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Absorptive capacity components: Performance effects in related and unrelated diversification

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ABSTRACT

We study how firms can benefit from external knowledge resources contingent on absorptive capacity. We separate the three components of absorptive capacity – acquiring, assimilating, and exploiting external knowledge – and posit that the benefits of a firm's knowledge expansion through diversification into related and unrelated business domains differ by the firm's relative emphasis on the three components. We test our predictions on a panel of 153 large US-traded ICT firms. Our analysis broadly supports our hypotheses, highlighting the unique contribution of individual absorptive capacity components to organizational learning through diversification strategy.

1. Introduction

When firms source knowledge externally, the extent to which it complements their internal knowledge depends on their *absorptive capacity*, i.e., their ability to make use of new knowledge (Cohen and Levinthal, 1990). It also depends on the type of knowledge acquired; other things being equal, it is easier to absorb knowledge closer to one's existing knowledge base than distant knowledge that has no close equivalent inside the firm (Vasudeva and Anand, 2011). The conceptual literature on absorptive capacity divides the overall construct into three components: the ability to *acquire*, *assimilate,* and *exploit* new knowledge.[1] This distinction has been useful in sharpening the process of knowledge acquisition in firms based on firm characteristics broadly captured by absorptive capacity.

However, despite the plethora of research on absorptive capacity in general (Song et al., 2018) and its multifaceted nature in particular (Lane et al., 2006; Lane and Lubatkin, 1998; Song et al., 2018; Todorova and Durisin, 2007; Zahra and George, 2002), we still do not know enough about the role the individual components play in the absorption of specific types of knowledge. Put simply, while *all* components of absorptive capacity improve the firm's ability to absorb *any* kind of new knowledge, we ask if *certain components* facilitate *some types* of knowledge more than others. In our context, diversification decisions can bring different kinds of knowledge (close and distant to the firm's existing knowledge base) into the firm, which might require a specific combination of the individual components of absorptive capacity to benefit from the new knowledge acquired fully.

We propose that the components of absorptive capacity shift the balance of the *relative merits* of related and unrelated diversification. Hence, depending on their specific absorptive capacity profile (but the same overall level of absorptive capacity), some firms do

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[1] Some scholars offer conceptual extensions of the basic framework, most notably Zahra and George (2002), who introduce a fourth component, *transformation* ability.

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better with related diversification, while others fare better with unrelated diversification. We develop three hypotheses on the effects of the individual components of absorptive capacity on the relative merits of related and unrelated diversification: Specifically, a superior ability to *acquire* and *exploit* new knowledge benefits unrelated more than related diversification, while greater *assimilation* ability matters more for related diversification. We test these hypotheses in a 34-year panel of 153 firms in the US Telecom and ICT sectors and find them broadly confirmed and robust to numerous controls, selection and endogeneity concerns, and alternative specifications.

We make three main contributions. First, building on the literature separating absorptive capacity (Cohen and Levinthal, 1990), we show conceptually and empirically that the components have differential effects on the merits of related and unrelated diversification. Identifying and evaluating mechanisms in terms of their benefits and costs highlights the trade-offs of diversification decisions given a specific profile of absorptive capacity. Second, we study how a firm's ability to deal with new knowledge can moderate the relative performance of diversification types. This helps reconcile the often inconsistent and conflicting results on the relative merits of different diversification types – their attractiveness depends on the firm's presence and profile of absorptive capacity. Finally, we add to the debate over the relative attractiveness of related vs. unrelated diversification.

2. Theory and hypotheses

2.1. Absorptive capacity

Cohen and Levinthal (1989: 569–570) introduced absorptive capacity as *"the firm's ability to identify, assimilate, and exploit knowledge from the environment."* It is a set of interrelated abilities (Lane et al., 2006; Lane and Lubatkin, 1998; Liao et al., 2003; Todorova and Durisin, 2007): a firm's ability to scan the external environment, identify learning opportunities, and acquire relevant knowledge (Narasimhan et al., 2006; Zahra and George, 2002); an ability to analyze, process, and understand information from external sources (Kim et al., 2013; Lewin et al., 2011); and an ability to refine, extend, and leverage existing competencies or to create new ones by incorporating acquired and transformed knowledge into its operations (Lane and Lubatkin, 1998; Lewin et al., 2011; Wales et al., 2013).

Absorptive capacity tends to be treated *"like a general-purpose solution to an increasing number of problems"* (Lane et al., 2006: 835). However, the combination of individual components into a single one implicitly assumes the components are near-perfect substitutes: if a firm is terrible at the acquisition of new knowledge, it can compensate by investing in the exploitation of knowledge. This is both conceptually murky and empirically doubtful. It is also at odds with findings that the components evolve independently, serve different organizational tasks, and affect outcomes differently (Bierly et al., 2009; Ebers and Maurer, 2014; Song et al., 2018; Zou et al., 2018).

Reducing absorptive capacity to the extent of prior knowledge in the firm (Ahuja and Katila, 2001) has led to a consolidation of its components. Focusing on the technological knowledge the firm needs to acquire ignores the process knowledge needed to assimilate and apply it. While researchers have discussed absorptive capacity as a process or capability in many papers, very few have attempted to operationalize and test the assimilation or application of external knowledge (i.e., Lane and Lubatkin, 1998; Lane et al., 2001).

A handful of studies tried to separate the individual components and refine the concept (Lane et al., 2006). Probably the most influential is that of Zahra and George (2002), who expand absorptive capacity by proposing 'transformation' as a new component following assimilation and group the four components into two subsets (potential and realized absorptive capacity) with separate contributions to value creation. However, several studies do not confirm Zahra and George's (2002) four components (e.g., Thomas and Wood, 2014) or the distinction between potential and realized absorptive capacity (e.g., Jansen et al., 2005). Further, while Todorova and Durisin (2007) harmonize Zahra and George (2002) with the original Cohen and Levinthal (1990) model, Lane et al. (2006) emphasize a process perspective that preserves the original components.

Indeed, most prior work adopts the definition of Cohen and Levinthal (1990), as do we. Cohen and Levinthal emphasize the absorption of technological knowledge, though applying absorptive capacity to market knowledge is consistent with their definition (Volberda et al., 2010). Both technological and market knowledge absorption are consistent with our study on how the separate components of absorptive capacity can help organizations benefit from externally acquired knowledge through different diversification strategies. Diversification is a major organizational learning mechanism (Ahuja and Novelli, 2017; Kazanjian and Drazin, 1987), serving as a "laboratory" for examining how firms can better capitalize on externally acquired knowledge given their absorptive capacity. To better understand the organizational learning task, we study the impact of individual absorptive capacity components on the diversification-performance relationship.

2.2. Resources and diversification performance

The relationship between diversification and performance is widely studied (Mackey et al., 2017). Diversification can generate economies of scale and scope through cross-utilization and exploitation of resources, operational capabilities, physical and informational resources, and reputation. The literature distinguishes between related and unrelated diversification, capturing varying degrees of an expansion's cognitive distance from a firm's base (Pennings et al., 1994). The rationale for the two differs fundamentally.

Related diversification delivers advantages through substitutability or complementarities between resources across multiple businesses simultaneously (Rabier, 2017). Sharing these resources can create an economy of scope such that the value of multiple businesses combined exceeds the value of these businesses separately. Unrelated firms are incentivized mainly by the efficiency benefits of an "internal capital market." However, internal capital markets create competition between business units, which may hamper collaboration (Ng, 2007). This suggests that diversification strategies that do not leverage economies of scope across multiple businesses are unlikely to enhance value.

Despite its intuitive appeal, related diversification requires coordination and control, making it more complex and information-processing intensive (Chari et al., 2008) and possibly more costly (Chari et al., 2008; Hill et al., 1992; Jones and Hill, 1988; Nayyar, 1992; Zhou, 2011) than unrelated diversification. Rawley (2010) and Zhou (2011) both find that coordination costs and organizational rigidity can limit or even outweigh economies of scope for related diversifiers. Markides and Williamson (1994: 155) refer to 'exaggerated relatedness,' where markets served by two SBUs share many similarities, but these similarities cannot create a competitive advantage. Ahuja and Novelli (2017: 359) suggest that so-called 'compromise costs' may "*emerge from the overestimation of similarities between businesses and the potential of the firm to benefit by sharing resources between them*." This reflects concerns that related firms may not realize the anticipated synergies of related businesses. Any portfolio of related businesses will encounter such obstacles (Palich et al., 2000), reducing the key benefit of related over unrelated diversification.

Hence, it seems crucial to consider the impediments to (un)relatedness or the advantages that accrue only to (un)related firms and especially that firms often engage in both types of diversification concurrently (Argyres, 1996; Mayer and Whittington, 2003) and diversify more broadly than predicted (Ng, 2007). It is difficult to define *a priori* which diversification type is superior. While related diversifiers outperform unrelated diversifiers *on average*, there is wide variation. Also, high levels of unrelated diversification may harm performance (Mackey et al., 2017), and Schommer et al. (2019) show that the negative relationship between unrelated diversification and firm performance has weakened over time.

To develop the knowledge necessary to compete in new domains (Kazanjian and Drazin, 1987), diversifiers must create a context or a set of contingencies (Sakhartov and Folta, 2014) in which value-creating mechanisms are triggered. This aligns with Mackey et al. (2017: 323), who state that "*the value-maximizing strategy for a particular firm depends on that firm's resources and capabilities and the context within which it is operating.*" We posit that the potential synergies from combining new and existing knowledge depend on a firm's absorptive capacity components.

2.3. Acquisition ability, related and unrelated knowledge

A firm's *acquisition ability* is mainly driven by external knowledge search routines enabled by knowledge-building investments like R&D (Song et al., 2018). External knowledge search routines improve over time in helping a firm scan the external environment, identify learning opportunities, and acquire relevant knowledge (Narasimhan et al., 2006; Zahra and George, 2002). Acquisition ability helps firms recognize potentially valuable external knowledge, assess external developments, and internalize knowledge.

As a forward-looking ability, acquisition ability gives the organization a better sense of environmental changes and emerging technologies (Cohen and Levinthal, 1994) and skill in picking technologies and knowledge that could span organizational, technological, and market boundaries (Narasimhan et al., 2006). Acquisition ability also enables organization-wide 'active listening' and scanning of external information not directly related to its core activities (Lewin et al., 2011; Liao et al., 2003).

The extent to which acquisition ability contributes to the different diversification types depends on how much of the newly gathered information already exists in a similar form in the organization. For related diversification, most new information overlaps with knowledge already in the firm. Consequently, the ability to anticipate technological advancements and new markets is less useful. Vasudeva and Anand (2011) study knowledge utilization from alliance portfolios and find that alliances with partners whose technological approaches overlap can increase the redundancy of ideas, skill sets, and knowledge, leading to subadditive value creation. Relatedly, inter-organizational learning will be low if partner firms share the same basic and specialized knowledge (Lane and Lubatkin, 1998).

Conversely, stronger acquisition ability can increase the benefit of knowledge acquired through unrelated diversification in two ways. First, firms can evaluate unrelated knowledge to identify and select the most promising activities irrespective of potential synergies with existing activities (Chen et al., 2019; Gomes and Livdan, 2004; Maksimovic and Phillips, 2002). Acquisition ability helps firms process unrelated knowledge in its uncombined form (Matusik and Hill, 1998). Indeed, diversified firms may be better off realizing only the most important synergies between businesses, leaving the rest untapped to reduce coordination costs (Rawley, 2010; Zhou, 2011) and maintain flexibility (Chen et al., 2019).

Second, stronger acquisition ability helps unrelated diversification to expand the available options to maximize synergies. Firms can spot novel combinations with existing knowledge and new product market applications. For example, Yli-Renko et al. (2001) suggest that acquisition ability contributes more to new product development when external knowledge comprises specialized knowledge inputs. Diverse external knowledge requires integrating and combining specialized knowledge inputs from different types of technological competence. By enhancing the breadth and depth of knowledge available to the firm, acquisition ability enables new innovative combinations. Thus, firms with a stronger ability to acquire external knowledge will profit especially from unrelated diversification.

Hypothesis 1. Firms with higher acquisition ability will benefit more from a stronger relative focus on unrelated versus related diversification.

2.4. Assimilation ability, related and unrelated knowledge

Assimilation ability reflects a firm's abilities of associative learning and problem-solving. It is supported by communication structures, routines, and processes that enable the firm to process information from external sources (Kim et al., 2013; Lewin et al., 2011) and recombine it with internal knowledge (Zahra and George, 2002). Assimilating knowledge involves comparing and contrasting existing and novel structures, e.g., through cross-functional integration (Troy et al., 2008), socialization, and job rotation (Jansen et al., 2005). Knowledge search (e.g., employees regularly visiting other business units) and processing (e.g., regular meetings for analyzing market information) help develop common knowledge, identify multiple applications of that knowledge, and facilitate knowledge transmission to units and entities within the organization (Jansen et al., 2005).

Because learning from new knowledge is cumulative and associative, superior assimilation ability is more useful if existing and acquired knowledge overlap. Also, established communication structures (Troy et al., 2008) are better at facilitating the diffusion and sharing of related rather than unrelated knowledge (Zahra and Hayton, 2008). Hence, new knowledge reinforces existing knowledge.

While a strong assimilation ability implies a broad existing knowledge base, aiding the processing of comparably diverse external knowledge, it may offer only moderate benefits to firms with a high share of unrelated diversification overall. First, the firm's existing communication structure and routines are better at facilitating the diffusion and sharing of related knowledge. Trying to integrate distant knowledge may disrupt existing routines, while the burden on communication routines is lower for related internal and externally acquired knowledge (Vasudeva and Anand, 2011). If demands on a firm's assimilation ability are high, its assimilation ability may be overstretched even for a low burden.

Second, processing knowledge from a diverse portfolio of businesses is costly. For unrelated diversification efforts, firms need more learning resources to augment their ability to process unrelated knowledge (Vasudeva and Anand (2011). Lower compatibility of diverse knowledge may render resources less useful across organizational units. Lower synergies and fewer shared experiences increase the effort required to learn about new knowledge domains. Thus, the high demands of unrelated diversification on assimilation ability may result in suboptimal use of diversification knowledge.

Third, learning to use novel and diverse knowledge becomes difficult if past efforts constrain assimilation ability. Assimilation ability is built on past behavior, which is useful mainly for related external knowledge (Song et al., 2018). While acquiring new unrelated knowledge is helped by a relatively diverse existing knowledge base, adding to the existing knowledge base by assimilating new knowledge relies on related internal knowledge that is slow to move away from familiar knowledge. A firm's knowledge base is thus quite stable and geared toward efficiency rather than flexibility, reducing the willingness to search for distant external knowledge (Ahuja and Lampert, 2001; Srivastava and Gnyawali, 2011).

Fourth, assimilation ability increases the value of related diversification by reducing coordination costs from sharing resources (Hashai, 2015; Zhou, 2011). Coordination costs are more complex and require more information processing in related diversification than in unrelated (Chari et al., 2008). Coordination costs from different units drawing on the same resources (Rawley, 2010; Zhou, 2011) are reduced if firms can easily assimilate new, related knowledge. These costs are affected by social integration mechanisms that create a shared identity and facilitate problem-solving, knowledge combinations, and distribution (Phene et al., 2006). Related diversification may lead to interunit competition, increase coordination costs, and potentially trigger conflict that social integration mechanisms mitigate. Such conflicts are less likely for unrelated diversification (Chari et al., 2008).

Fifth, assimilation ability can help firms realize scale economies from resource similarity and recombination, especially for related diversification. Conversely, unrelated diversification is often motivated by internal capital markets. When new and existing knowledge are similar, sharing mechanisms are more effective, and assimilation ability facilitates economies of scale. With unrelated diversification, organizations face difficulties effectively utilizing and integrating (unrelated) knowledge due to information overload and confusion (Ahuja and Lampert, 2001). Phene et al. (2006) note that scale diseconomies set in as firms redirect resources from their primary technological context to other contexts.

Finally, Lane and Lubatkin (1998) find that the learning benefits of assimilation are greater where compensation practices are similar. As compensation practices of an unrelated diversifier are heterogeneous (Napier and Smith, 1987), the learning benefits of assimilation should be more significant for related diversification. Therefore, we propose that:

Hypothesis 2. Firms with higher assimilation ability will benefit more from a stronger relative focus on related versus unrelated diversification.

2.5. Exploitation ability, related and unrelated knowledge

Exploitation ability lies in routines that help firms refine, extend, and leverage existing competencies or create new ones by bringing new knowledge into the organization (Cohen and Levinthal, 1990; Lewin et al., 2011). Exploitation routines enable sustained knowledge exploitation (Zahra and George, 2002) and affect communication within the organization (Grant, 1996), the speed of knowledge retrieval (Moreira et al., 2018), define interfaces between knowledge fields (Garud and Nayyar, 1994), and secure transferability of "know-how knowledge" (Kogut and Zander, 1992). They support the creation of new goods, systems, processes, or knowledge (Lane and Lubatkin, 1998; Zahra and George, 2002).

How, then, does exploitation ability contribute to diversified firms? Stronger exploitation ability applied to related diversification may cause several problems. First, if external knowledge overlaps strongly with existing knowledge, exploiting the new cannibalizes existing knowledge. Exploitation ability improves a firm's ability to abandon such less valuable initiatives. However, it also improves a firm's ability to capitalize on more promising innovation opportunities by enabling firms to manage and exploit increasing knowledge diversity by identifying and commercializing viable innovations from a broad range of alternatives (Patel et al., 2015). Second, the ability to exploit any type of new knowledge may lead to an over-selection of projects, resulting in coordination costs (Rawley, 2010; Zhou, 2011), opportunity costs (Helfat and Eisenhardt, 2004), and internal conflict (Sears and Hoetker, 2014). Ultimately, a firm may spread its resources too thin across similar projects (Ahuja and Novelli, 2017; Zahavi and Lavie, 2013).

Conversely, unrelated diversification can benefit more from exploitation ability. Although redeploying resources into unrelated contexts is more costly ex-ante, these costs can be offset if firms can combine complementary resources effectively with those of other units (Sakhartov and Folta, 2014), as these may lead to significant discoveries (Katila and Ahuja, 2002). Stronger exploitation ability helps identify complementary knowledge across the organization (Teece, 1986) and reduce the time needed to apply and commercialize new knowledge. Thus, higher exploitation ability enables combining diverse knowledge to create novel combinations (Wales et al., 2013). Phene et al. (2006) confirm this logic in examining breakthrough innovations in the biotechnology industry, which require knowledge from different disciplines and firms that can integrate diverse knowledge inputs. Firms look to other industries for useful inputs, and the lack of a shared knowledge base and unfamiliarity with external knowledge makes it difficult to access and utilize such knowledge.

Firms engaging in unrelated diversification face fewer interactions among products and activities (Kim et al. (2013), which lets them pursue unexpected, possibly breakthrough successes more freely. Unrelated diversification is motivated by the efficiencies of an internal capital market. Firms can cultivate new technology through financial and knowledge resource allocation and identify subsequent extensions to existing technology. Moreover, they are less constrained in developing new innovations than related diversifiers, which must coordinate innovation more closely according to the joint needs of the business units in the corporation (Kim et al., 2013). Hence, stronger exploitation ability renders unrelated diversification more attractive than related diversification.

Hypothesis 3. Firms with higher exploitation ability will benefit more from a stronger relative focus on unrelated versus related diversification.

3. Methods

3.1. Data and sample

Our empirical analysis is set in the information and communication technology (ICT) industries (Matusik and Heeley, 2005; Patel et al., 2015; Wales et al., 2013; Yayavaram et al., 2018). ICT industries are dynamic with rapid technological change and intense restructuring activity and depend on technological knowledge for developing and sustaining competitive advantage. ICT firms tend to be growth-oriented and possess diverse levels of absorptive capacity (Patel et al., 2015). They routinely and systematically protect and document their inventions by patenting, which lets us rely on patent information to proxy components of absorptive capacity (Song et al., 2018; Zahra and George, 2002). We examine the strategy-performance relationship in a focused set of industries (Ahuja and Novelli, 2017; Palich et al., 2000) so that, along with the explicit control for (sub-)industry effects and concentration effects that affect firm performance, we cover a fairly homogenous industry environment. Moreover, it limits potential confounding effects on absorptive capacity due to industry heterogeneity (Matusik and Heeley, 2005; Wales et al., 2013).

Our initial sample was all 212 US-traded ICT firms with a minimum of $1bn in sales for 2013. Sample firms were from the following 2-digit SIC Codes: 35 (Industrial And Commercial Machinery And Computer Equipment); 36 (Electronic And Other Electrical Equipment And Components, Except Computer Equipment); 37 (Transportation Equipment); 38 (Measuring, Analyzing, And Controlling Instruments; Photographic, Medical And Optical Goods; Watches And Clocks); 48 (Communications); 50 (Wholesale Trade-durable Goods); and 73 (Business Services).[2]

Focusing on large ICT firms ensured the availability and reliability of key variables (Ahuja and Katila, 2001; Schildt et al., 2012) and that firms were active patent developers and engaged consistently in diversification. Our sample firms' size is comparable to that of Nasiriyar et al. (2014), who studied the role of technological resources in the diversification-performance relationship of 101 publicly traded Fortune 500 firms (1998's list) with at least $3bn in sales. It is also comparable to Tsai (2001), who studies absorptive capacity across business units in two large firms with annual revenues of $10.7bn and $4.1bn, respectively.

We used Thomson Reuters' Derwent database, the world's most comprehensive database of patent documents for patent data. Since large multi-business firms frequently assign patents to subsidiaries, we used Bureau Van Dijk's Orbis database to identify all (domestic and foreign) subsidiaries of our sample firms. We then searched the Derwent database for patents assigned to parent or subsidiary names and aggregated all patents to the parent level. We collected 485,001 patents assigned to sample firms and their subsidiaries between 1966 and 2013. Each patent and its cited patents are identified by International Patent Class (IPC).

We used Refinitiv's Compustat for financial,[3] industry, and segment data and Refinitiv's Datastream database to collect M&A data. We complemented missing data with data from Thomson Reuters' Eikon database. Still, 59 firms were excluded: two merged with two others already in the sample, and 57 were dropped because they did not report data on at least one of our independent or control variables, including patenting activity, R&D expenses, segment data, and international sales data.[4] Our final dataset comprises an unbalanced panel of 2,047 firm-year observations with 153 firms from 1979 to 2013.

3.2. Dependent variable

We measure performance by a firm's return on assets (ROA) (Miller, 2004; Robins and Wiersema, 1995). ROA is widely used in the strategy-performance literature (Hoskisson and Hitt, 1990) and is related to other financial indicators. It also ensures comparability

[2] We identified 901 ICT firms of which 212 (23.5 %) met our sales size condition.
[3] Financial data were deflated and converted to constant US$ of 2005 using the CPI.
[4] In our empirical analysis we account for potential selection bias.

with prior work on diversification and performance.

3.3. Independent variables

Absorptive capacity. Absorptive capacity is a multilevel construct and may be studied at various levels of analysis (Volberda et al., 2010). We examine it at the firm level (Bierly et al., 2009; Kotabe et al., 2014) primarily because we focus on the interaction between absorptive capacity and diversification strategy, a firm-level decision (Teece et al., 1994). Secondly, the absorptive capacity of a diversified firm is the collective absorptive capacity of its individual business units (Helfat and Eisenhardt, 2004; Miller et al., 2007; Tsai, 2001).

Studies that attempt to disaggregate the component abilities highlight that they exhibit some overlap in their functions, but no single component is equipped to perform all three functions very well. In a meta-analysis, Song et al. (2018) show that each ability may have a secondary function beyond its primary function. It is, therefore, challenging to completely detach one ability from another, making it difficult to measure individual components. Direct measures based on survey responses are context-specific, which reduces generalizability (Camisón and Forés, 2010; Delmas et al., 2011; Flatten et al., 2011; Jiménez-Barrionuevo et al., 2011; Thomas and Wood, 2014). We rely on archival data to improve generalizability and avoid static operationalizations.

Acquisition ability. We drew on the organizational learning literature to capture a firm's acquisition ability. Knowledge acquisition refers to the scientific, technological, organizational, or general knowledge the firm obtains from external sources (Lane et al., 2006), and it can include gaining new knowledge from other firms (e.g., Lane and Lubatkin, 1998) and different units of an organization (e.g., Tsai, 2001). Prior (survey-based) work has operationalized knowledge acquisition as the rate of external learning, knowledge transfer, and improvement in the firm's stock of knowledge (Song et al., 2018).

Knowledge acquisition is effective when knowledge is accessible before it can be acquired, connections exist between the firm's internal knowledge base and external sources, and there is a basic understanding of the acquired knowledge, skills, and capabilities (Inkpen, 2000). Moreover, Song et al. (2018) add that the knowledge type ("what"), governance mode used for accessing external knowledge ("how"), and the learning source ("from whom") influence effective knowledge acquisition. Our yearly measure of acquisition ability incorporates these three underlying premises and lets us observe variation in a firm's strength of acquisition ability.

Firstly, we consider the governance mode organizations use to increase their store of knowledge using information about M&As. M&As let firms acquire knowledge not previously available within the organization and that can potentially be shared and internalized or integrated within the organization (Inkpen, 2000). We used Datastream to collect yearly historical data on company acquisitions made by our sample firms. We used information on the SIC codes of acquired companies to develop an entropy measure (Jacquemin and Berry, 1979) of the degree of diversification of acquisitions. We computed acquisition diversification (*AD*) as follows:

$$AD_t = \sum_{i=j}^{N} P_{it}\, ln\left(\frac{1}{P_{it}}\right),$$

where N is the number of 3-digit SIC industries in which a firm has made acquisitions, and P_{it} is the share of total acquisitions of 3-digit SIC i in year t. Measuring the industry diversity of the acquired companies also captures the acquisition ability's learning source premise.

Secondly, we analyze patent documents to identify whether the acquiring company cited the target organizations before the acquisition. This captures the premise that acquisition ability is affected by knowledge type. Patent citations indicate that the acquiring firm must have some understanding of the acquired firm's knowledge (Moreira et al., 2018). We constructed a yearly cumulative measure of the percentage of cited targets (*Cited Percent*).

Finally, we consider the accessibility of external knowledge and the learning source premises of acquisition ability by asking whether a particular target was outside the USA. Foreign acquisitions suggest a more potent acquisition ability (Zou and Ghauri, 2008). We develop a yearly cumulative measure of the percentage of foreign targets (*Foreign Percent*).

Our measure of acquisition ability is the product of the three separate measures of the "how," "what," and "from whom" premises (i. e., *Acquisition ability (ACA)* = *AD* x *Cited Percent* x *Foreign Percent*[5]). The variable suggests stronger acquisition ability when the company's acquisitions are more diverse, target companies are cited in the acquirer's patent documents, and they pertain to foreign acquisitions.

Assimilation ability. Theoretical work posits that assimilation ability "*can be measured by the number of cross-firm patent citations or the number of citations made in a firm's publications to research developed in other firms*" (Zahra and George, 2002: 199). Patent citations show knowledge domains that patent creators understand, assimilate, transform, and combine with existing knowledge in a new patent. Drawing on cross-firm patent citations is theoretically and empirically attractive as it accounts for two elements underlying assimilation ability: existing knowledge base and internal sharing processes.

Song et al. (2018: 2347) discuss absorptive knowledge base conceptualized as "*a firm's accumulated stock of knowledge that helps to understand, recombine, and transform external knowledge*" and absorptive process that "*concerns a firm's internal procedures and practices that facilitate in sharing and internal diffusion of external knowledge.*" Absorptive knowledge base and process mirror Zahra and George (2002: 189, 190) assimilation ability ("*the firm's routines and processes that allow it to analyze, process, interpret, and understand the*

[5] We add the value of one to each of *AD*, *Cited Percent*, and *Foreign Percent* so that acquisition ability never takes a zero value when target firms are not cited and are local.

information obtained from external sources") and transformation ability ("*a firm's capability to develop and refine the routines that facilitate combining existing knowledge and the newly acquired and assimilated knowledge.*"), which Lane et al. (2006) and Todorova and Durisin (2007) aggregate to assimilation ability.

Regarding the stock of knowledge, patent citations track knowledge associations across technological classes (Almeida et al., 2002; Kim et al., 2013). The more diverse the technologies cited by a focal patent, the broader the technological roots of the underlying research, and the more advanced the firm's ability to analyze, process, interpret, and understand a broader knowledge domain obtained externally.[6] Patent citations also indicate internal sharing practices that help firm business units draw on diverse knowledge domains. Research has shown that patent citations indicate knowledge and communication flows between inventors (Moreira et al., 2018), albeit with some noise (Jaffe et al., 2000). According to Moreira et al. (2018), citations suggest a network of intrafirm inventor task relationships. Inventors in this network can provide one another with specialized and relevant technological knowledge that favors external knowledge assimilation. Those flows are mediated by face-to-face communication since senders and receivers must exchange bits of knowledge that escape complete codification. Thus, patent citations indicate the existence of a social chain between collaborating inventors underpinned by some personal exchanges.

Following Miller (2004), we associate patenting activity with particular industries following Silverman (1999), who relates patent classes to the industries in which the respective products are manufactured and used based on the observation that some patent classes are more closely tied to a particular industry than others. This concordance links the International Patent Classification system to the U.S. Standard Industrial Classification system at the four-digit SIC level to obtain an SIC code for each citing and cited patent in our sample. We used these to construct our assimilation ability measure to capture the breadth of industries from which firms source knowledge.

We operationalize assimilation ability as the diversity in citations the firm draws on for their patents. We use a concentric measure of diversity (Caves et al. (1980), which compares the firm's SIC-translated patents against its SIC-translated citations. Following Argyres (1996), we calculate the concentric distance between patents and citations as follows[7]:

$$\textit{Assimilation ability}\left(ASA_t\right) = \sum_{it} p_{it} \sum_{jt} d_{ij} p_{jt},$$

where p_{it} is the proportion of patents in 4-digit SIC i in year t; p_{jt} is the proportion of citations in 4-digit SIC j in year t; and d_{ij} equals 1,2,3,4 if i and j are in the same 4,3,2,1-digit SIC, respectively. The index ranges from 1 to 4 and is increasing in diversity. Larger values suggest broader technological roots of the underlying research, a more advanced understanding of a broad technological domain, and, thus, greater assimilation ability.

Exploitation ability. We follow Lane et al. (2006: 856), who view exploitation ability as the firm's ability of *"using the assimilated knowledge to create new knowledge and commercial outputs through exploitative learning."* This indicates how firms apply their newly assimilated knowledge in various ways, such as replenishing their knowledge base, forecasting technological trends, and creating innovative products and services (Cohen and Levinthal, 1994; Van Den Bosch et al., 1999). We operationalize it by first capturing the novel knowledge outputs reflected in the firm's new patents and, second, assigning a likelihood of commercial value to the patents by translating the technological domains of the patents to markets that patents can be applied in as we did with assimilation ability.

Specifically, we derive a concentric diversity measure of the "distance" among firm patents (Argyres, 1996) to capture the breadth of the markets and industries in which the firm's (intermediate) products and knowledge can be applied. Again, we draw on the four-digit SIC concordance by Silverman (1999). The measure is given by:

$$\textit{Exploitation ability}\left(EXA_t\right) = \sum_{it} p_{it} \sum_{jt} d_{ij} p_{jt},$$

where p_{it} is the proportion of patents translated in 4-digit SIC i in year t; p_{jt} is the proportion of patents in 4-digit SIC j in year t; and d_{ij} equals 1,2,3,4 if i and j are in the same 4,3,2,1-digit SIC, respectively. The index ranges from 1 to 4 and is again increasing in diversity. Larger values suggest that the firm produces (intermediate) products and knowledge that can be applied in a broader range of markets and industries. Patents assigned to multiple SICs were treated as distinct to capture firm-level technological diversity better.

Our measure of exploitation ability is in line with Zahra and George (2002: 199), who suggest that an exploitation ability measure could *"include intermediate outputs, such as the number of patents, new product announcements, or length of product development cycle."* Prior work drawing on archival data to operationalize exploitation ability includes George et al. (2001), who use patent counts, and Lane and Lubatkin (1998), who count the number of different research fields in which pharmaceutical and biotechnology firms published.

Diversification. Prior work measures diversification types through product (Rumelt, 1974), technological (Robins and Wiersema,

[6] As we explain below, we use a 3-year lagged variable structure that provides for sufficient time that new knowledge combined with the firm's prior knowledge to develop new knowledge has been absorbed and become part of the firm's current knowledge stock. This enables us to capture the developmental, lagged, and path dependent characteristics of assimilation ability that are consistent with Cohen and Levinthal's definition (Volberda et al., 2010).

[7] Note that this measure does not discriminate which patent cited which SICs, it considers assimilation ability a firm-wide ability and measures the respective diversity of firm patents and citations.

1995; Silverman, 1999), managerial (Prahalad and Bettis, 1986), or human resource relatedness (Farjoun, 1998), or a combination (Tanriverdi and Venkatraman, 2005) thereof. They all capture the industries a firm is active in and their resource similarities (Tanriverdi and Venkatraman, 2005).

We use the entropy measure of diversification by Jacquemin and Berry (1979), which is replicable and rich (Kim et al., 2013; Li and Greenwood, 2004) and lets us calculate total, related, and unrelated diversification. Total diversification (DT) is computed as follows:

$$DT_t = \sum_{i=j}^{N} P_{it}\, ln\left(\frac{1}{P_{it}}\right),$$

where N is the number of 4-digit SIC industry segments a firm operates in and P_{it} is the share of total firm sales of segment i in year t. If we let N 4-digit SIC industry segments aggregate into M 2-digit SIC industry groups, $(N \geq M)$, related diversification arising out of operating in several segments within an industry group j (DR_{jt}) can be written as follows:

$$DR_{jt} = \sum_{i\epsilon j} P_{it}^{j}\, ln\left(\frac{1}{P_{it}^{j}}\right),$$

where P_{it}^{j} is defined as the share of segment i of group j in the total sales of group j in year t. Since a firm may operate in several industry groups, its total related diversification DR_t is a function of DR_{jt}, j = 1, …,M, and is defined as:

$$DR_t = \sum_{j=1}^{M} DR_{jt} P_{jt},$$

where P_{jt} is the share of the jth group sales in the total sales of the firm in year t. Lastly, unrelated diversification (DU_t) is the difference between DT_t and DR_t.

The entropy measure captures three crucial elements of diversification (Palepu (1985): the number of segments a firm operates in, their degree of relatedness, and their importance for total firm sales. We model diversification in two complementary analyses. First, we use the ratio of related (DR) to total diversification (DT) to develop a measure of diversification direction. The higher the DR/DT ratio (≤1), the higher the related share of total diversification. Diversification direction accounts for firms using more of one diversification type or the other, which ultimately shifts firms closer to or away from their core. Kim et al. (2013) use a similar measure to study how diversified firms' search behavior moderates the diversification type's impact on innovation. Second, we use DR and DU separately to capture interactions of different diversification types with absorptive capacity.

3.4. Control variables

Absorptive effort. Song et al. (2018) suggest that knowledge-building investments, typically in the form of R&D, reflect the absorptive effort of the firm that enables external knowledge search and processing routines underlying absorptive capacity. R&D investments help exploit new technological developments and envision the emergence of new ones. Empirical evidence shows that firms' ability to tap more efficiently into external sources of knowledge improves by investing in their R&D (Berchicci, 2013). We control for absorptive effort using the firm's ratio of R&D expenditure to total sales. As most empirical work operationalizes overall absorptive capacity with R&D intensity, we can better assess the added value of absorptive capacity components over and above the established measure of absorptive capacity (Lane and Lubatkin, 1998).

Absorptive knowledge base. Absorptive capacity depends on prior knowledge. The absorptive knowledge base captures a firm's accumulated knowledge stock. Following Song et al. (2018), we control for absorptive knowledge base using the cumulative number of patents (in logs). This also lets us account for the relationship between technological output and firm performance (Miller, 2006).

Total diversification. The overall *extent* of firm diversification may drive the effect of diversification on performance. We thus control for total diversification.

Firm size. Firm size indicates market power and scale economies (Robins and Wiersema, 1995). We control for firm size with the (log) number of employees and expect it to have a positive relationship with performance.

Industry concentration. Market concentration helps firms sustain higher profits. Our measure is the weighted (by firm sales) average industry concentration (defined in terms of 2-digit SICs) in which a firm is active. We multiply the proportion of firm sales in a focal industry with the concentration ratio of the respective industry and aggregate as follows:

$$Industry\ Concentration_t = \sum CR4_i P_i,$$

where $CR4_i$ is the four-firm concentration ratio for the 2-digit SIC industry i and P_i is the proportion of a firm's sales in 2-digit SIC industry i.

Industry profitability. To control for industry effects not captured by industry concentration, we construct a weighted average of industry profitability by computing the average profitability of each 4-digit SIC industry in which a focal firm operates, multiply it by the proportion of firm sales in the industry, and aggregate to the firm level as follows:

$$Industry\ Profitability = \sum ROA_i P_i,$$

where ROA_i is the average ROA for industry i and P_i is the proportion of firm sales in i.

Debt burden. Managerial discretion in allocating organizational resources across the organization's operations is reduced if the firm has high debts (George, 2005). We measure debt burden as the firm's debt-to-shareholder equity ratio (Markides, 1995).

Labor productivity. Changes in labor productivity from renegotiated labor contracts, new investments in technology, and improvements in management during the study period can affect firm performance (Markides, 1995). We control for labor productivity using the ratio of firm sales to the number of employees.

Foreign sales. Prior literature suggests a positive relationship between foreign operations and profitability (Wan and Hoskisson, 2003). Moreover, foreign market seeking may suggest synergy seeking and greater reliance on related diversification (Seth et al., 2002). We control for the firm's foreign-to-domestic sales ratio to capture variation in foreign market seeking that can influence firm performance.

Time Effects. We use year dummies to control for unobserved time-specific effects and serial correlation (Phene et al., 2012).

Industry Effects. Following Palich et al. (2000), we include 2-digit SIC industry dummies to capture industry effects. However, note that we already capture the greatest source of heterogeneity, especially concerning unrelated diversification, by focusing on ICT firms.

4. Results

We centered our independent variables around their mean to ease the interpretation of our direct and interaction effects (Aguinis et al., 2013) and examined the variance inflation factors (VIF) for multicollinearity. All scores were below 2.2, and the mean score was 1.87, well below the cutoff of 10 (Cameron and Trivedi, 2009). Table 1 gives summary statistics and pairwise correlations for our variables (prior to variable centering). Tables 2 and 3 give our results based on diversification direction and separate related and unrelated diversification measures, respectively.[8] Following Markides (1995), Garud and Nayyar (1994), and Makri et al. (2010), we tested alternate models that involved the 1- to 2-year lagged effects of diversification and the 2- to 3-year lagged effects of the components of absorptive capacity. We used the Akaike and Bayesian Information Criteria to evaluate alternative model specifications. The specification resulting in the loss of the fewest data points and yielding the lowest AIC and BIC values involved three-year and two-year lags for the effects of the components of absorptive capacity and diversification, respectively.

As we lost 59 firms through missing data, we use a two-stage Heckman selection correction to help us address potential selection bias. It entails using a first-stage probit model of all initial observations to predict inclusion in the sample. The first stage requires an exclusion restriction. This variable should affect the probability of a firm being in the sample but be "excluded" from the second-stage model based upon theoretical logic for why this variable does not affect firm performance (ROA). We draw on research that shows that adopting a superior set of accounting standards, such as the International Financial Reporting Standards (IFRS), is associated with finer information on line items in annual reports and accounting disclosure quality and has no direct effect on firms' performance (Li et al., 2021). The accounting standard a firm in our sample adopts may thus be related to the exclusion process. We used data from Compustat to construct a dummy indicating whether the sample firm adopted the IFRS in our sample period. We used this variable as the exclusion restriction in the first stage along with all independent variables of the primary model, excluding absorptive effort, absorptive capacity, and diversification, which were the ones mainly causing firms to drop from the sample. From this equation, we derive the inverse Mills' ratio representing the selection hazard of entering the sample and use it as a control in the second stage, yielding consistent estimates of the predictor of the outcome.

Endogeneity is a concern in most diversification research (Mackey et al., 2017; Miller, 2004, 2006). The causal relation between diversification and economic performance may run in both directions. To address potential endogeneity, we use a two-step system Generalized Method of Moments (GMM), an instrumental variable estimator suggested by Blundell and Bond (1998) used to study the effect of diversification on performance (e.g., Andrés et al., 2017). Following previous practice (e.g., Eklund and Kapoor, 2022), we used the lags of the diversification variable as its instruments. Reed (2015) showed that using lagged values of the endogenous explanatory variable as instruments can be an effective estimation strategy if the lagged values do not belong in the main estimating equation and are sufficiently correlated with the simultaneously determined explanatory variable. Both conditions are satisfied in our sample. The diversification variable, which appears in our models lagged by two years, is instrumented with its 3-year and 4-year lags. The two instruments are not in the main model and are highly correlated with the endogenous variable (Pearson's $r > 0.76$; $p < 0.05$). The GMM estimator yields more efficient estimates than conventional IV estimators, such as 2-stage least squares (2SLS), and is consistent in the presence of arbitrary heteroskedasticity (Wooldridge, 2010). The Pagan-Hall test statistic (Chi-sq = 91.964; p = 0.000) rejects the null of no heteroskedasticity in our data. Thus, following Driscoll and Kraay (1998), we apply estimation techniques that yield standard error estimates that are robust to very general forms of spatial and temporal dependence as the time dimension becomes large. This generates efficient coefficient estimates and consistent estimates of the standard errors.

We assess our instruments' validity by conducting tests for over-identification, under-identification, and weak identification (Murray, 2006), reporting the relevant test statistics below all estimations. We invoke the Sargan-Hansen test for over-identifying restrictions (Andrés et al., 2017). Hansen's J-statistic suggests that the instruments are valid, i.e., uncorrelated with the error term and correctly excluded from the estimated equation. The Kleibergen-Paap rk LM test statistic suggests rejection of the null hypothesis of under-identification, meaning that excluded instruments are correlated with endogenous regressors. Last, we rely on Stock and Yogo

[8] We scaled ROA up by a 100 so that we avoided reporting very small nominal values.

Table 1
Summary statistics and correlations matrix.

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. Return on Assets (ROA)	.143	.087	1																
2. Acquisition ability (ACA)	3.031	1.997	−0.086	1															
3. Assimilation ability (ASA)	2.249	0.908	0.152	−0.104	1														
4. Exploitation ability (EXA)	3.068	3.469	0.168	−0.024	0.349	1													
5. Related diversification (DR)	0.392	0.481	0.047	0.329	0.083	0.082	1												
6. Unrelated diversification (DU)	0.434	0.623	−0.251	0.309	−0.039	−0.142	0.056	1											
7. Diversification direction (DR/DT)	0.76	0.49	0.126	0.043	0.058	0.208	0.454	−0.211	1										
8. Absorptive effort	0.056	0.058	0.001	0.023	−0.237	0.131	−0.021	−0.107	0.136	1									
9. Absorptive knowledge base	3.975	2.683	−0.083	0.302	−0.358	−0.104	0.176	0.284	0.022	0.130	1								
10. Total Diversification (DT)	0.826	0.805	−0.164	0.435	0.020	−0.060	0.643	0.800	0.110	−0.095	0.323	1							
11. Firm size	3.48	1.351	−0.067	0.421	0.066	−0.017	0.266	0.356	−0.035	−0.194	0.500	0.433	1						
12. Industry concentration	0.166	0.144	−0.193	0.092	−0.260	−0.194	−0.109	0.209	−0.033	0.025	0.354	0.169	0.307	1					
13. Industry profitability	1.01	5.46	−0.012	−0.040	0.009	−0.007	0.022	0.014	0.027	0.000	0.030	0.029	−0.000	0.144	1				
14. Debt burden	0.58	10.29	0.019	0.032	−0.006	−0.020	0.067	0.018	0.016	−0.010	0.051	0.033	0.048	−0.015	0.002	1			
15. Labor productivity	399.942	460.369	0.019	−0.071	0.068	−0.078	−0.057	−0.052	0.000	−0.113	−0.002	−0.047	−0.220	−0.079	0.037	0.019	1		
16. Foreign sales	0.372	0.293	0.008	0.287	−0.266	0.007	0.201	−0.072	0.211	0.335	0.238	−0.090	0.153	0.252	0.022	0.019	−0.104	1	
17. Inverse Mills' ratio	1.888	1.294	0.0659	−0.1673	0.3005	0.1215	−0.0149	−0.1756	−0.0357	−0.1409	−0.4507	−0.1435	−0.5218	−0.7220	−0.1018	0.0085	0.2287	−0.5278	1

Correlation coefficients greater than |0.06| are statistically significant at the 0.05 significance level. Statistics were calculated before centering.

Table 2
Regression analysis results (Diversification direction).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Selection model	Controls	Base	H1	H2	H3	H1,2,3
	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)
Acquisition ability (ACA_{t-3})			−0.2406*	−0.2593**	−0.2381*	−0.2448*	−0.2986**
			(0.1113)	(0.0933)	(0.1075)	(0.1123)	(0.0915)
Assimilation ability (ASA_{t-3})			0.8720**	1.0108**	0.8748**	0.8979**	1.0299**
			(0.3290)	(0.3212)	(0.3227)	(0.3340)	(0.3174)
Exploitation ability (EXA_{t-3})			0.0955±	0.0281	0.0984±	0.1191*	0.0571
			(0.0546)	(0.0691)	(0.0506)	(0.0481)	(0.0589)
Diversification Direction $(DR/DT)_{t-2}$		0.0190*	0.0180*	0.0346***	0.0188*	0.0261*	0.0525***
		(0.0091)	(0.0092)	(0.0065)	(0.0090)	(0.0106)	(0.0073)
$(DR/DT)_{t-2}$ x ACA_{t-3}				−0.0286***			−0.0337***
				(0.0042)			(0.0036)
$(DR/DT)_{t-2}$ x ASA_{t-3}					−0.0065		0.0198*
					(0.0092)		(0.0090)
$(DR/DT)_{t-2}$ x EXA_{t-3}						−0.0025**	−0.0054***
						(0.0010)	(0.0008)
Absorptive $effort_{t-3}$		−1.5016**	−1.4624**	−1.4387**	−1.4227**	−1.3825**	−1.3959**
		(0.5653)	(0.5156)	(0.4904)	(0.4835)	(0.4790)	(0.4755)
Absorptive knowledge $base_{t-3}$		0.1391*	0.1927*	0.1962*	0.1946*	0.2057**	0.2170*
		(0.0698)	(0.0804)	(0.0873)	(0.0800)	(0.0796)	(0.0862)
Total $diversification_{t-2}$		−3.3604***	−3.3992***	−3.7185***	−3.3945***	−3.3274***	−3.6385***
		(0.2790)	(0.2574)	(0.3032)	(0.2571)	(0.2592)	(0.3033)
Firm $Size_{t-1}$	0.3541*	−0.5284	−0.5155	−0.3162	−0.4928	−0.5662	−0.3752
	(0.1751)	(0.3967)	(0.4387)	(0.4665)	(0.4563)	(0.4338)	(0.4615)
Industry $Concentration_{t-1}$	11.9131***	−17.5016***	−17.3754***	−16.5605***	−17.2628***	−17.4743***	−16.7093***
	(2.2133)	(2.3635)	(2.3015)	(2.4371)	(2.3521)	(2.3047)	(2.4982)
Industry $Profitability_{t-1}$	−0.0013	0.0249**	0.0220*	0.0263**	0.0231*	0.0205*	0.0202*
	(0.0486)	(0.0083)	(0.0090)	(0.0082)	(0.0108)	(0.0087)	(0.0092)
Debt $burden_{t-1}$	−0.0008	−0.0087	−0.0061	−0.0056	−0.0059	−0.0057	−0.0048
	(0.0161)	(0.0090)	(0.0087)	(0.0104)	(0.0088)	(0.0086)	(0.0101)
Labor $productivity_{t-1}$	−0.0000	0.0013***	0.0013***	0.0010**	0.0012***	0.0013***	0.0011**
	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)
Foreign $sales_{t-1}$	2.2381*	−1.2098	−0.7338	−0.2703	−0.6058	−0.7517	−0.3673
	(0.9557)	(0.9151)	(1.0109)	(0.9746)	(1.1244)	(0.9921)	(0.9877)
Inverse Mills' Ratio		−1.9484**	−1.8342**	−1.4649*	−1.7780*	−1.8814**	−1.5164*
		(0.6878)	(0.6787)	(0.7260)	(0.7248)	(0.6768)	(0.7485)
Exclusion restriction (IFRS)	1.0664						
	(1.1740)						
ROA	1.2749						
	(2.6932)						
Constant	−1.6722						
	(2.4585)						
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4029	2047	2047	2047	2047	2047	2047
R-squared (centered)		0.13	0.14	0.16	0.14	0.14	0.16
F-statistic		443.54	430.45	813.98	573.72	463.75	1000.42
Hansen J statistic		1.02	1.06	0.24	1.06	1.30	0.54
P-value		0.31	0.30	0.62	0.30	0.25	0.46
Underidentification test (Kleibergen-Paap rk LM statistic)		6.23	6.25	6.74	6.32	6.04	6.49
P-value		0.04	0.04	0.03	0.04	0.05	0.04
Wald F statistic for weak identification (Cragg-Donald)		1901.152	1867.791	1766.273	1812.583	1421.117	1294.008
Stock-Yogo weak ID test critical values: 5 % maximal IV relative bias		19.93[a]	19.93[a]	19.93[a]	19.93[a]	19.93[a]	19.93[a]

± $p < 0.10$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.
[a] Stock-Yogo weak ID test critical values for 5 % maximal IV relative bias are not available. Instead, we report Stock-Yogo weak ID test critical values for 10 % maximal IV size.

(2005) to test for weak identification. The Cragg-Donald Wald F statistic exceeds the Stock and Yogo critical value, rejecting the null hypothesis of a weak instruments problem. Thus, IV estimates and their corresponding estimated standard errors are likely unbiased, and inference based on them is probably valid.

Table 2 gives the results for diversification direction. Column (1) reports the selection model used to construct the inverse Mills' ratio. Column (2) reports the results when ROA is regressed on the control variables. Column (3) includes linear effects of the main

Table 3
Regression analysis results (Related and Unrelated diversification).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Base	H1 (DR)	H1 (DU)	H1	H2 (DR)	H2 (DU)	H2	H3 (DR)	H3 (DU)	H3	H1,2,3
	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)
Acquisition ability (ACA_{t-3})	−0.2022±	−0.0291	−0.2569*	−0.0923	−0.1915	−0.2342*	−0.2243±	−0.2557*	−0.2091±	−0.2628*	−0.1244
	(0.1181)	(0.0776)	(0.1298)	(0.0790)	(0.1198)	(0.1143)	(0.1146)	(0.1302)	(0.1132)	(0.1270)	(0.0827)
Assimilation ability (ASA_{t-3})	0.9382**	0.8861***	1.0455**	0.9910***	0.8905**	0.9748***	0.9159**	0.9858***	0.9205**	0.9814***	0.9194**
	(0.2867)	(0.2673)	(0.3190)	(0.2966)	(0.2745)	(0.2918)	(0.2794)	(0.2951)	(0.2909)	(0.2901)	(0.3095)
Exploitation ability (EXA_{t-3})	0.0860±	0.0647	0.0925±	0.0691	0.0832±	0.0878±	0.0847±	0.0931*	0.0748	0.0801±	0.0598±
	(0.0513)	(0.0530)	(0.0485)	(0.0506)	(0.0503)	(0.0497)	(0.0486)	(0.0453)	(0.0456)	(0.0420)	(0.0354)
Related diversification (DR_{t-2})	1.5697***	2.2190***	1.7169***	2.3810***	1.4778***	1.5308***	1.4027***	2.0184***	1.5767***	1.9926***	2.7898***
	(0.3528)	(0.4989)	(0.4107)	(0.5501)	(0.3732)	(0.3696)	(0.3920)	(0.4031)	(0.4022)	(0.4465)	(0.6049)
Unrelated diversification (DU_{t-2})	−1.7770**	−1.6837*	−2.1496***	−2.0337**	−1.7815**	−1.8468**	−1.8631**	−1.3427*	−1.6653**	−1.3069*	−1.2666±
	(0.6167)	(0.7284)	(0.6414)	(0.7570)	(0.6288)	(0.5643)	(0.5745)	(0.6131)	(0.5960)	(0.5912)	(0.6833)
DR_{t-2} x ACA_{t-3}		−0.9341***		−0.9310***							−1.0456***
		(0.2564)		(0.2514)							(0.2380)
DU_{t-2} x ACA_{t-3}			0.2883*	0.2905**							0.1636
			(0.1232)	(0.1124)							(0.1193)
DR_{t-2} x ASA_{t-3}					0.7741		1.0336*				1.7762***
					(0.4934)		(0.5193)				(0.4876)
DU_{t-2} x ASA_{t-3}						−0.7889***	−0.8941***				−0.4677*
						(0.1878)	(0.2028)				(0.2318)
DR_{t-2} x EXA_{t-3}								−0.2811***		−0.2622***	−0.4260***
								(0.0761)		(0.0735)	(0.0610)
DU_{t-2} x EXA_{t-3}									−0.2497**	−0.2253*	−0.2033*
									(0.0947)	(0.0905)	(0.0996)
Absorptive $effort_{t-3}$	−1.2571**	−1.1380**	−1.2680**	−1.1575**	−1.3440***	−1.2140**	−1.3244***	−1.2043**	−1.3058**	−1.2742**	−1.2905***
	(0.3948)	(0.3679)	(0.3860)	(0.3607)	(0.3917)	(0.4084)	(0.4006)	(0.3688)	(0.4373)	(0.4050)	(0.3620)
Absorptive knowledge $base_{t-1}$	0.1574*	0.1415*	0.1602*	0.1439*	0.1515*	0.1483*	0.1399*	0.1834**	0.1604*	0.1904**	0.1683*
	(0.0614)	(0.0601)	(0.0643)	(0.0632)	(0.0608)	(0.0589)	(0.0585)	(0.0616)	(0.0639)	(0.0655)	(0.0723)
Total $diversification_{t-2}$	−2.2126***	−2.4618**	−2.2322***	−2.5241***	−2.1334***	−2.1236***	−2.0044**	−2.9299***	−2.2760***	−2.8999***	−3.3260***
	(0.6039)	(0.7541)	(0.6231)	(0.7580)	(0.6290)	(0.5879)	(0.6192)	(0.6516)	(0.6515)	(0.6718)	(0.7311)
Firm $size_{t-1}$	−0.4877	−0.4545	−0.5599	−0.5124	−0.4892	−0.5282	−0.5402	−0.4450	−0.6246	−0.5418	−0.5567
	(0.4327)	(0.4256)	(0.4018)	(0.4025)	(0.4361)	(0.4156)	(0.4206)	(0.4538)	(0.4204)	(0.4479)	(0.4200)
Industry $concentration_{t-1}$	−16.0388***	−15.4275***	−16.1228***	−15.4650***	−16.3395***	−16.1250***	−16.5574***	−15.7945***	−16.2443***	−15.8286***	−15.9054***
	(2.6159)	(2.8052)	(2.5159)	(2.7049)	(2.7747)	(2.5149)	(2.6770)	(2.6478)	(2.5534)	(2.5948)	(2.8272)
Industry $profitability_{t-1}$	0.0184±	0.0194*	0.0174±	0.0186*	0.0196*	0.0176	0.0191±	0.0191±	0.0147	0.0159	0.0191*
	(0.0108)	(0.0091)	(0.0103)	(0.0086)	(0.0099)	(0.0108)	(0.0097)	(0.0115)	(0.0103)	(0.0111)	(0.0080)
Debt $burden_{t-1}$	−0.0153	−0.0152	−0.0139	−0.0139	−0.0161	−0.0151	−0.0161	−0.0180	−0.0147	−0.0170	−0.0190
	(0.0116)	(0.0119)	(0.0119)	(0.0121)	(0.0117)	(0.0115)	(0.0115)	(0.0126)	(0.0116)	(0.0124)	(0.0128)
$Productivity_{t-1}$	0.0010**	0.0011**	0.0010**	0.0011**	0.0010**	0.0010**	0.0011**	0.0010**	0.0010**	0.0010**	0.0013***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0004)	(0.0003)	(0.0004)	(0.0003)	(0.0004)
Foreign $sales_{t-1}$	−1.5494±	−0.9811	−1.8259*	−1.2269	−1.8152±	−1.5465±	−1.9055*	−1.3181	−1.7297*	−1.4625±	−1.4869±
	(0.8377)	(0.8419)	(0.8133)	(0.8120)	(0.9431)	(0.8214)	(0.9298)	(0.9132)	(0.8063)	(0.8889)	(0.8733)
Inverse Mills' Ratio	−1.8014**	−1.5602*	−1.9196**	−1.6560*	−1.8993*	−1.8420**	−1.9860**	−1.7360*	−1.9887**	−1.8574**	−1.8930**
	(0.6826)	(0.7057)	(0.6452)	(0.6727)	(0.7414)	(0.6638)	(0.7266)	(0.7058)	(0.6653)	(0.6963)	(0.7242)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

(*continued on next page*)

Table 3 (*continued*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Base	H1 (DR)	H1 (DU)	H1	H2 (DR)	H2 (DU)	H2	H3 (DR)	H3 (DU)	H3	H1,2,3
	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2047	2047	2047	2047	2047	2047	2047	2047	2047	2047	2047
R-squared (centered)	0.14	0.15	0.15	0.16	0.15	0.15	0.15	0.15	0.15	0.15	0.17
F-statistic	285.75	303.61	428.96	338.91	737.74	371.65	1204.02	304.90	956.74	704.08	1171.85
Hansen J statistic	0.11	0.04	0.30	0.18	0.17	0.12	0.20	0.04	0.77	0.27	0.19
P-value	0.95	0.98	0.86	0.92	0.92	0.94	0.91	0.98	0.68	0.87	0.91
Underidentification test (Kleibergen-Paap rk LM statistic)	7.18	7.03	7.59	7.52	7.13	7.15	7.03	7.43	7.08	7.19	7.58
P-value	0.07	0.07	0.06	0.06	0.07	0.07	0.07	0.06	0.07	0.07	0.06
Wald F statistic for weak identification (Cragg-Donald)	489.093	485.998	455.339	453.266	488.759	486.177	485.621	448.825	487.905	448.129	409.355
Stock-Yogo weak ID test critical values: 5 % maximal IV relative bias	11.04	11.04	11.04	11.04	11.04	11.04	11.04	11.04	11.04	11.04	11.04

± $p < 0.10$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

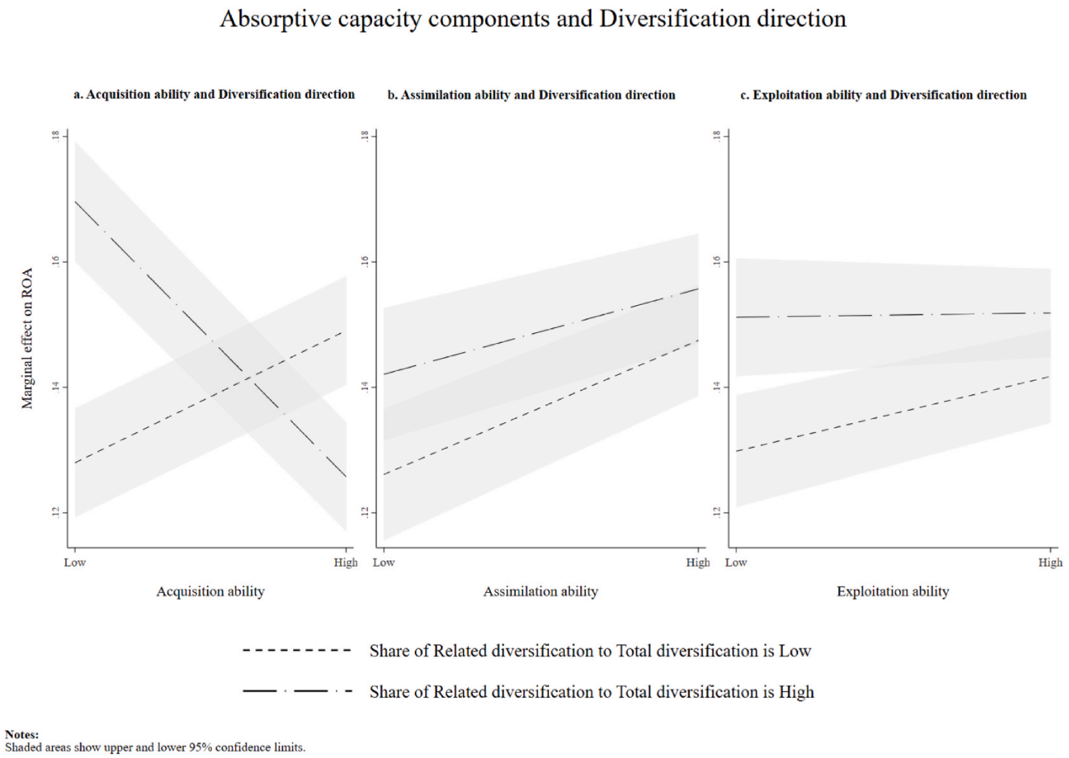

Fig. 1. Absorptive capacity components and Diversification direction.

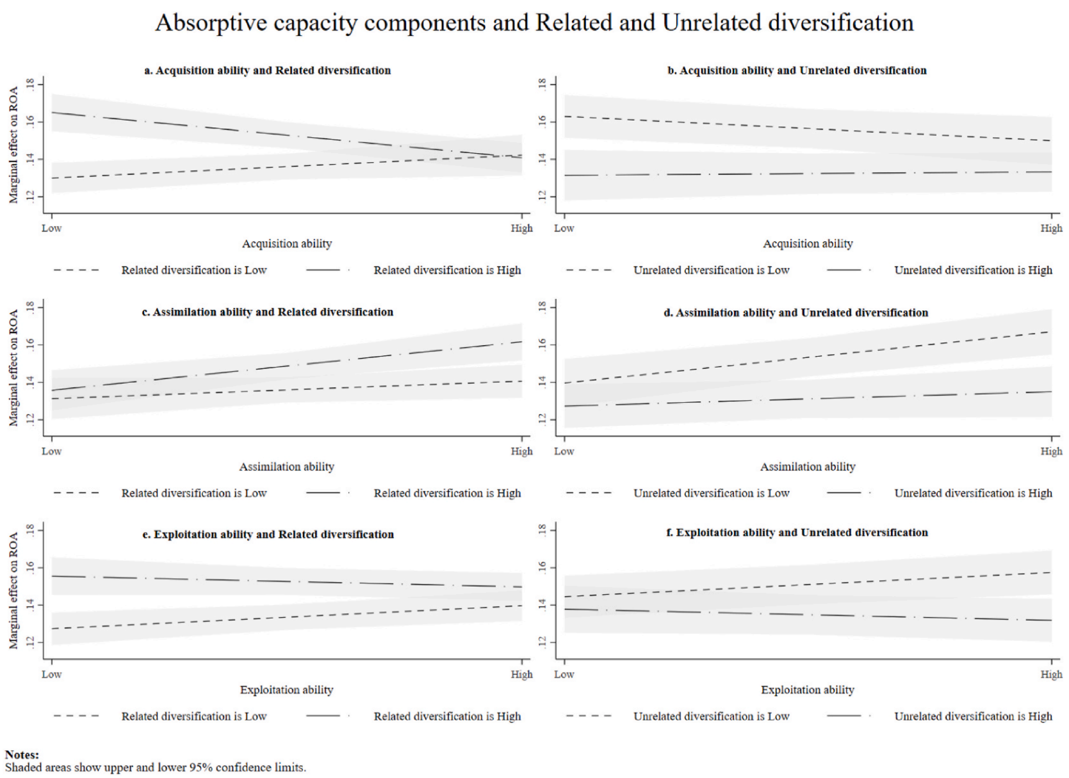

Fig. 2. Absorptive capacity components and Related and Unrelated diversification.

Table 4
Robustness analysis.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	H1	H2	H3	H1	H2	H3	H1	H2	H3
	No Mills' ratio	No Mills' ratio	No Mills' ratio	No Mills' ratio	No Mills' ratio	No Mills' ratio	2SLS	2SLS	2SLS
	DR/DT	DR/DT	DR/DT	DR, DU	DR, DU	DR, DU	DR/DT	DR/DT	DR/DT
	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)
Acquisition ability (ACA$_{t-3}$)	−0.3200***	−0.3059**	−0.3205**	−0.1439*	−0.3196***	−0.3522***	−0.2420*	−0.2291*	−0.2408*
	(0.0855)	(0.0950)	(0.1001)	(0.0706)	(0.0947)	(0.1009)	(0.0997)	(0.1078)	(0.1124)
Assimilation ability (ASA$_{t-3}$)	0.9608**	0.8416*	0.8637*	0.9206**	0.8835**	0.9181**	1.0720**	0.9747**	1.0012**
	(0.3281)	(0.3322)	(0.3460)	(0.2979)	(0.2890)	(0.2892)	(0.3443)	(0.3370)	(0.3461)
Exploitation ability (EXA$_{t-3}$)	0.0341	0.1099*	0.1286**	0.0722	0.0934*	0.0867*	0.0265	0.0733	0.0952±
	(0.0692)	(0.0524)	(0.0488)	(0.0476)	(0.0454)	(0.0377)	(0.0692)	(0.0562)	(0.0524)
Diversification Direction (DR/DT)$_{t-2}$	0.0364***	0.0215*	0.0288*				0.0349***	0.0203*	0.0280**
	(0.0056)	(0.0092)	(0.0112)				(0.0066)	(0.0092)	(0.0108)
Related diversification (DR)$_{t-2}$				2.4274***	1.4580***	2.0130***			
				(0.5338)	(0.3800)	(0.4382)			
Unrelated diversification (DU)$_{t-2}$				−1.7324*	−1.5486**	−0.9805±			
				(0.7513)	(0.5222)	(0.5046)			
(DR/DT)$_{t-2}$ x ACA$_{t-3}$	−0.0294***						−0.0283***		
	(0.0039)						(0.0042)		
(DR/DT)$_{t-2}$ x ASA$_{t-3}$		−0.0106						−0.0075	
		(0.0080)						(0.0092)	
(DR/DT)$_{t-2}$ x EXA$_{t-3}$			−0.0026**						−0.0028**
			(0.0010)						(0.0010)
DR$_{t-2}$ x ACA$_{t-3}$				−1.0335***					
				(0.2384)					
DU$_{t-2}$ x ACA$_{t-3}$				0.2633*					
				(0.1130)					
DR$_{t-2}$ x ASA$_{t-3}$					0.5013				
					(0.3399)				
DU$_{t-2}$ x ASA$_{t-3}$					−0.8105***				
					(0.1851)				
DR$_{t-2}$ x EXA$_{t-3}$						−0.2685***			
						(0.0685)			
DU$_{t-2}$ x EXA$_{t-3}$						−0.2084*			
						(0.0887)			
DR/DT (squared)$_{t-2}$									
Expectation of Latent Diversification Direction (DR/DT)									
Absorptive effort$_{t-3}$	−1.4508**	−1.3781*	−1.3585*	−1.1338**	−1.2585*	−1.2559**	−1.3944**	−1.4045**	−1.3610**
	(0.5597)	(0.5480)	(0.5531)	(0.4214)	(0.4887)	(0.4857)	(0.4986)	(0.4838)	(0.4794)
Absorptive knowledge base$_{t-1}$	0.1893*	0.1853*	0.1937*	0.1303*	0.1320*	0.1774**	0.1943*	0.1797*	0.1927*
	(0.0857)	(0.0788)	(0.0784)	(0.0651)	(0.0609)	(0.0687)	(0.0874)	(0.0813)	(0.0804)
Total diversification$_{t-2}$	−3.7278***	−3.3829***	−3.3157***	−2.8062***	−2.3801***	−3.2581***	−3.6626***	−3.3234***	−3.2391***
	(0.3229)	(0.2782)	(0.2782)	(0.7000)	(0.5235)	(0.5521)	(0.3238)	(0.2662)	(0.2705)
Firm size$_{t-1}$	0.1886	0.1228	0.0876	0.0690	0.1410	0.1142	−0.3412	−0.3246	−0.3624
	(0.2390)	(0.2356)	(0.2303)	(0.1951)	(0.1969)	(0.2146)	(0.4692)	(0.4847)	(0.4692)
Industry concentration$_{t-1}$	−11.1711***	−10.7570***	−10.5628***	−9.5490***	−9.4232***	−9.1334***	−16.5327***	−16.5435***	−16.5834***

(*continued on next page*)

Table 4 (*continued*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	H1	H2	H3	H1	H2	H3	H1	H2	H3
	No Mills' ratio	No Mills' ratio	No Mills' ratio	No Mills' ratio	No Mills' ratio	No Mills' ratio	2SLS	2SLS	2SLS
	DR/DT	DR/DT	DR/DT	DR, DU	DR, DU	DR, DU	DR/DT	DR/DT	DR/DT
	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)
	(1.4072)	(1.5119)	(1.4368)	(1.1496)	(1.2250)	(1.2491)	(2.4378)	(2.4538)	(2.4335)
Industry profitability$_{t-1}$	0.0366***	0.0356***	0.0331***	0.0307***	0.0322***	0.0293**	0.0273**	0.0291*	0.0268**
	(0.0068)	(0.0102)	(0.0087)	(0.0080)	(0.0096)	(0.0092)	(0.0085)	(0.0123)	(0.0103)
Debt burden$_{t-1}$	−0.0095	−0.0105	−0.0107	−0.0184	−0.0210±	−0.0220±	−0.0091	−0.0132	−0.0138
	(0.0101)	(0.0089)	(0.0088)	(0.0115)	(0.0108)	(0.0117)	(0.0125)	(0.0113)	(0.0112)
Productivity$_{t-1}$	0.0011**	0.0013***	0.0014***	0.0011**	0.0011**	0.0011**	0.0010*	0.0010*	0.0010*
	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Foreign sales$_{t-1}$	2.1298**	2.3344***	2.3381***	1.5733*	1.4825*	1.6728*	−0.4929	−0.5307	−0.6222
	(0.6555)	(0.6190)	(0.6089)	(0.7255)	(0.7082)	(0.6948)	(1.0742)	(1.1268)	(0.9986)
Inverse Mills' Ratio							−1.5149*	−1.5446*	−1.5776*
							(0.7331)	(0.7595)	(0.7273)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2047	2047	2047	2047	2047	2047	2047	2047	2047
R-squared (centered)	0.15	0.13	0.13	0.15	0.14	0.14	0.16	0.14	0.14
F-statistic	957.81	776.15	677.42	409.78	633.50	655.23	554.70	573.64	463.14
Hansen J statistic	0.33	1.24	1.52	0.15	0.15	0.16	0.24	1.06	1.30
P-value	0.56	0.27	0.22	0.93	0.93	0.92	0.62	0.30	0.25
Underidentification test (Kleibergen-Paap rk LM statistic)	6.76	6.35	6.05	7.53	7.10	7.30	6.74	6.32	6.04
P-value	0.03	0.04	0.05	0.06	0.07	0.06	0.03	0.04	0.05
Wald F statistic for weak identification (Cragg-Donald)	1769,72	1817,82	1422,45	460,49	491,99	453,13	1766,27	1812,58	1421,12
Stock-Yogo weak ID test critical values: 5 % maximal IV relative bias	19.93[a]	19.93[a]	19.93[a]	11.04	11.04	11.04	19.93[a]	19.93[a]	19.93[a]

	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	H1	H2	H3	H1	H2	H3	H1	H2	H3
	2SLS	2SLS	2SLS	DR/DT Squared	DR/DT Squared	DR/DT Squared	Censored	Censored	Censored
	DR, DU	DR, DU	DR, DU	DR/DT	DR/DT	DR/DT	DR/DT	DR/DT	DR/DT
	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)
Acquisition ability (ACA$_{t-3}$)	−0.0987	−0.2351*	−0.2758*	−0.2663**	−0.2910**	−0.2886**	−0.2605**	−0.2396*	−0.2463*
	(0.0922)	(0.1199)	(0.1317)	(0.0899)	(0.1076)	(0.1108)	(0.0931)	(0.1071)	(0.1120)
Assimilation ability (ASA$_{t-3}$)	1.0094**	0.9438**	0.9460**	1.0296**	0.9035**	0.9213**	0.9985**	0.8607**	0.8834**
	(0.3831)	(0.3443)	(0.3579)	(0.3206)	(0.3227)	(0.3302)	(0.3235)	(0.3250)	(0.3361)
Exploitation ability (EXA$_{t-3}$)	0.0597	0.0783	0.0741	0.0317	0.0910±	0.1070*	0.0287	0.0991±	0.1199*
	(0.0581)	(0.0533)	(0.0522)	(0.0667)	(0.0515)	(0.0534)	(0.0694)	(0.0508)	(0.0483)
Diversification Direction (DR/DT)$_{t-2}$				0.0604**	0.1009***	0.0985***	0.0346***	0.0188*	0.0261*
				(0.0225)	(0.0227)	(0.0226)	(0.0066)	(0.0090)	(0.0106)
Related diversification (DR)$_{t-2}$	2.3752**	1.4280**	2.0464***						
	(0.7420)	(0.5364)	(0.5643)						
Unrelated diversification (DU)$_{t-2}$	−2.1336**	−1.8764**	−1.2494*						

(*continued on next page*)

Table 4 (*continued*)

	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	H1	H2	H3	H1	H2	H3	H1	H2	H3
	2SLS	2SLS	2SLS	DR/DT Squared	DR/DT Squared	DR/DT Squared	Censored	Censored	Censored
	DR, DU	DR, DU	DR, DU	DR/DT	DR/DT	DR/DT	DR/DT	DR/DT	DR/DT
	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)
	(0.8035)	(0.6062)	(0.6029)						
$(DR/DT)_{t-2}$ x ACA_{t-3}				−0.0275***			−0.0286***		
				(0.0039)			(0.0042)		
$(DR/DT)_{t-2}$ x ASA_{t-3}					0.0061			−0.0064	
					(0.0093)			(0.0092)	
$(DR/DT)_{t-2}$ x EXA_{t-3}						−0.0013±			−0.0025**
						(0.0007)			(0.0010)
DR_{t-2} x ACA_{t-3}	−0.9464**								
	(0.2902)								
DU_{t-2} x ACA_{t-3}	0.2975**								
	(0.1152)								
DR_{t-2} x ASA_{t-3}		0.9460							
		(0.6977)							
DU_{t-2} x ASA_{t-3}		−0.8668***							
		(0.2480)							
DR_{t-2} x EXA_{t-3}			−0.2706***						
			(0.0753)						
DU_{t-2} x EXA_{t-3}			−0.2192*						
			(0.0937)						
DR/DT $(squared)_{t-2}$				−0.0002	−0.0007***	−0.0007***			
				(0.0002)	(0.0002)	(0.0002)			
Expectation of Latent Diversification Direction (DR/DT)							−0.0004***	−0.0004***	−0.0004***
							(0.0001)	(0.0001)	(0.0001)
Absorptive $effort_{t-3}$	−1.1720**	−1.3642**	−1.3289**	−1.4329**	−1.5581**	−1.4685**	−1.4503**	−1.4354**	−1.3945**
	(0.3651)	(0.4217)	(0.4292)	(0.5055)	(0.5793)	(0.5399)	(0.4927)	(0.4864)	(0.4816)
Absorptive knowledge $base_{t-1}$	0.1418±	0.1372*	0.1804*	0.1943*	0.1779*	0.1887*	0.1973*	0.1959*	0.2071**
	(0.0796)	(0.0683)	(0.0771)	(0.0877)	(0.0814)	(0.0810)	(0.0874)	(0.0800)	(0.0797)
Total $diversification_{t-2}$	−2.4643**	−2.0422**	−3.0265***	−3.5926***	−3.0924***	−3.0780***	−3.7078***	−3.3818***	−3.3140***
	(0.8165)	(0.6675)	(0.7222)	(0.3340)	(0.2770)	(0.2780)	(0.3007)	(0.2529)	(0.2549)
Firm $size_{t-1}$	−0.4501	−0.4845	−0.4801	−0.2935	−0.3496	−0.3686	−0.3218	−0.4998	−0.5734
	(0.4782)	(0.4753)	(0.4779)	(0.4677)	(0.4858)	(0.4839)	(0.4682)	(0.4576)	(0.4351)
Industry $concentration_{t-1}$	−15.3754***	−16.4421***	−15.8242***	−16.3790***	−16.6415***	−16.6559***	−16.5223***	−17.2225***	−17.4318***
	(2.7141)	(2.6899)	(2.6159)	(2.4721)	(2.4438)	(2.4356)	(2.4317)	(2.3481)	(2.3010)
Industry $profitability_{t-1}$	0.0194*	0.0195±	0.0175	0.0286**	0.0280*	0.0275*	0.0263**	0.0231*	0.0205*
	(0.0096)	(0.0101)	(0.0118)	(0.0093)	(0.0133)	(0.0125)	(0.0082)	(0.0109)	(0.0087)
Debt $burden_{t-1}$	−0.0148	−0.0171	−0.0175	−0.0073	−0.0101	−0.0092	−0.0056	−0.0059	−0.0057
	(0.0123)	(0.0118)	(0.0125)	(0.0107)	(0.0092)	(0.0092)	(0.0104)	(0.0087)	(0.0086)
$Productivity_{t-1}$	0.0010**	0.0011**	0.0011**	0.0011**	0.0014***	0.0014***	0.0010**	0.0012***	0.0013***
	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Foreign $sales_{t-1}$	−1.1436	−1.8069	−1.3258	−0.1791	−0.2351	−0.1776	−0.2291	−0.5613	−0.7042
	(1.0217)	(1.1712)	(1.0358)	(0.9790)	(1.1890)	(1.1183)	(0.9706)	(1.1227)	(0.9914)
Inverse Mills' Ratio	−1.5873*	−1.9161*	−1.7965*	−1.4149±	−1.5566*	−1.5555*	−1.4507*	−1.7634*	−1.8659**
	(0.7311)	(0.7875)	(0.7150)	(0.7318)	(0.7676)	(0.7534)	(0.7230)	(0.7225)	(0.6746)

(*continued on next page*)

Table 4 (*continued*)

	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	H1	H2	H3	H1	H2	H3	H1	H2	H3
	2SLS	2SLS	2SLS	DR/DT Squared	DR/DT Squared	DR/DT Squared	Censored	Censored	Censored
	DR, DU	DR, DU	DR, DU	DR/DT	DR/DT	DR/DT	DR/DT	DR/DT	DR/DT
	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2047	2047	2047	2047	2047	2047	2047	2047	2047
R-squared (centered)	0.16	0.15	0.15	0.16	0.14	0.14	0.16	0.14	0.14
F-statistic	260.75	498.05	569.91	792.63	1128.88	651.90	960.01	572.05	499.91
Hansen J statistic	0.18	0.20	0.27	0.15	0.62	0.76	0.25	1.06	1.30
P-value	0.92	0.91	0.87	0.70	0.43	0.38	0.62	0.30	0.25
Underidentification test (Kleibergen-Paap rk LM statistic)	7.52	7.03	7.19	3.62	3.57	3.70	6.74	6.32	6.04
P-value	0.06	0.07	0.07	0.16	0.17	0.16	0.03	0.04	0.05
Wald F statistic for weak identification (Cragg-Donald)	453,27	485,62	448,13	291,44	264,42	290,43	1765,47	1811,74	1420,43
Stock-Yogo weak ID test critical values: 5 % maximal IV relative bias	11.04	11.04	11.04	19.93[a]	19.93[a]	19.93[a]	19.93[a]	19.93[a]	19.93[a]

	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)
	H1	H2	H3	H1	H2	H3	H1	H2	H3
	Tobin's q	Tobin's q	Tobin's q	ROA deviation	ROA deviation	ROA deviation	ROA Mov. Av.	ROA Mov. Av.	ROA Mov. Av.
	DR/DT	DR/DT	DR/DT	DR/DT	DR/DT	DR/DT	DR/DT	DR/DT	DR/DT
	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)
Acquisition ability ($ACA_{t\text{-}3}$)	−0.0482	−0.0608	−0.0629	−0.0033***	−0.0030**	−0.0031**	−0.0034***	−0.0033***	−0.0034***
	(0.0389)	(0.0427)	(0.0433)	(0.0008)	(0.0010)	(0.0010)	(0.0008)	(0.0009)	(0.0010)
Assimilation ability ($ASA_{t\text{-}3}$)	0.0407	0.0185	0.0316	0.0082*	0.0067*	0.0069*	0.0109***	0.0101**	0.0104***
	(0.0744)	(0.0801)	(0.0766)	(0.0033)	(0.0033)	(0.0034)	(0.0032)	(0.0031)	(0.0031)
Exploitation ability ($EXA_{t\text{-}3}$)	0.0745**	0.0691**	0.0791**	0.0004	0.0012*	0.0014**	0.0001	0.0009*	0.0011***
	(0.0248)	(0.0252)	(0.0246)	(0.0007)	(0.0006)	(0.0005)	(0.0006)	(0.0004)	(0.0003)
Diversification Direction $(DR/DT)_{t\text{-}2}$	0.0017	−0.0020	0.0024	0.0004***	0.0003**	0.0003**	0.0005***	0.0003**	0.0004**
	(0.0013)	(0.0019)	(0.0020)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Related diversification $(DR)_{t\text{-}2}$									
Unrelated diversification $(DU)_{t\text{-}2}$									
$(DR/DT)_{t\text{-}2}$ x $ACA_{t\text{-}3}$	−0.0032***			−0.0003***			−0.0003***		
	(0.0006)			(0.0000)			(0.0000)		
$(DR/DT)_{t\text{-}2}$ x $ASA_{t\text{-}3}$		0.0040±			−0.0000			−0.0001	
		(0.0024)			(0.0001)			(0.0001)	
$(DR/DT)_{t\text{-}2}$ x $EXA_{t\text{-}3}$			−0.0007**			−0.0000*			−0.0000*
			(0.0003)			(0.0000)			(0.0000)
$DR_{t\text{-}2}$ x $ACA_{t\text{-}3}$									
$DU_{t\text{-}2}$ x $ACA_{t\text{-}3}$									
$DR_{t\text{-}2}$ x $ASA_{t\text{-}3}$									

(*continued on next page*)

Table 4 (*continued*)

	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)
	H1	H2	H3	H1	H2	H3	H1	H2	H3
	Tobin's q	Tobin's q	Tobin's q	ROA deviation	ROA deviation	ROA deviation	ROA Mov. Av.	ROA Mov. Av.	ROA Mov. Av.
	DR/DT	DR/DT	DR/DT	DR/DT	DR/DT	DR/DT	DR/DT	DR/DT	DR/DT
	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)	Coeff./(SE)
DU_{t-2} x ASA_{t-3}									
DR_{t-2} x EXA_{t-3}									
DU_{t-2} x EXA_{t-3}									
DR/DT $(squared)_{t-2}$									
Expectation of Latent Diversification Direction (DR/DT)									
Absorptive $effort_{t-3}$	0.2721	0.3537	0.4149	−0.0097*	−0.0101*	−0.0098*	−0.0167**	−0.0168**	−0.0165**
	(0.2577)	(0.2428)	(0.2658)	(0.0042)	(0.0042)	(0.0041)	(0.0058)	(0.0056)	(0.0057)
Absorptive knowledge $base_{t-1}$	0.0663**	0.0541*	0.0566*	0.0019*	0.0019*	0.0020**	0.0017*	0.0017*	0.0018*
	(0.0218)	(0.0234)	(0.0229)	(0.0008)	(0.0007)	(0.0007)	(0.0008)	(0.0008)	(0.0008)
Total $diversification_{t-2}$	−0.3986***	−0.3284**	−0.2946*	−0.0363***	−0.0324***	−0.0318***	−0.0387***	−0.0352***	−0.0346***
	(0.1124)	(0.1199)	(0.1214)	(0.0030)	(0.0024)	(0.0024)	(0.0029)	(0.0027)	(0.0028)
Firm $size_{t-1}$	−0.4242***	−0.3909***	−0.3842***	−0.0036	−0.0060	−0.0066	0.0003	−0.0013	−0.0020
	(0.1036)	(0.1146)	(0.1119)	(0.0045)	(0.0044)	(0.0042)	(0.0040)	(0.0036)	(0.0033)
Industry $concentration_{t-1}$	−2.5036***	−2.3145***	−2.2798***	−0.1790***	−0.1890***	−0.1912***	−0.1337***	−0.1398***	−0.1423***
	(0.4371)	(0.4879)	(0.4709)	(0.0226)	(0.0213)	(0.0206)	(0.0242)	(0.0228)	(0.0224)
Industry $profitability_{t-1}$	0.0197	0.0238±	0.0228±	0.0005***	0.0004*	0.0004*	0.0004***	0.0003**	0.0003***
	(0.0127)	(0.0124)	(0.0123)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Debt $burden_{t-1}$	−0.0011	−0.0017±	−0.0016±	−0.0000	−0.0000	−0.0000	−0.0001	−0.0001	−0.0001
	(0.0011)	(0.0009)	(0.0009)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$Productivity_{t-1}$	0.0000	−0.0000	0.0000	0.0000**	0.0000***	0.0000***	0.0000**	0.0000***	0.0000***
	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Foreign $sales_{t-1}$	0.7707***	0.7885***	0.8358***	−0.0125	−0.0180±	−0.0191*	0.0074	0.0044	0.0026
	(0.1472)	(0.1790)	(0.1636)	(0.0093)	(0.0107)	(0.0095)	(0.0094)	(0.0089)	(0.0078)
Inverse Mills' Ratio	−0.1929*	−0.1702	−0.1520	−0.0205**	−0.0247***	−0.0256***	−0.0084	−0.0115*	−0.0127*
	(0.0898)	(0.1055)	(0.0991)	(0.0070)	(0.0070)	(0.0065)	(0.0067)	(0.0058)	(0.0053)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1600	1600	1600	2047	2047	2047	2043	2043	2043
R-squared (centered)	0.21	0.20	0.21	0.13	0.10	0.10	0.19	0.16	0.16
F-statistic	391.60	463.57	419.82	348.51	195.36	179.29	1624.37	1176.93	2040.42
Hansen J statistic	3.21	2.42	1.83	0.69	1.77	1.99	0.01	0.58	0.83
P-value	0.07	0.12	0.18	0.41	0.18	0.16	0.93	0.44	0.36
Underidentification test (Kleibergen-Paap rk LM statistic)	7.20	6.78	5.81	6.74	6.32	6.04	6.74	6.32	6.05
P-value	0.03	0.03	0.05	0.03	0.04	0.05	0.03	0.04	0.05
Wald F statistic for weak identification (Cragg-Donald)	1114,14	1043,11	880,53	1766,27	1812,58	1421,12	1760,92	1806,95	1416,74
Stock-Yogo weak ID test critical values: 5 % maximal IV relative bias	19.93[a]	19.93[a]	19.93[a]	19.93[a]	19.93[a]	19.93[a]	19.93[a]	19.93[a]	19.93[a]

± $p < 0.10$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

[a] Stock-Yogo weak ID test critical values for 5 % maximal IV relative bias are not available. Instead, we report Stock-Yogo weak ID test critical values for 10 % maximal IV size.

independent variables: the components of absorptive capacity and the measure of diversification direction. Columns (4)–(6) introduce interactions between each component and diversification direction one by one. Column (7) gives the results for the full model.

The controls have similar coefficients across models. The inverse Mills' ratio is negative and statistically significant, suggesting that correcting for selection bias was necessary as omitted firms seem to perform worse than the sample average.

Diversification direction is positive and statistically significant, suggesting that related diversification contributes more value to firms than unrelated diversification. The coefficients of assimilation and exploitation ability are positive and statistically significant, whereas that of acquisition ability is negative and statistically significant. These results suggest that the component abilities make distinct value contributions in organizations (Song et al., 2018). A tentative interpretation of the negative effect of acquisition ability is that M&As, which proxy for knowledge acquisition, are associated with negative firm performance (Laamanen and Keil, 2008). The positive coefficients of assimilation and exploitation ability can be attributed to assimilation ability being past-oriented and exploitation ability referring to current organizational practices.

In column (4), the coefficient of the interaction of acquisition ability with diversification direction ($b = -0.0286$, $SE_b = 0.0042$), and in column (6), the coefficient of the interaction of exploitation ability with diversification direction ($b = -0.0025$, $SE_b = 0.010$) are negative and statistically significant as predicted by hypotheses H1 and H3. In column (5), the coefficient of the interaction of assimilation ability with diversification direction ($b = -0.0065$, $SE_b = 0.0092$) is negative and not statistically significant against H2. The full model shows very similar results, although the interaction of assimilation ability with diversification direction becomes positive and statistically significant ($b = 0.0198$, $SE_b = 0.009$), consistent with H2. Our results suggest that firms focusing on unrelated versus related diversification benefit more from acquisition and exploitation ability. We find mixed support for assimilation ability benefiting firms with a focus on related diversification.[9]

We further examine these results by graphing their effects on performance in Fig. 1a–c. The graphs show how the marginal effect of diversification direction on firm performance changes for different levels of acquisition, assimilation, and exploitation ability. In all three graphs, we consider the representative values of 1S.D. above and below the sample average of diversification direction and absorptive component abilities. All interaction effects in this range of values are statistically significant at the 5 % level. Fig. 1a shows that high acquisition ability benefits a company that focuses on unrelated diversification than related diversification more (i.e., "Share of Related diversification to Total diversification is Low") in support of H1. Fig. 1b suggests that high assimilation ability benefits both types of diversification. However, it benefits a company that focuses on related diversification than unrelated diversification more (i.e., "Share of Related diversification to Total diversification is High"), supporting H2. The benefit of assimilation ability for both diversification types may underlie the mixed support we find from the interaction coefficients. Fig. 1c suggests that high exploitation ability contributes more to diversification value when the firm's portfolio emphasizes unrelated diversification more (i.e., "Share of Related diversification to Total diversification is Low"), supporting H3.

Table 3 presents the results based on the separate measures for related and unrelated diversification[10]. Column (1) is the base model. The baseline relationships are very similar to those of the previous analysis. Columns (2)–(4) introduce the interaction terms between acquisition ability and related and unrelated diversification. Columns (5)–(7) introduce the interaction terms between assimilation ability and related and unrelated diversification. Columns (8)–(10) introduce the interaction terms between exploitation ability and related and unrelated diversification. Column (11) shows results for the full model.

We first test H1 based on the results in column (4). The coefficient of the interaction term between acquisition ability and related diversification is negative and statistically significant ($b = -0.931$, $SE_b = 0.2514$), and the interaction term between acquisition ability and unrelated diversification is positive and statistically significant ($b = 0.2905$, $SE_b = 0.1124$). These results support H1. We test H2 based on the results in column (7). The coefficient of the interaction term between assimilation ability and related diversification is positive and statistically significant ($b = 1.0336$, $SE_b = 0.5193$), and the interaction term between assimilation ability and unrelated diversification is negative and statistically significant ($b = -0.8941$, $SE_b = 0.2028$). These results support H2. We test H3 based on the results in column (10). The coefficient of the interaction term between exploitation ability and related diversification is negative and statistically significant ($b = -0.2622$, $SE_b = 0.0735$), and the interaction term between acquisition ability and unrelated diversification is negative and statistically significant ($b = -0.2253$, $SE_b = 0.0905$). These results offer weak support for H3, suggesting that unrelated

[9] The relationships between the components of absorptive capacity and diversification direction with ROA are both statistically and economically significant. For example, in column (6), the coefficient of exploitation ability (0.0012) means that a one-SD increase in the exploitation ability of a firm is associated with an increase of 4.8 % of a SD in ROA (=0.0012*3.469/.087), ceteris paribus, where 3.469 and 0.087 are the SDs of exploitation ability and ROA, respectively. Additionally, the coefficient of diversification direction (0.0003) means that a one-SD increase in the diversification direction (i.e. more related diversification) of a firm is associated with an increase of 0.17 % of a SD in ROA (=0.0003*0.49/0.087), ceteris paribus, where 0.49 and 0.087 are the SDs of diversification direction and ROA, respectively. If we wish to consider the interaction term between exploitation ability and diversification direction, we can take the first derivative of the model with respect to diversification direction. The effects that remain to consider is the baseline effect of diversification direction (b = 0.00026) and the effect of its interaction with exploitation ability (−0.000025). For a sample firm with exploitation ability one SD above the sample mean, the overall effect for diversification direction on ROA is 0.02 % [= 0.00026 + (−0.000025*3.469)]. Therefore, as previously, a one-SD increase in the diversification direction of a firm that possesses a superior exploitation ability by one SD above the sample mean will increase its economic performance by 0.19 % of a SD in ROA. This is a 0.02 % more improvement to ROA compared to a comparable firm that increases its diversification direction by one SD but possesses average exploitation ability.

[10] DT correlates highly with DU. All models with separate variables for related and unrelated diversification were estimated with DT both included and excluded as a control. The results did not differ in any notable fashion. For comparability reasons, we show model estimations with DT included as a control.

diversification will benefit more than related diversification from stronger exploitation ability. Finally, the full model in column (10) shows similar results to the partial models, though the interaction term between acquisition ability and unrelated diversification loses statistical significance.

We again graph the effects in Fig. 2a–f at representative values of the terms involved in the interaction (i.e., 1S.D. above and below the sample average of diversification and absorptive component abilities variables). All interaction terms in this range are statistically significant at the 5 % level. Fig. 2a and b shows the interactions between acquisition ability and related and unrelated diversification, respectively. High acquisition ability increases the performance effect of related diversification at lower levels, whereas the opposite applies to unrelated diversification. This result is in support of H1.

Fig. 2c and d graph the interaction effects between assimilation ability and related and unrelated diversification, respectively. High assimilation ability appears to increase the performance effect of both related and unrelated diversification. Consistent with H2, Fig. 2c shows that assimilation ability increases the performance effect of related diversification on performance when related diversification is greater. Conversely, Fig. 2d shows that assimilation ability decreases the performance effect of unrelated diversification when unrelated diversification is higher. This result also supports H2.

Fig. 2e and f graph the interaction effects involving exploitation ability. High exploitation ability appears to decrease the performance effect of related diversification as the latter increases, which is in accord with H3. Conversely, high exploitation ability appears to increase the performance effect of unrelated diversification as the latter decreases, which conflicts with our prediction. Thus, H3 receives mixed support.

4.1. Robustness tests

We conducted several robustness tests and report them in Table 4. Columns (1)–(6) show our standard models without the inverse Mills' ratio. The new estimates are similar to those of the main analysis, suggesting that selection bias does not influence our results.

In columns (7)–(12), we report the results from a 2SLS instrumental estimation. Similar to our main analysis, we instrument the diversification variables with their 3-year and 4-year lags. The 2SLS estimates are consistent with our main results.

We relax some implicit assumptions about firms' diversification strategy.[11] First, we add a quadratic term of diversification direction to test for non-linear effects. Columns (13)–(15) show that the squared diversification direction is negative and statistically significant, suggesting that the benefits of related diversification over unrelated diversification taper out. After that, related diversification shows decreasing returns likely associated with coordination complexity and knowledge overlap. Our main results remain unchanged.

Related and unrelated diversification are both censored at zero. We follow Vella's (1993) and Vella and Verbeek's (1999) approach for panel data models employing generalized residuals to adjust for censored regressors. We first estimate a Tobit model for the diversification variable (regressed on all remaining independent variables plus the lagged dependent variable to account for dynamics in the diversification decision) to obtain generalized Tobit residuals, which we then add to our model as a regressor. Our results are presented in columns (16)–(18) and are very similar to those of the main analysis.

We use Tobin's q as an alternative performance outcome, widely used in prior studies on diversification (Miller, 2004, 2006; Wernerfelt and Montgomery, 1988) and to measure rent-generating intangible resources (Lev, 2000; Teece et al., 1994; Villalonga, 2004). Despite a substantial loss of observations due to missing values, our estimates in columns (19)–(21) continue to support our main results.

Last, we estimate models using the deviation of a firm's ROA from its industry mean (Miller, 2004) and a firm's 3-year moving average of ROA (Zahra and Hayton, 2008). The results are shown in columns (22)–(27) and are consistent with our main analysis.

We replaced the exclusion criterion we used in the Heckman model addressing sample selection bias. We used instead a variable indicating whether the firm had listed its shares on non-US exchanges at any time during the sample period. The underlying logic is that cross-listing may influence the level of detail of reporting for the sample firms due to increased disclosure demands and scrutiny (Fernandes and Ferreira, 2008) and thus influence the exclusion process but not economic performance. The primary relationships were not affected (results available from the authors).

We complemented our instruments with one that did not share the same logic to improve confidence in instrument validity (Murray, 2006). Following Chari et al. (2008), we used industry averages to create instruments for diversification. Industry diversification level is unaffected by firm idiosyncratic shocks (e.g., a corporate diversification change), reducing its correlation with the original regression residual. At the same time, firm diversification, often guided by industry norms, is expected to correlate with the industry average. Adding industry diversification to the group of instruments and re-estimating the main models produced comparable results (results available from the authors).

Finally, we ran two additional tests to check if our revenue selection criterion ($1bn in 2013) created survivorship bias. First, we re-estimated our models on a sample of only all firm-year observations above the $1bn revenue threshold (e.g., Andrés et al., 2017; Mackey et al., 2017). By excluding all firm-year observations below the revenue threshold, 67 firms and 908 observations were dropped from the sample, resulting in a reduced sample of 86 firms and 1,139 observations. Our results remain qualitatively unchanged, albeit at lower statistical significance, due to the heavily reduced sample size. Second, we ran another Heckman selection model on a subsample of our initial sample of 901 firms in the relevant SIC codes. We included all firms that ever reported revenues of

[11] Hereafter, we discuss robustness tests only based on diversification direction for brevity. The robustness tests results based on separate measures of related and unrelated diversification are qualitatively similar and are available from the authors.

> $1bn, not necessarily in 2013. There were 25 firms in addition to our 212 initially selected firms. In the first stage, we used a probit model on all 237 firms (212 selected and 25 non-selected) to predict selection into our preferred sample. We regressed a binary variable denoting whether a firm had initially been selected in the sample on firm sales, year fixed-effects, and industry fixed-effects. As an exclusion restriction, we used firms' adoption of IFRS reporting standards associated with changes in accounting disclosure quality (Li et al., 2021) that might influence the selection probability. We then used the inverse Mills' ratio from this equation as an additional control in the second-stage model, testing our hypotheses. The results are very similar to those of the main analysis, suggesting that survivorship bias is not a concern in our study (results available from the authors).

5. Discussion and conclusion

Given their absorptive capacity, how can firms better benefit from externally acquired knowledge resources? We address this question by examining how the individual components of absorptive capacity correspond to the success of different types of diversification. We draw on a panel of US firms in ICT industries to test our predictions on the respective effects. Our results broadly support our hypotheses and are robust to alternative specifications. Firms with a higher focus on unrelated diversification profit more from higher acquisition and exploitation abilities, whereas firms with a higher focus on related diversification benefit more from stronger assimilation ability.

We contribute to three important areas in strategy research. First, we add to the literature on the separate components of absorptive capacity. We offer a fine-grained study of the moderating role of the components in the diversification-performance relationship and show that absorptive capacity helps firms adapt to changing environments by supporting growth strategies in distinct ways, giving us insights into the underlying processes and their effects on performance. Treating absorptive capacity as a unified measure would steer managers away from directing their efforts toward improving specific components if the planned diversification direction demands it.

We also show that the original components of absorptive capacity (Cohen and Levinthal, 1990) still matter. Each of the components contributes uniquely to performance through interactions with diversification. Indeed, Todorova and Durisin (2007: 783) argue that researchers who "do not reintegrate Cohen and Levinthal (1990)'s conceptualization […] may miss out on knowledge already existing in the scientific community."

Our study responds to a recent call by Song et al. (2018: 2370), who note that recognizing "the conceptual and empirical distinctions among the three absorptive capacity dimensions will help improve the precision in theory building and answering some of the fundamental questions regarding how, why, when, and to what extent absorptive capacity matters." Articulating the three dimensions and their unique features and mapping measures to these dimensions bring the theory and measures of absorptive capacity closer together.

Second, we extend work studying how absorptive capacity moderates the effects of strategy on firm outcomes (Fernhaber and Patel, 2012; George et al., 2001) and how the individual components of absorptive capacity shape the success of different strategies. The constituent elements of absorptive capacity, or components, interact subtly with diversification strategy. Diversification can challenge a firm's organizational and communication structures (Van Den Bosch et al., 1999; Weigelt and Miller, 2013), knowledge-sharing incentives (Helfat and Eisenhardt, 2004), and inter-divisional coordination (Arora et al., 2014; Schleimer and Pedersen, 2013), which all depend on absorptive capacity. Thus, absorptive capacity and diversification should be studied jointly because absorptive capacity drives which and how much new knowledge a firm can absorb.

Our finding that the components of absorptive capacity interact with diversification in different ways can guide managerial decisions on how far their activities should be from their core. It also lets managers build optimal portfolios of activities and design activities to improve component abilities of absorptive capacity, which benefit a firm's unique configurations the most. This is consistent with a strategic fit perspective (Kim et al., 2013).

Third, we add to the ongoing debate over the relative attractiveness of related and unrelated diversification. We complement the prevailing resource-based perspective on diversification that states that related diversification is more likely to generate super-additive value and sub-additive costs (Farjoun, 1998; Markides and Williamson, 1994; Robins and Wiersema, 1995). Our work shows that while related diversification indeed positively affects firm performance as a baseline effect, unrelated diversification can also contribute to performance in the presence of enhanced acquisition and exploitation abilities.

Our research challenges arguments suggesting that combinations of the two diversification types are detrimental to value creation. For instance, Helfat and Eisenhardt (2004) argue that collaborative arrangements associated with related diversification and competitive organizational arrangements associated with unrelated diversification are incompatible. Our results suggest that the right "mix" of diversification activities depends on the firm's respective levels of acquisition, assimilation, and exploitation abilities. This has implications for strategy formulation, particularly when (especially unrelated) diversification is not driven by learning purposes. Firms can still enter unrelated business domains without jeopardizing economic performance if they possess strong acquisition and exploitation abilities. Moreover, given that many firms expand into both related and unrelated domains (Argyres, 1996; Mayer and Whittington, 2003; Sakhartov, 2017), we also view diversification strategy from a relative rather than an absolute perspective. We found effects for both the relative measure of diversification and absolute measures.

Most existing work cannot answer why unrelated diversification becomes a valuable strategic option for some firms and why diversifying relatedly does not consistently guarantee higher value. We contribute to the growing conversation that firm-specific organizational capabilities in diversified firms can offset some of the limitations of diversification while capitalizing on its benefits (Zhou, 2011).

Our study has several limitations. Our geographical and sectoral focus has the advantage of creating a more homogeneous subsample, but extending the empirical setting to a wider and more heterogeneous set of industries may reveal boundary conditions of (un)relatedness beyond which absorptive capacity does not aid or hinder diversification performance because potential synergies do not rely on the use of new knowledge. Moreover, our empirical implementation of the three components of absorptive capacity represents an early attempt to capture a highly complex construct. While we consider patent-based measures of acquisition, assimilation, and exploitation ability appropriate for a highly patent-affine industry, these measures may have to be modified in other settings. Relatedly, our measure of assimilation ability gives the concentric distance of patent citations with all other patent citations of the firm. An alternative would be to measure the firm's patents in groups of SIC classes and cross-compare the citations in separate classes.

Although we propose a set of mechanisms through which diversification influences performance, we cannot avoid the "aggregation" issue that makes providing clean answers to managers difficult (Ahuja and Novelli, 2017). We face two issues. First, diversification is a multifaceted construct. We capture market diversification, but firms can be diversified in terms of technology, inputs, or geography. Moreover, firms diversify for many reasons. Second, performance is also a multifaceted construct with different facets that do not necessarily correlate strongly, such as market share, growth, and new product introduction. We offer a first take to let different dimensions of diversification and absorptive capacity components interact. Future work should recognize the micromechanisms underlying diversification and identify how interactions with absorptive capacity drive performance.

Further, the causal relationship among diversification strategy, absorptive capacity, and economic performance is complex. We used a 2-year lag structure for diversification, a 3-year lag structure for absorptive capacity, and multiple other lag lengths as robustness checks. This helped us capture a plausible causal nature among the constructs in our model. However, establishing a direct causal relationship beyond any doubt is challenging.

Future research should consider the interdependence of absorptive capacity and diversification strategy and how the two coevolve over time. We captured both absorptive capacity and diversification strategy based on the firm's "home" industry. However, as growth strategy alters the knowledge stock within the firm and the relatedness of the firm's industry compared to external industries, knowledge acquired and industries entered in the future must be put in perspective to the then-active firm. Incorporating dynamic aspects of the interdependence of absorptive capacity and diversification would be a fruitful path.

Author statement

Symeou: Conceptualization, Methodology, Formal Analysis, Investigation, Writing,
Kretschmer: Conceptualization, Methodology, Writing.

Data availability

Data will be made available on request.

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