	0.10	− 0.08	0.08	− 0.07	0.07	0.00	− 0.04	0.00	0.01	− 0.07	0.12	0.04	0.02	0.05	− 0.12
(33)	Bottom 25% income at workplace (d)	− 0.09	0.03	0.03	0.03	0.03	− 0.05	− 0.25	− 0.04	0.01	− 0.11	0.01	− 0.08	0.04	− 0.10	0.10	− 0.27
(34)	Bottom 50% income at workplace (d)	− 0.05	0.02	0.10	0.00	0.10	− 0.03	− 0.18	− 0.02	0.07	− 0.12	0.09	− 0.12	0.03	0.01	0.03	− 0.20
(35)	Bottom 75% income at workplace (d)	0.01	− 0.01	0.04	− 0.02	0.04	− 0.01	− 0.02	0.02	0.02	0.00	0.04	− 0.02	− 0.01	0.03	− 0.01	− 0.05
(36)	Real estate value (in DKK)	0.03	− 0.03	− 0.03	− 0.07	− 0.02	0.04	0.24	0.05	− 0.02	0.07	− 0.02	0.03	− 0.04	0.04	− 0.07	0.34

Table 2 continued

		(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)	(33)	(34)	(35)	(36)
(1)	ln(digital expertise)																		
(2)	International diversity																		
(3)	ln(no. of patents)																		
(4)	Digital expertise cluster																		
(6)	At least one patent (d)																		
(7)	Mean years of tenure at workplace/firm age																		
(8)	ln(hypothetical income in domestic firm (DKK))																		
(9)	No. of employees																		
(10)	Exporting (d)																		
(11)	Industry & regional R&D worker intensity																		
(12)	Industry & regional R&D patenting intensity																		
(13)	No. of firms digital prof. in industry & region																		
(14)	No. of hierarchy levels scaled by firm size																		
(15)	ln(mean sick leave pay (in DKK))																		
(16)	Churn rate																		
(18)	Years of working experience																		
(19)	Years of tenure	1.00																	
(20)	Return employee (d)	0.05	1.00																
(21)	TMT member (d)	0.03	0.00	1.00															
(22)	Management team member (d)	0.01	0.01	− 0.27	1.00														
(23)	At least MA (d)	− 0.03	0.00	0.02	0.14	1.00													
(24)	Stock of person's patents	0.02	0.00	− 0.01	0.04	0.09	1.00												
(25)	No. of jobs in past five years	− 0.61	0.02	− 0.02	− 0.05	0.02	− 0.01	1.00											
(26)	Has been promoted past 5 years (d)	− 0.18	− 0.01	0.08	0.00	− 0.03	− 0.02	0.19	1.00										
(27)	Married (d)	0.17	0.01	0.07	0.04	0.07	0.02	− 0.17	− 0.06	1.00									
(28)	Danish (d)	0.06	0.01	0.03	− 0.03	0.03	0.01	− 0.06	0.00	0.01	1.00								
(29)	Female (d)	0.04	0.00	0.00	− 0.05	− 0.03	− 0.02	− 0.03	0.00	0.04	− 0.04	1.00							
(30)	No. of children	0.13	0.01	0.07	0.03	0.09	0.02	− 0.14	− 0.04	0.52	0.03	0.05	1.00						
(31)	Same municipality work & home (d)	0.04	− 0.01	− 0.03	0.05	0.02	0.01	0.00	0.00	− 0.11	0.00	− 0.02	− 0.10	1.00					
(32)	Same municipality work & home in CPH (d)	− 0.03	− 0.01	− 0.03	0.04	0.00	0.00	0.04	0.01	− 0.13	− 0.02	0.00	− 0.15	0.70	1.00				
(33)	Bottom 25% income at workplace (d)	− 0.20	− 0.01	− 0.05	− 0.11	− 0.03	− 0.01	0.32	0.09	− 0.16	− 0.06	0.07	− 0.12	0.04	0.02	1.00			
(34)	Bottom 50% income at workplace (d)	− 0.07	− 0.01	− 0.07	− 0.08	− 0.08	− 0.02	0.08	0.03	− 0.13	− 0.03	0.07	− 0.12	0.07	0.01	− 0.14	1.00		
(35)	Bottom 75% income at workplace (d)	0.02	− 0.01	− 0.08	0.04	− 0.07	− 0.01	− 0.06	0.01	− 0.04	− 0.02	0.02	− 0.04	0.02	0.01	− 0.19	− 0.29	1.00	
(36)	Real estate value (in DKK)	0.21	0.01	0.08	0.03	0.06	0.02	− 0.23	− 0.07	0.36	0.10	0.02	0.32	− 0.12	− 0.16	− 0.25	− 0.16	− 0.01	1.00

(d) dummy variable

Table 3 Binary logit estimation results for an individual's propensity to leave the present employer in the next period (n = 37,731)

	Model 1	Model 2	Model 3	Model 4	Model 5
Hypotheses-related variables					
ln(digital expertise) (H1)	− 0.099	− 0.084	− 0.433	− 0.075	− 0.391
	(0.023)	(0.025)	(0.082)	(0.025)	(0.084)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
ln(digital expertise) * international diversity (H2)		− 0.239			− 0.233
		(0.134)			(0.133)
		[0.07]			[0.08]
ln(digital expertise) * ln(no. of patents) (H3)			− 0.053		− 0.052
			(0.012)		(0.013)
			[0.00]		[0.00]
ln(digital expertise) * digital expertise cluster (H4)				1.720	1.764
				(0.512)	(0.514)
				[0.00]	[0.00]
Firm-level variables					
International diversity	− 0.112	− 0.785	− 0.066	− 0.133	− 0.748
	(0.163)	(0.430)	(0.178)	(0.180)	(0.432)
	[0.49]	[0.07]	[0.71]	[0.46]	[0.08]
ln(no. of patents)	0.092	0.092	− 0.062	0.094	− 0.057
	(0.026)	(0.026)	(0.045)	(0.026)	(0.045)
	[0.00]	[0.00]	[0.16]	[0.00]	[0.21]
Digital expertise cluster	− 0.005	− 0.009	0.011	3.562	3.662
	(0.397)	(0.410)	(0.410)	(1.153)	(1.157)
	[0.99]	[0.98]	[0.98]	[0.00]	[0.00]
At least one patent (d)	− 0.496	− 0.491	− 0.487	− 0.507	− 0.494
	(0.092)	(0.087)	(0.088)	(0.088)	(0.087)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Mean years of tenure at workplace/firm age	0.134	0.136	0.143	0.140	0.151
	(0.085)	(0.083)	(0.083)	(0.083)	(0.083)
	[0.12]	[0.10]	[0.08]	[0.09]	[0.07]
ln(hypothetical income in domestic firm (DKK))	− 1.097	− 1.101	− 1.100	− 1.072	− 1.080
	(0.150)	(0.135)	(0.135)	(0.136)	(0.135)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
ln(no. of employees)	− 0.131	− 0.131	− 0.129	− 0.129	− 0.126
	(0.015)	(0.016)	(0.017)	(0.017)	(0.017)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Exporting (d)	0.100	0.103	0.092	0.088	0.084
	(0.042)	(0.041)	(0.041)	(0.041)	(0.041)
	[0.02]	[0.01]	[0.03]	[0.03]	[0.04]
Industry & regional R&D worker intensity	1.689	1.659	1.635	1.933	1.860
	(0.850)	(0.804)	(0.809)	(0.800)	(0.803)
	[0.05]	[0.04]	[0.04]	[0.02]	[0.02]

Table 3 *continued*

	Model 1	Model 2	Model 3	Model 4	Model 5
Industry & regional patenting intensity	− 1.651	− 1.664	− 1.853	− 1.702	− 1.909
	(0.593)	(0.627)	(0.630)	(0.626)	(0.629)
	[0.01]	[0.01]	[0.00]	[0.01]	[0.00]
ln(no. of firms digital prof. in industry & region)	0.002	0.003	− 0.007	− 0.002	− 0.010
	(0.021)	(0.022)	(0.022)	(0.022)	(0.022)
	[0.92]	[0.90]	[0.75]	[0.94]	[0.65]
No. of hierarchy levels scaled by firm size	− 1.674	− 1.626	− 1.652	− 1.604	− 1.533
	(0.480)	(0.519)	(0.518)	(0.524)	(0.518)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
ln(mean sick leave pay (in DKK))	− 0.039	− 0.038	− 0.039	− 0.039	− 0.039
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
ln(mean sick leave pay (in DKK))^2	− 0.008	− 0.008	− 0.008	− 0.008	− 0.008
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Churn rate	0.700	0.698	0.714	0.687	0.698
	(0.073)	(0.080)	(0.080)	(0.080)	(0.080)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Human capital variables					
Years of working experience	− 0.018	− 0.018	− 0.019	− 0.018	− 0.019
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Years of tenure	− 0.049	− 0.049	− 0.050	− 0.050	− 0.050
	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Return employee (d)	0.232	0.235	0.245	0.234	0.249
	(0.295)	(0.297)	(0.297)	(0.297)	(0.297)
	[0.43]	[0.43]	[0.41]	[0.43]	[0.40]
Human capital variables					
TMT member (d)	− 0.335	− 0.332	− 0.329	− 0.339	− 0.331
	(0.083)	(0.083)	(0.083)	(0.083)	(0.083)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Management team member (d)	− 0.233	− 0.230	− 0.231	− 0.231	− 0.226
	(0.037)	(0.038)	(0.038)	(0.038)	(0.038)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
At least MA (d)	0.187	0.184	0.186	0.186	0.183
	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Stock of person's patents	− 0.026	− 0.026	− 0.022	− 0.027	− 0.024
	(0.041)	(0.037)	(0.035)	(0.037)	(0.036)
	[0.52]	[0.48]	[0.53]	[0.47]	[0.50]

Table 3 *continued*

	Model 1	Model 2	Model 3	Model 4	Model 5
No. of jobs in past five years	0.385	0.382	0.382	0.379	0.374
	(0.085)	(0.085)	(0.085)	(0.085)	(0.085)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Has been promoted past 5 years (d)	0.090	0.090	0.089	0.090	0.089
	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Person-level variables					
Married (d)	0.013	0.013	0.012	0.013	0.013
	(0.041)	(0.043)	(0.043)	(0.043)	(0.043)
	[0.76]	[0.75]	[0.79]	[0.76]	[0.76]
Danish (d)	0.166	0.164	0.170	0.167	0.169
	(0.101)	(0.103)	(0.103)	(0.103)	(0.103)
	[0.10]	[0.11]	[0.10]	[0.11]	[0.10]
Female (d)	0.135	0.136	0.134	0.136	0.136
	(0.045)	(0.044)	(0.044)	(0.044)	(0.044)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
No. of children	0.042	0.042	0.042	0.041	0.041
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
	[0.03]	[0.03]	[0.03]	[0.03]	[0.03]
Same municipality work & home (d)	− 0.081	− 0.084	− 0.091	− 0.086	− 0.098
	(0.080)	(0.076)	(0.076)	(0.076)	(0.077)
	[0.31]	[0.27]	[0.24]	[0.26]	[0.20]
Same municipality work & home in CPH (d)	− 0.014	− 0.007	− 0.012	− 0.011	− 0.002
	(0.099)	(0.097)	(0.097)	(0.097)	(0.097)
	[0.89]	[0.94]	[0.91]	[0.91]	[0.98]
Income and wealth					
Bottom 25% income at workplace (d)	− 0.521	− 0.523	− 0.524	− 0.520	− 0.524
	(0.069)	(0.073)	(0.073)	(0.073)	(0.073)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Bottom 50% income at workplace (d)	− 0.381	− 0.382	− 0.383	− 0.381	− 0.384
	(0.054)	(0.055)	(0.055)	(0.055)	(0.055)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Bottom 75% income at workplace (d)	− 0.229	− 0.230	− 0.230	− 0.230	− 0.233
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
ln(real estate value (in DKK))	− 0.026	− 0.026	− 0.023	− 0.027	− 0.025
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
	[0.50]	[0.50]	[0.54]	[0.48]	[0.51]
Possesses real estate (d)	0.363	0.367	0.333	0.380	0.356
	(0.527)	(0.530)	(0.530)	(0.530)	(0.530)
	[0.49]	[0.49]	[0.53]	[0.47]	[0.50]

Table 3 *continued*

	Model 1	Model 2	Model 3	Model 4	Model 5
McKelvey and Zavoina pseudo R^2	0.154	0.156	0.155	0.154	0.157

(d) dummy variable; standard errors in parentheses are bootstrapped; *p* values in brackets; the specifications additionally include a set of region, sector and time dummies.

intervals that are based on standard errors calculated via the "Delta" method (Greene, 2003), setting all but the variable under consideration to their mean values. These predicted conditional probabilities can easily be translated into marginal effects by letting digital expertise vary and reading off the corresponding change from the (sub-)figures.

As a reading example, the subfigure on the top right shows how the predicted conditional probability of leaving the present employer varies with different values of digital expertise and high or low values of the subsidiary's patent stock. For very low digital expertise and a low number of patents the probability of leaving is around 40% but quickly decreases to around 5% for a digital expertise value of 0.85, the highest value observed in our data. The patent stock turns out to play a relatively smaller role for the effect size. We find similar patterns for international diversity and the degree to which a region resembles a digital expertise cluster. Following Meyer, Witteloostuijn van and Beugelsdijk (2017), we then compare the magnitude of these effects with an employee's years of tenure at the current employer which is a meaningful comparison since this variable is not in the focus of this study. Years of tenure play an important role in employee retention and the variable also turns out to be a highly significant determinant in our setting. We display the predicted conditional probabilities for tenure on the bottom right of Figure 1 (note the common *y*-axis among the subfigures). Comparing these effects with the other three conditional probabilities suggests that one additional year of tenure decreases the probability of leaving by much less than an increase in digital expertise from 1 to 5, from 5 to 10 or from 10 to 15% (in decreasing effects order). By contrast, for higher values of digital expertise an additional increase has linear effects which are comparable to the effects of increases in years of tenure.

The results for the control variables presented in Table 3 turn out to be consistent across the five model specifications. The larger the employer is, the more years of working experience and years of tenure and the lower the income is at the current employer, the less likely it is that an individual will leave the subsidiary. The negative coefficient on tenure along with the high precision with which it is estimated indicates positive "duration dependence". The probability of leaving is, by contrast, increasing in the jobs an individual held during the past 5 years. Moreover, TMT membership and

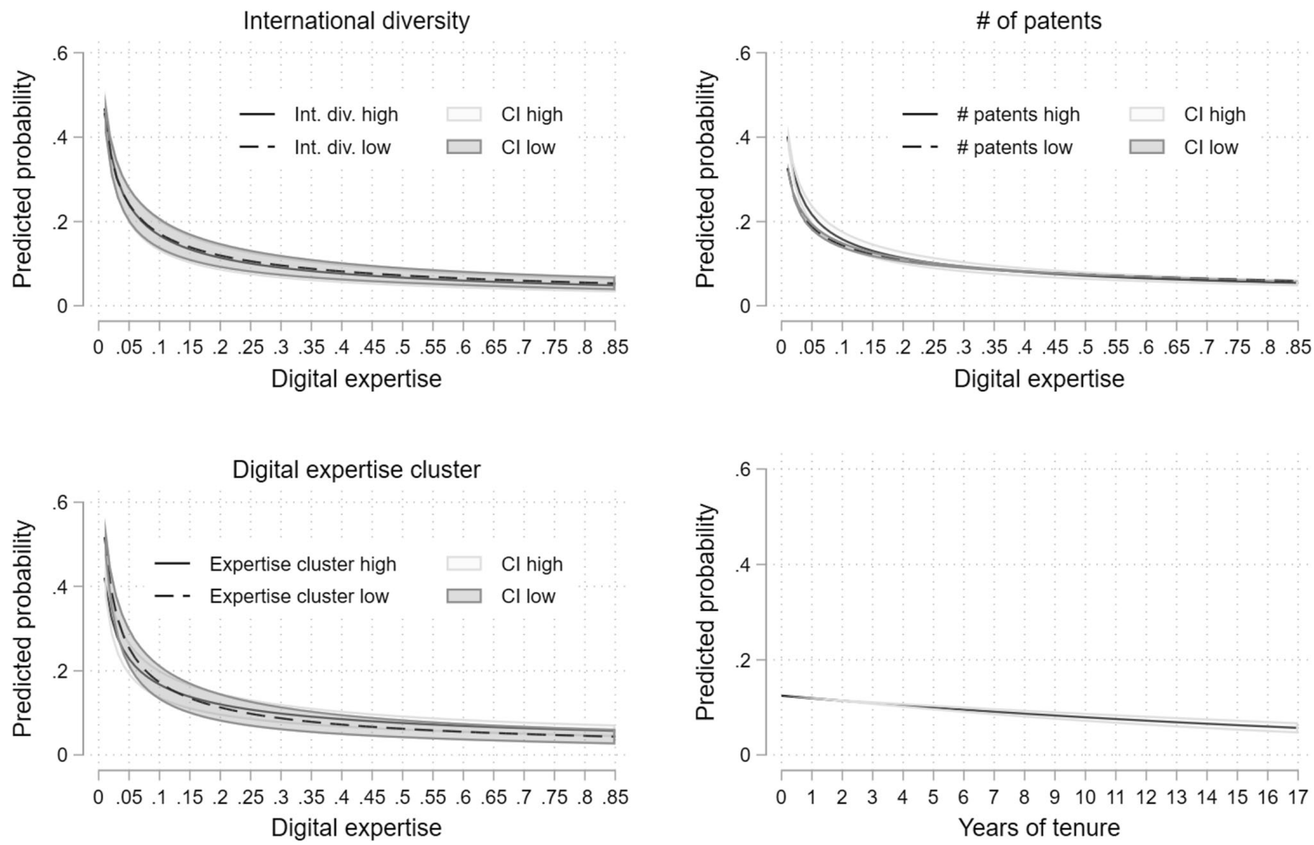

Figure 1 Predicted conditional probabilities.

management team membership both reduce the likelihood of leaving the current employer.

Robustness Checks

We conduct a number of consistency check estimations whose results are shown in the Appendix. A main area of concern underlying our results is the potential endogeneity of a subsidiary's digital expertise. Factors that are unobservable to us like management quality might simultaneously determine both digital expertise and an individual's propensity to leave the current employer. This correlation is likely to be positive which implies that our coefficient estimate on digital expertise could be biased.

We seek to address the endogeneity problem in two ways. First, we take unobserved individual heterogeneity (or "frailty" as it is called in duration modeling) into account by running a random effects model. Table 4 in the appendix shows the results. Accounting for random effects leads to coefficient estimates very similar to our main model. Random effects models only imperfectly account for possible endogeneity caused by unobserved factors which is why we additionally employ a "control function" approach (Choi & McNamara, 2018; Heckman & Robb, 1985) of which Heckman's classic sample selection model constitutes a special case. The basic idea behind the control function approach is to account ("control") for possible endogeneity bias by adding the residual term of a first stage regression of the endogenous variable on the set of explanatory variables plus a set of instruments, or "exclusion restrictions". The control function model is therefore a two-stage instrumental variables estimator. Adding the first stage residual to the equation of interest requires the use of bootstrapped standard errors as with any generated regressor. Valid instruments are variables that are highly correlated with the potential endogenous variable (i.e., digital expertise at the subsidiary) but orthogonal to the error term in the estimation equation of main interest. To construct such instrumental variables, we make the plausible assumption that the rollout of broadband Internet is exogenous to an individual's propensity to leave the employer. At the same time, broadband Internet access is likely to be highly correlated with the share of employees with digital human capital. The effect of broadband Internet may differ greatly between different firms which is why we interact broadband Internet access with firm-specific dummy variables. We use the number of fixed broadband subscriptions in Denmark as our measure of broadband Internet access following Briglauer, et al. (2021).

We test the first property, the correlation of the instruments with the endogenous variable using an F-test. The F-test for joint significance of the instruments is 870 and hence substantially larger than the critical value of 10 suggested by Staiger and Stock (1997) and even larger than the recently suggested critical value of 24 (Olea & Pflueger, 2013). We test the second property using a Hansen J-test which cannot reject orthogonality of our instruments at the 98.8% marginal significance level for the model without interactions and at the 95% marginal significance level for the model with interactions. As shown in Table 4, re-estimating our main model with the control function approach leads to a statistically highly significant point estimate on digital expertise that is about three times larger than in the main model without interactions and about twice as large as in the model with all interactions, leaving the interaction effects largely unchanged. The estimates for our main effect generated by our main models are hence conservative and, if anything, biased towards 0.

Our analysis has so far dealt with employees who leave for alternative employment while we have not considered differences between leaving for domestic firms or other foreign MNC subsidiaries. The appropriate approach to model leaving for a domestic firm or another foreign MNC subsidiary (compared with staying at the present MNC subsidiary) is a multinomial logit model, i.e., a "competing risk" model in the context of duration models. The competing risk model splits up the two forms of employee mobility and relates it to the probability of staying, i.e., the base category. The model generates two sets of estimates: one that relates to leaving to a domestic firm and one that relates to leaving to another MNC subsidiary. Both sets are to be interpreted relative to the probability of staying with the present employer. For our main model, the competing risk approach generates a point estimate on digital expertise of – 0.096 for leaving for a domestic firm and a point estimate of – 0.103 for leaving for another foreign MNC subsidiary as shown in Table 4. The two point estimates are not significantly different from each other (two-sided test *p* value 0.86). In that sense, we find that the likelihood to leave the current employer does not differ with respect to the destination, i.e., whether the new employer is a domestic firm or a foreign MNC subsidiary. Including all interaction effects in the competing risk model shows no significant differences either (*p* value 0.13). This shows that our theoretical mechanisms are not affected by the choice that an employee makes for either another foreign MNC subsidiary or a domestic firm when they decide to leave their current employer.

We also check if there are differences between MNC subsidiaries with any versus majority foreign ownership in Table 4 and find the results to be fully consistent with the main model. Finally, we conduct a number of robustness checks for which detailed results can be obtained from the authors upon request. First, we seek to make sure that the employee turnover we look at is in fact voluntary and not driven by layoffs by excluding (a) employees who received unemployment benefits in the year after they left the subsidiary and (b) employees who received a lower salary in their new employment compared to their salary at the subsidiary. Excluding these cases of potentially involuntary job mobility does not affect any results of the hypothesis tests. Second, we exclude employees whose departure from the subsidiary is linked to transferring to a spin-off company, and third, we exclude subsidiaries in the ICT industry for which the importance of digital expertise may be different compared to subsidiaries in other industries. It turns out that our results are fully consistent with the main models which is partly due to the fact that the number of observations left out is rather small. For example, only 495 observations are left out when we exclude individuals who subsequently receive unemployment benefits and 1387 are left out if we consider *any* decrease in salary at the next employer. Moreover, just 17 individuals left for a spin-off company.

Exploratory Analysis Comparing Retention Effects in Foreign MNC Subsidiaries with Domestic Firms

Our hypotheses predict heterogeneity in the retention effects for digital human capital within the group of foreign MNC subsidiaries based on their digital expertise. We conduct an exploratory analysis that compares these effects to employees with digital human capital working for domestic firms. These additional estimations allow us to assess how distinct the retention effects are for foreign MNC subsidiaries in a host country.

Naturally, foreign MNC subsidiaries are different from the average domestic firm across many structural dimensions, e.g., size or knowledge intensity. These structural features may affect their attractiveness as an employer and potential retention effects. Therefore, we construct a matched sample of individuals with digital human capital working for domestic firms, i.e., firms that are 100% domestically owned, using propensity score matching for all control variables in our main models. As a result, we obtain a sample of all individuals with digital human capital working for domestic firms which are highly comparable to their counterparts working for foreign MNC subsidiaries. The resulting matched sample consists of 35687 individuals with digital human capital working for 4681 domestic firms. We repeat all estimations from the main models for this matched sample and compare the hypothesized effects. Table 5 in the appendix shows the regression results for the matched sample and reproduces the results from the main models for the sample of employees with digital human capital working for foreign MNC subsidiaries for ease of comparison.

Focusing first on the main effects of digital expertise in domestic firms, we find that it also reduces the likelihood of employees with digital human capital to leave their employer but the effect is far from reaching significant levels. While there is no significant main effect of digital expertise in domestic firms, we nevertheless re-estimate the models including all moderation effects for full transparency. When we add the moderation effects postulated for foreign MNC subsidiaries in Hypotheses 2, 3, and 4, we find diverging effects for domestic firms. The location in a regional cluster of digital expertise exhibits an interaction effect that is lower than the 90% significance level for the matched sample while the interaction effects with the international diversity of the workforce as well as the number of patents have the opposite signs for domestic firms compared with foreign MNC subsidiaries. We test the equality of all coefficients mentioned before between the samples of digital human capital in domestic firms compared with those in foreign MNC subsidiaries and find that that equality is rejected at the 99% or 98% (interaction with cluster) significance levels respectively.

The estimation results for employees with digital human capital of domestic firms should be interpreted carefully since they are not representative for the population of domestic firms but for the matched sample with foreign MNC subsidiaries. For our purposes, it is important to note that digital expertise has a distinct retention effect for digital human capital in foreign MNC subsidiaries that we cannot establish for domestic firms. This finding is in line with prior research which has highlighted the particular role that foreign MNC subsidiaries have as host-country employers (Newburry et al., 2006; Ono, 2007; Sofka et al., 2021). Moreover, the comparison hints at interesting differences that deserve a dedicated study.

DISCUSSION

In this study, we provide a theoretical logic for how MNC subsidiaries can retain skilled employees which are also in high demand on host-country labor markets. Digitalization and the use of digital technologies are pervasive phenomena for MNCs (Banalieva & Dhanaraj, 2019), making digital human capital strategic for MNCs. However, the retention of digital human capital is difficult, given that such individuals are typically scarce on host-country labor markets and in high demand. While such "hot" host-country labor markets have been identified in previous research (Becker et al., 2020), the mechanisms by which important employees decide to stay or leave an MNC subsidiary are hardly laid out.

We provide a first step towards a theory of retention in MNC subsidiaries by integrating theoretical mechanisms from the literature on subsidiary-specific advantages (Phene & Almeida, 2008; Rugman & Verbeke, 2001) into models explaining the retention of human capital based on firm-specific incentives (Call & Ployhart, 2021; Kryscynski et al., 2021). This theory integration allows us to go beyond the mere identification of salary premia (e.g., van der Straaten et al., 2020) and introduce benefits to the theoretical discussion that have non-monetary utility for employees. Accordingly, our findings suggest that MNC subsidiaries can succeed with retaining employees with digital human capital when they offer an attractive work environment that creates important learning opportunities (Tambe et al., 2020). We show this to be the case when subsidiaries have an increasingly high degree of digital expertise. We argue that offering such learning opportunities leads employees to create voluntary mobility constraints for themselves (Call & Ployhart, 2021). Digital expertise can in that sense be conceptualized as subsidiary-specific incentives that other employers may find hard to replicate (Kryscynski et al., 2021).

Moreover, we qualify the importance of digital expertise for employee retention by investigating three contingencies that limit the retention effects for employees with digital human capital but are important dimensions of subsidiary-specific advantages. Our results confirm that the effect of digital expertise on retention is stronger if subsidiaries have an internationally diverse workforce since such a work environment provides a distinct context in which individuals make new experiences and develop skills. Moreover, we find that subsidiaries that possess patented technologies can provide unique, state-of-the-art learning opportunities that other firms are, due to the exclusionary nature of patents, unable to offer, which in turn increases the firm-specific incentives from digital expertise. Finally, we find that the retention effects from digital expertise are weaker when the subsidiary is located in a regional cluster of digital expertise in which other employers offer many attractive outside options.

Our research makes two important contributions to the extant literature. First, we advance theory on the effects of subsidiary-specific advantages (Blomkvist et al., 2010; Rugman & Verbeke, 2001) in the context of subsidiaries' digital expertise. We theorize that this particular type of advantage is not just consequential within the MNC but also has important retention effects for subsidiary employees. For this purpose, we build on the defining feature of subsidiary-specific advantages, i.e., a concentration of assets and skills that is not available to other host-country firms because it stems partly from the MNC and not available in other subsidiaries because it stems partly from the host country (Meyer et al., 2020). When this particular type of specificity is integrated into strategic human capital theory (e.g., Chadwick, 2017; Coff & Kryscynski, 2011), it allows theorizing about distinct work conditions at subsidiaries in a host country and learning opportunities that skilled employees could not find with other employers. Hence, subsidiary-specific advantages set foreign MNC subsidiaries apart as employers in the host country and elevate the subsidiary's ability to retain strategic human capital. This theoretical model explaining retention is useful because it enables MNCs to assess their risks for loosing skilled employees on competitive host-country labor markets. In this regard, it is also important to explicate the limits of the retention effects. For this purpose we explore boundary conditions from three important dimensions of subsidiary-specific advantages (internationally diverse workforce, patented technologies and the location in regional clusters of digital expertise). These moderation effects indicate that (a) retention-relevant learning effects can accumulate beyond digital expertise and (b) the outside options on regional labor markets constrain the retention effects of digital expertise in a subsidiary. Our theory could be a platform for identifying specific attributes of subsidiary-specific advantages and how they affect labor mobility, e.g., based on how easily the attributes can be observed or how credibly they are communicated.

Second, we move beyond defining the labor market interaction between foreign MNC subsidiaries and the host country merely as an issue of hiring and attraction (e.g., Distel et al., 2019). Instead, we offer a theoretical model that focusses explicitly on retention, arguably an important yet understudied aspect of how MNCs can benefit from strategic human capital in their host countries (Almeida & Phene, 2004; Lewin et al., 2009). We focus on distinct learning opportunities that MNC subsidiaries can offer to employees with digital human capital but we suspect that a more comprehensive theory of subsidiary retention will include other factors that are subsidiary-specific, for example the global employer brand of the MNC.

The findings of our study also have substantial implications for the management of MNC subsidiaries as well as host-country firms. First, we identify the labor market benefits of digital expertise for foreign MNC subsidiaries. HR management of those subsidiaries benefits from retaining digital human capital especially when the subsidiaries are internationally diverse and hold many patents. Put differently, subsidiaries without digital expertise are comparatively more likely to lose digital human capital and should focus retention efforts on those individuals, e.g., by providing attractive learning opportunities through collaborations or personnel exchanges with other subsidiaries with more advanced digital expertise. This will be of particular importance if the subsidiary is located in a cluster in which domestic firms are digitally leading since they constitute attractive potential alternative employers for individuals with digital human capital. Second, our results dampen the hopes of host-country rivals for hiring digital human capital from MNC subsidiaries even when they offer high salaries. Instead, more promising hiring strategies by host-country rivals should target digital human capital in MNC subsidiaries with low levels of digital expertise. Conversely, while the build-up of digital expertise constitutes a long-term effort, short-term options to increase retention in MNC subsidiaries include a concerted recruitment of a more diverse workforce or the provision of incentives for patenting.

LIMITATIONS AND CONCLUSIONS

Our study is not without limitations. They can provide fruitful pathways for future research along four primary dimensions. First, our study benefits from a rich dataset covering career decisions of employees of MNC subsidiaries with digital human capital and their salaries. The empirical findings are consistent with our theoretical reasoning. Ideally, we would like to observe the decision making of these employees when they receive another job offer and the breadth of firm-specific incentives that they take into account. Experimental research designs could uncover these important insights in future research.

Second, we present and test a general theory of the effect of digital expertise on the retention of digital human capital in subsidiaries. Obviously, digitalization activities, knowledge and skills are a broad domain. We suspect that certain aspects, e.g., artificial intelligence, provide particularly attractive learning opportunities and create high demand on labor markets while others might be comparatively outdated. Hence, we encourage future studies that unpack the dimensions of digital expertise and digital human capital for theoretically meaningful distinctions.

Third, many of the mechanisms that we describe from the learning opportunities for retaining employees with digital human capital would also apply to their motivation, another central aspect of performance effects from strategic human capital (Kryscynski et al., 2021). Future studies with dedicated research designs might be able to incorporate all major aspects of strategic human capital in MNC subsidiaries, i.e., attraction, motivation, retention, into a single model and explore diverging effects from various employers including their digital expertise. Relatedly, the retention of digital human capital may also be driven by factors such as reputation of the subsidiary or the ability to work independently. While we cannot control for these aspects with our data, they also deserve dedicated theorizing.

Fourth, our exploratory analysis comparing retention effects of digital expertise for employees with digital human capital of foreign MNC subsidiaries and domestic firms respectively yields interesting differences. Future research might specifically focus on the differences in retention mechanisms between domestic and foreign firms. Our empirical findings hint at diverging assessments of valuable learning opportunities that individuals make when they occur with domestic employers or in foreign MNC subsidiaries but the mechanisms underlying these differences would benefit from dedicated theorizing.

Finally, we benefit from population-level, longitudinal data for digital human capital of foreign MNC subsidiaries in Denmark. However, many MNCs explain their investments in emerging economies, e.g., India or China, or even specific regions, e.g., Bangalore, with access to digital human capital. Labor mobility of such individuals in these countries and regions can be intense (Lamin & Ramos, 2016). Then again, learning opportunities might be important considerations for individuals with digital human capital in emerging economies. We suspect that Denmark provides a conservative context for testing our hypotheses but we encourage comparative studies that explicitly take the institutional context into account in order to highlight similarities and differences.

In closing, our study establishes digital expertise as a distinct subsidiary-specific advantage that connects it with the retention of digital human capital based on voluntary mobility constraints (Call & Ployhart, 2021; Kryscynski et al., 2021), arguably a major concern in the competition for strategic human capital. We show that this type of expertise leads to meaningful, non-monetary benefits for individuals with digital human capital that keep them with the MNC. These insights pave the way for more research into the individual level considerations of strategic human capital in MNC subsidiaries facing competitive host-country labor markets (Becker et al., 2020) while taking the heterogeneity of host-country employees and their preferences into account (Mezias & Mezias, 2010).

NOTES

[1]https://www.blog.google/around-the-globe/google-europe/global-hub-privacy-engineering-heart-europe/; accessed on September 22, 2020.

[2]http://newsroom.vw.com/company/innovating-the-future-at-vws-electronics-research-lab/; accessed on September 22, 2020.

[3]Source: https://www.dst.dk/da/Statistik/dokumentation/Times/uddannelseregister/audd#; accessed on September 28, 2020.

[4]The list of keywords includes the following stemmed terms (in Danish): data, software, IT, multimedie, digital, kommunik, interaktiv, computer, tele, programmering, web, netv, system, elektronik, informatik, EDB, Internet, e-business, maskinlæring, games, virtuelt, interaktiv, robot.

[5]This classification includes individuals with relevant degrees obtained outside of Denmark as long as they have applied for equivalence accreditation, e.g., after returning from studies abroad.

[6]It is calculated as $B = \frac{n}{n-1}\left(1 - \sum_{k=1}^{n} s_k^2\right)$ where k denotes the unique citizenships in a firm and n denotes the number of employees.

[7]We run our regressions using the software package Stata and use its "stset" command to adequately organize our data.

[8]Minimum, maximum, and median values of any variable may not be shown because of anonymity rules established by Statistics Denmark.

[9]Source: https://www.dst.dk/en/Statistik/Publikationer/gennemsnitsdanskeren; accessed September 28, 2020.

[10]Note that a fixed effects model is not an option here since its identification solely hinges upon individuals who depart from their MNC subsidiary employer at least once.

[11]Denmark is a highly digitized country. However, broadband access was much less pervasive between 2002 and 2012, our period of consideration, than it is today. In 2002, the beginning of our observation period, the number of fixed-broadband subscriptions was 451,297 and it increased five-fold until 2012 (Briglauer, et al., 2021).

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APPENDIX

See Tables 4 and 5.

Table 4 Robustness check estimations (n = 37,731 and 27,709 in the subsample for majority ownership)

	Random effects model		Control function approach		Multinomial logit for leaving to…				Subsample foreign majority ownership	
					Other MNC	Domestic firm	Other MNC	Domestic firm		
Hypotheses-related variables										
ln(digital expertise) (H1)	– 0.153	– 0.320	– 0.323	– 0.617	– 0.103	– 0.096	– 0.244	– 0.527	– 0.059	– 0.221
	(0.072)	(0.079)	(0.056)	(0.098)	(0.017)	(0.014)	(0.046)	(0.070)	(0.005)	(0.033)
	[0.03]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
ln(digital expertise) * international diversity (H2)		– 0.292		– 0.194			– 0.191	– 0.273		– 0.368
		(0.285)		(0.124)			(0.121)	(0.083)		(0.022)
		[0.31]		[0.12]			[0.11]	[0.00]		[0.00]
ln(digital expertise) * ln(no. of patents) (H3)		– 0.037		– 0.053			– 0.026	– 0.076		– 0.034
		(0.021)		(0.012)			(0.011)	(0.012)		(0.005)
		[0.08]		[0.00]			[0.02]	[0.00]		[0.00]
ln(digital expertise) * digital expertise cluster (H4)		2.016		1.751			1.026	2.357		2.533
		(0.078)		(0.525)			(1.156)	(0.194)		(0.473)
		[0.00]		[0.00]			[0.38]	[0.00]		[0.00]
All control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
McKelvey and Zavoina pseudo R^2	0.157	0.157	0.156	0.156	–		–		0.141	0.154

(d) dummy variable; standard errors in parentheses are bootstrapped; p values in brackets; the specifications additionally include a set of region, sector and time dummies.

Table 5 Exploratory analysis comparing retention effects in foreign MNC subsidiaries with domestic firms

	Main models		MNC subs.	Leaving from…		
				Domestic firm	MNC subs.	Domestic firm
Hypotheses-related variables						
ln(digital expertise) (H1)	− 0.099	− 0.391	− 0.099	− 0.005	− 0.391	0.155
	(0.023)	(0.084)	(0.023)	(0.022)	(0.082)	(0.079)
	[0.00]	[0.00]	[0.00]	[0.81]	[0.00]	[0.05]
ln(digital expertise) * international diversity (H2)		− 0.233			− 0.233	0.501
		(0.133)			(0.124)	(0.089)
		[0.08]			[0.06]	[0.00]
ln(digital expertise) * ln(no. of patents) (H3)		− 0.052			− 0.052	0.032
		(0.013)			(0.012)	(0.012)
		[0.00]			[0.00]	[0.01]
ln(digital expertise) * digital expertise cluster (H4)		1.764			1.764	− 0.758
		(0.514)			(0.525)	(0.465)
		[0.00]			[0.00]	[0.10]
All control variables	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	37,731	37,731	37,731	144,410	37,731	144,410
McKelvey and Zavoina pseudo R^2	0.154	0.156	0.154	0.053	0.157	0.054

(d) dummy variable; standard errors in parentheses are bootstrapped; *p* values in brackets; the specifications additionally include a set of region, sector, and time dummies

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