

Should business angels diversify their investment portfolios to achieve higher performance? The role of knowledge access through co-investment networks

Torben Antretter^a, Charlotta Sirén^{a,b}, Dietmar Grichnik^{a,*}, Joakim Wincent^{a,c}

^a University of St.Gallen, Dufourstrasse 40a, St.Gallen CH-9000, Switzerland

^b University of Queensland, UQ Business School, Brisbane Qld. Queensland, St. Lucia 4072, Australia

^c Hanken School of Economics, Arkadiankatu 22, Helsinki FI-00101, Finland

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ABSTRACT

This paper investigates the performance effects of business angel portfolio industry diversification. Using a unique bi-annual panel dataset of 142 members of a professional angel investment platform and their portfolio returns between 2013 and 2017, we consider the costs and benefits of diversifying investments into various industries. Drawing upon theoretical arguments about distant search, we theorize and find a nonlinear (S-shaped) relationship between portfolio industry diversification and performance. Further, we pay specific attention to a proposed over-diversification effect that takes place at high levels of portfolio industry diversification and show that this effect is moderated by individuals' access to industry knowledge through their co-investment networks. For business angels who have a central position within a diverse network of industry specialists, the overdiversification effect is less pronounced.

1. Executive summary

In recent years, there has been an increase of business angel (BA) investing via structured angel investment platforms—both online and offline. This development of the angel market has changed the way BAs approach their investment strategies. By syndicating their deals with other investors, BAs can make more deals and diversify their portfolios into a variety of industries. Thus, limited funds and knowledge no longer prevent BAs from building diversified investment portfolios.

This paper investigates the performance effects of portfolio industry diversification of BAs who invest via an angel investment platform. This approach is different from prior studies in the venture capital (VC) field that have highlighted the costs and benefits of specialized or diversified knowledge through industry-specific investment funds. When BAs choose to diversify, their decision making relies on their own knowledge, which is often distant from knowledge that is necessary to make investments in unknown industries. Therefore, the results from VC fund portfolio diversification may not directly reflect the performance effects of individual BA portfolios. In our study, we theorize a nonlinear (S-shaped) relationship between portfolio industry diversification and performance for individual BAs that highlights the long-tail limitations of building largely diversified investment portfolios. As angel group members build co-investment networks through syndication, we further examine the moderating role of industry knowledge access and how it may alleviate the costs of generating distant knowledge at higher levels of portfolio industry diversification.

* Corresponding author.

E-mail addresses: torben.antretter@unisg.ch (T. Antretter), charlotta.siren@unisg.ch (C. Sirén), dietmar.grichnik@unisg.ch (D. Grichnik), joakim.vincent@unisg.ch, joakim.vincent@hanken.fi (J. Wincent).

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Our sample originates from one of the largest European angel investment platforms and contains detailed information at the individual and deal level, including cash flow data for each of the 2,600 investment tickets between 2013 and 2017. We study a bi-annual panel dataset of 142 BAs who invested in 65 portfolio companies within 34 industry sectors. We employ two measures of portfolio performance: internal rate of return (IRR) and capital gains multiple (CGM). We find support for our theoretical predictions of a nonlinear (S-shaped) relationship between portfolio industry diversification and performance. Specifically, we demonstrate that although information-processing limitations associated with distant search are a challenge, BAs can successfully engage in moderate levels of portfolio industry diversification. Furthermore, we find evidence that BAs' access to industry knowledge through a central position in their co-investment network moderates the main relationship. High access to specialized industry knowledge within a co-investment network allows BAs to mitigate the proposed overdiversification effect.

This study makes several contributions to both research and practice. First, our results provide insights into BA portfolio industry diversification and investment returns, thereby adding to the ongoing discussion on the diversification-performance linkage in venture finance. Our study pays specific attention to the overdiversification effect in BA investing by showing that diversifying into distant knowledge domains (i.e., unknown industries) may have countervailing influences on BAs' investment returns. Second, our study contributes to the literature about the emerging phenomenon of angel investment platforms in entrepreneurial finance. Third, we elaborate on how these platforms help BAs access distant industry knowledge through their co-investment networks. We find support for the argument that access to complementary industry knowledge through a co-investment network helps BAs alleviate the negative performance consequences of an overdiversification effect that otherwise becomes evident at high levels of BA portfolio industry diversification.

2. Introduction

Over the last couple of years, research has noted that despite the long history of “home turf” investments and limited deal flow, the angel market has fundamentally changed (Gregson et al., 2013; Mason et al., 2016). BAs have started to form larger and more visible membership groups, which research has found to have significant effects on BAs' investment practices (Bonini et al., 2018; Mitteness et al., 2016). For example, while individual BAs are often restricted by the amount of investment proposals they receive (Landström, 1995), BAs acting via an angel investment platform have equal access to a large deal flow of pre-screened investment opportunities¹ (Bonini et al., 2018). Sharing deal flow allows BAs to pool their capital (i.e., syndicate) with fellow investors via the angel investment platform, thus enabling them to make more investments and to diversify their portfolios into a variety of industries.

Although portfolio industry diversification—a combination of investments from a variety of industries in an early-stage investment portfolio (Landström, 1995)—enables BAs to optimize the risk of their portfolios, scientific research on angel group members is scarce, with only a handful of studies primarily studying their investment activities (e.g., Bonini et al., 2018; Gregson et al., 2013; Mason et al., 2016) as well as their decision and rejection criteria (e.g., Carpentier and Suret, 2015; Croce et al., 2017). In fact, no study has paid explicit attention to the effect of angel group members' strategic portfolio decisions on their financial returns. The question of whether portfolio diversification into different industries is positive or negative has attracted attention in the VC literature (e.g., Buchner et al., 2017; Knill, 2009; Matusik and Fitza, 2012), where studies have mainly discussed the role of accumulated in-depth knowledge through specialized investment funds (e.g., Cressy et al., 2014; Gompers et al., 2009; Norton and Tenenbaum, 1993). However, when individual BAs choose to diversify, their available industry knowledge exclusively relies on their individual experience (Huang and Pearce, 2015), which is different from the experience a VC fund accumulates through a team of investment professionals (e.g., Matusik and Fitza, 2012; De Clercq and Dimov, 2008). This difference implies that research has yet to explore the performance effects of BAs' portfolio diversification into various industries.

The costs of generating new knowledge (i.e., distant search; the quest for information outside the neighborhood of what one already knows) may be challenging (Afuah and Tucci, 2012; Piezunka and Dahlander, 2015) for BAs. When BAs invest in new industries, the knowledge required to make an informed investment decision is usually distant from their previous knowledge. As a result, they may experience significant difficulties in generating attractive investment returns when diversifying their investments. Prior studies often assumed that individuals avoid distant search to circumvent its negative effects (e.g., Nelson and Winter, 1982). The rise of angel investment platforms, through which individuals can access and benefit from their fellow investors' complementary industry knowledge, however, allows us to study the effects of BAs reaching outside their knowledge base when diversifying their portfolios. Previous research has paid scant attention to how BAs develop interpersonal, knowledge-sharing relationships with other investors and how these relationships may influence their investment returns (see Mitteness et al., 2016; Werth and Boert, 2013, for exceptions).

We address this research gap by asking the following research questions: what performance consequences does BAs' portfolio industry diversification have, and do BAs benefit from forming relationships with other angel group members when building diversified investment portfolios? To answer these questions, we draw upon theoretical arguments about the costs and benefits of distant search (e.g., Nelson and Winter, 1982; Piezunka and Dahlander, 2015). We develop our core hypothesis by evaluating the influence of portfolio industry diversification among three diversification groups (low-, mid-, and high-level industry diversifiers). More specifically, we expect a cubic relationship between portfolio industry diversification and investment returns that has two inflection points and resembles a sideways-S pattern (Contractor et al., 2003; Hashai, 2015; Lu and Beamish, 2004). Moreover, building upon recent developments and the fact that large angel investment platforms are increasingly influencing BA investing, we

¹ It is important to note that in most angel investment platforms, as in this study, BAs have equal opportunity to participate in a given deal. In our case, BAs can view all deals via the online platform and decide whether they would like to participate in the next live pitching event.

additionally propose a moderating effect of each individual's centrality in her or his co-investment network. We theorize that BAs who act as information brokers in their co-investment networks can compensate for and avoid the costs of distant search because they can access their peers' industry knowledge. This prediction integrates previous arguments of the BA literature suggesting that co-investment networks help BAs "learn the ropes" from their fellow investors and thus make superior investment decisions (Paul and Whittam, 2010; Sørheim and Landström, 2001). This argument offers a theoretically appealing alternative to the negative baseline argument of distant search (Nelson and Winter, 1982). We test our hypotheses on the individual portfolio level with a longitudinal bi-annual dataset of 142 angel group members and their portfolio returns between 2013 and 2017. During this period, BAs in our sample made > 2,600 investments in 65 individual companies within 34 industry sectors.

Our work contributes to several areas of previous research. First, we develop theory about the industry diversification of BA investments to show that efforts to diversify BA investments beyond an individual's area of expertise are costly but can pay off at medium levels of diversification. Our study further contributes to arguments from the distant search (e.g., March, 1991; Piezunka and Dahlander, 2015) and contemporary learning curve literatures (e.g., Musaji et al., 2019) indicating that portfolio diversity may have countervailing influences on performance. Above that, our study shows the limitations of trying to diversify too much. As such, our results provide evidence that the costs and difficulties related to distant search apply to the BA context, which is something that has recently been discussed in theory about distant search (e.g., Kim et al., 2013). We further discuss the contributions and implications of our theorizing in this paper.

Second, despite their growing importance, professional angel investment platforms are a very recent phenomenon in research that we do not know much about due to "the lack of databases which capture their [members'] investments and the reluctance amongst the small population of visible angels to take part in surveys" (Mason et al., 2016: 321). Overall, knowledge about BAs' investment returns is often described as incomplete because of their invisibility, their desire for anonymity, and the undocumented nature of their investments (Mason, 2016; Wetzel, 1983). Our access to an angel investment platform's deal-monitoring system allows us to shed light on this new phenomenon and study BAs' investment returns using standard performance measures from VC research, namely, IRR and CGM. Our direct access to BAs' performance data enables us to add to our knowledge on the returns of BA investments made via angel investment platforms and thus to contribute to the discussion on BAs' optimal investment behavior and the role of angel investment platforms in general.

Third, based on the recent trend to engage in large angel investment platforms, we show that developing networks in such communities matters. Although many BAs have started to engage in investment communities (Carpentier and Suret, 2015; Gregson et al., 2013; Mason et al., 2016), the role of developing networks and relationships with other angels to increase investment performance remains largely unexplored (e.g., see Mitteness et al., 2016). As such, we contribute to the literature on the role of information-sharing networks in new venture finance (e.g., Hochberg et al., 2007; Sorenson and Stuart, 2001; Ter Wal et al., 2016) and speak to those interested in the effects of accessing others' knowledge when engaging in distant search (e.g., Fontes, 2005; Rosenkopf and Almeida, 2003). We find that BAs who access complementary industry knowledge through a central position in their co-investment network do not suffer as much from the overdiversification effect than other BAs. Access to industry knowledge thus helps highly diversified investors overcome the burdens of distant knowledge and cope with information overload.

3. Theoretical background

3.1. Distant knowledge and business angel investments

BA investing is a challenging task because BAs, like all individuals, have knowledge limitations in their decision making. Behavioral and evolutionary theories of organizations (e.g., Cyert and March, 1963; Nelson and Winter, 1982; Simon, 1955), especially the search literature (e.g., Dosi and Marengo, 2007; March, 1991; Piezunka and Dahlander, 2015), have long considered that decision makers' bounded rationality restricts the information they can access, process, and store when exposed to new knowledge domains (Afuah and Tucci, 2012). When confronted with new knowledge that resides outside the individual's knowledge domain—namely, *distant knowledge*—BAs are expected to experience limitations when making out-of-scope investment decisions (Piezunka and Dahlander, 2015). The notion that decision makers face cognitive limitations in terms of time, information, attention, and resources when generating distant knowledge has influenced several associated research domains, such as the fundamentals of attention in decision making (Ocasio, 1997) and research on information overload (O'Reilly, 1980). These studies have addressed the characteristics, challenges, and experiences of exposure to environmental information or stimuli and the extent to which distant information can be noticed and processed in decision making.

These insights are relevant for the study of BA decision making because BAs experience limitations when processing and utilizing relevant information to make investment decisions (Maxwell et al., 2011). Previous studies have reported that BAs react to their personal limitations by undertaking little research and due diligence before investing (Mason and Harrison, 1996b) and instead make their decisions based more on feelings than analysis (Shane, 2008). As such, the arguments that BAs have a limited capacity to process information and generate distant knowledge and that this personal capacity decreases when BAs are engaged in increasingly more diverse investments are well grounded in prior literature (Mason and Harrison, 1996b; Ramos-Rodriguez et al., 2010).

Accessing and acting upon diverse information is often costly because individuals need to move beyond their current knowledge base to generate distant knowledge (Ahuja and Katila, 2001; Rosenkopf and Nerkar, 2001; Stuart and Podolny, 1996). As such, scholars have long reported how information overload and exposure to distant knowledge lead to decision bias and failure. For example, Tversky and Kahneman (1974) showed that decision makers use cognitive shortcuts that can lead to predictable deviations from normative decision making. However, the benefit of distant search is that one can access new knowledge that is not yet familiar.

With the ability to escape their limiting prior knowledge corridor (Hayek, 1945), BAs can source new knowledge from actors outside their current knowledge boundaries (Gruber et al., 2013) and “get to the learning curve” (Musaji et al., 2019: 30).

3.2. Business angels' networks, distant search, and access to knowledge

The new phenomenon of professional angel investment platforms changes how BAs are able to take on, pay attention to, and process information related to additional investments outside their comfort zone. Although BAs ultimately decide whether or not to invest individually, as part of a community with other members, they are able to participate in and discuss about a wider range of investment decisions. As such, they benefit from the knowledge of others when they invest, thus allowing them (at least theoretically) to diversify the industry scope of their investments (Kerr et al., 2011; Mason and Botelho, 2017).

In such a community, BAs can evaluate potential business targets in detailed discussions with fellow investors (Mason et al., 2016). Angel investment platforms thus offer a basis for portfolio investments and diversification into unknown industries (Bonini et al., 2018). Membership in these communities involves meetings online and offline and opportunities for networking and knowledge exchange among members. Specifically, BAs acting via angel investment platforms mostly apply a more professional approach to early-stage investing (Collewaert, 2012; Drover et al., 2017; Sohl, 2012). They seek investments in later stages of development (Kerr et al., 2011) and conduct more sophisticated due diligence than individual BAs (Sohl, 2012). In fact, angel investment platforms pre-screen investment opportunities submitted through their websites, which gives investors equal access to a curated deal flow, more time and resources to engage with investment proposals, and the opportunity to build networks with fellow investors (Drover et al., 2017; Kerr et al., 2011; Mitteness et al., 2016; Zu Knyphausen-Aufseß and Westphal, 2008). Consequently, BAs can access distant knowledge as a result of their membership and, according to our argument, can use the distant knowledge they receive from relationships in the community to inform future investment decisions. Gaining access to such knowledge is more convenient than generating it individually and enables BAs to make better decisions. Thus, we follow arguments and emerging evidence about distant search, suggesting that such input and access to knowledge can assist individuals in processing distant knowledge (Afuah and Tucci, 2012; Piezunka and Dahlander, 2015).

4. Hypotheses

4.1. The main effect between portfolio industry diversification and performance

Our theoretical argumentation suggests that BAs generally have difficulties generating the distant knowledge they need to make investments in unknown industries. Prior studies have indicated that BAs spend significantly more time than VCs deciding which (and how many) entrepreneurial ventures to invest in and whether they see a personal fit between themselves and a focal entrepreneur (Collewaert, 2012). Since most BAs engaged in professional angel investment platforms make several investments within a portfolio, they must also make decisions across investments, effectively choosing the composition of their investment portfolios. BAs can diversify in several ways: (1) geographical region, (2) development stage, and (3) industry. As BAs tend to invest locally (Sørheim, 2003) in seed or early-stage companies operating in various industries (Haar et al., 1988; Mason and Harrison, 1996a; Morrisette, 2007), our study focusses on the industry diversification of each individual platform member's investment portfolio.

Although not reported for BAs, prior research has shown that there is a tradeoff between the costs and benefits associated with diversification in general (e.g., Ahuja and Novelli, 2017) and with portfolio diversification in VC investing in particular. Recently, Matusik and Fitza (2012) reported a U-shaped relationship between industry diversification and portfolio performance in the VC context, contending that the tradeoff between the costs and benefits stems from the utilization of industry knowledge. However, previous research has not identified these costs and benefits in unison, nor has it addressed how they vary across all levels of portfolio diversification. Consistent with these arguments, we hypothesize that initial diversification outcomes may be negative for BAs but that diversification can pay off and lead to superior portfolio performance. We draw upon the results from previous BA research to argue that this specific context is particularly sensitive to information overload and tendencies to simplify and rationalize. This argument is supported in the search literature, where Dahlander et al. (2016: 283) note that the diminishing returns to distant search “may be even more relevant for individuals as they cannot scale themselves as well as firms and face finite search time.” However, in line with arguments in recent learning curve research (e.g., Musaji et al., 2019), experience may yield multiple benefits in terms of human cognition. Thus, industry diversification could yield substantial performance benefits. Drawing on theoretical arguments on distant search, learning curves, and information processing, we expect the benefits resulting from industry diversification to vary (both positively and negatively) for individual investors depending on the level of their portfolio diversification. We thus theorize a horizontal S-shaped relationship between BAs' portfolio diversification and portfolio performance (Fig. 1 illustrates this relationship).

4.1.1. Cost of distant search for initial portfolio industry diversification

It is often stated that BAs seek investments that are similar to their area of expertise (Aernoudt, 1999; Mitteness et al., 2012b). At low levels of diversification (i.e., specialization strategy), the investor's portfolio has a high concentration of industries, which minimizes coordination costs and allows for more efficient information processing within the investor's area of expertise (Simon, 1991). De Clercq and Dimov (2008) found that when individuals invest in industries they know more about, they are likely to have increased portfolio performance because their depth of knowledge leads to a more comprehensive understanding of any new information they receive. This foundational understanding of a domain's underlying dynamics, strengths, and weaknesses enables BAs to identify anomalies or inconsistencies in that specific knowledge domain (Sarah Kaplan and Vakili, 2015; Schillebeeckx et al., 2019) and

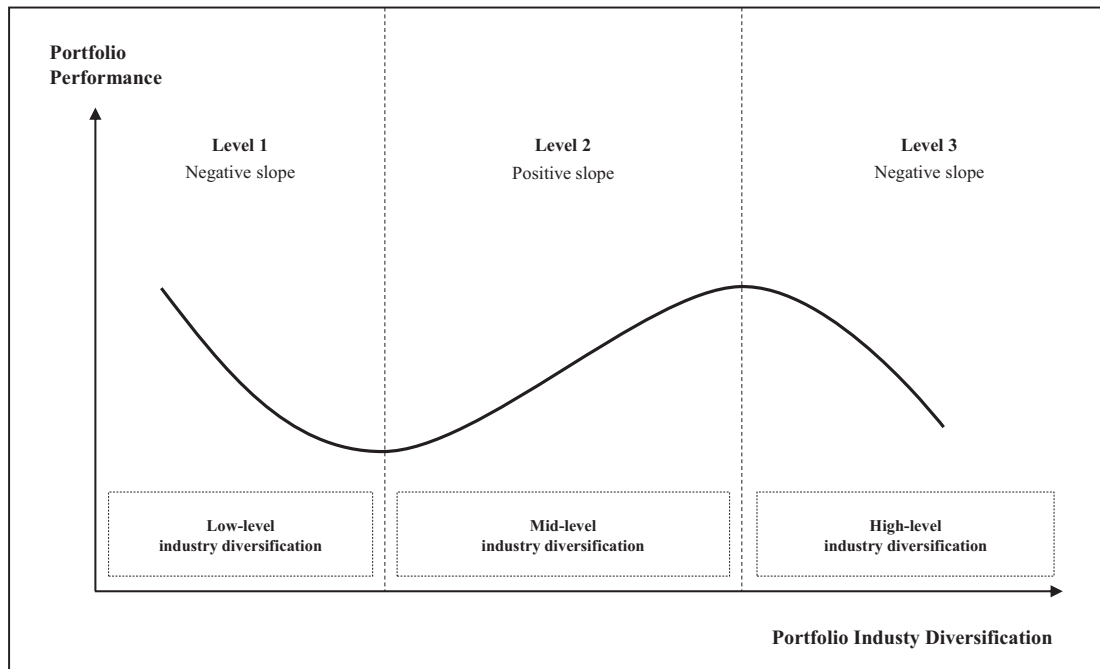


Fig. 1. The relationship between industry diversification and performance: A three-level model.

thus improves their ability to evaluate an investment proposal more adequately (Landström, 1995).

However, many BAs choose to diversify their portfolios into new industries despite their lack of knowledge in these new domains. Because of their unfamiliarity with the markets, technologies, and business models, BAs who start to diversify into new industries will face large search costs to make these investments (Dimov and De Clercq, 2006). The role of knowledge-acquisition costs has received much attention in the entrepreneurial finance literature. From a theoretical point of view, engaging in distant search forces BAs to seek access to and process unknown information. As such, attending to distant knowledge is challenging because individuals have limited attention and ability to process unknown information (Cohen and Levinthal, 1990). Therefore, BAs need to filter all the input elements they receive. Research has shown that it is particularly challenging for individuals to combine elements of their current knowledge base with newly elicited distant knowledge (Ahuja and Novelli, 2017; Hashai, 2015). In the entrepreneurial context, Gruber et al. (2013) argued that people's prior knowledge creates a corridor (i.e., “knowledge corridor”) that primes them to identify certain (investment) opportunities but to be blind to other potentially more lucrative opportunities. Initial steps to break out of this corridor and act upon distant knowledge often involve costly experimentation and mistake-correction patterns (Henderson and Clark, 1990).

Both the diversification and search literatures have highlighted that the opportunity costs of directing attention to new industries (i.e., the costs of not investing in or allocating attention to familiar industries) (Ahuja and Novelli, 2017; Dahlander et al., 2016) can be an additional driver of the potential negative outcomes of initial portfolio industry diversification. These costs arise from the fact that resources, such as decision makers' attention and mental focus, need to be allocated among alternative competing activities and choices. The allocation of attention to distant knowledge domains might also imply costs associated with missing out on better investment opportunities (e.g., Ahuja and Novelli, 2017; Helfat and Eisenhardt, 2004; Levinthal and Wu, 2010). Following this logic, we argue that in the BA context, allocating attention outside one's core industry takes attention away from the focus area and could thus lead BAs to miss deals or make inferior investment decisions within their core knowledge domain. Therefore, for initial diversifiers, we expect that their early out-of-scope investments will not be as successful as the first investments they carefully chose in their area of expertise. As such, a concentrated investment portfolio should provide BAs with more relevant information flow and thus a more comprehensive knowledge base. Building on these arguments, we expect a negative slope for the relationship between initial portfolio industry diversification and portfolio performance, as shown in Fig. 1.

4.1.2. Benefits of medium levels of portfolio industry diversification

After their first out-of-scope investments, we expect that mid-level diversifiers may break free from their “knowledge corridors,” focus their attention on a broader range of alternatives, and thus benefit from the classical risk-reduction effects of portfolio industry diversification (Bonini et al., 2018; Elton et al., 2009). The theoretical rationale for the turning point (i.e., when the negative performance trend in portfolio industry diversification becomes positive) is grounded in the contemporary learning curve literature (Musaji et al., 2019), which posits positive outcomes once BAs accumulate sufficient selection experience. In the BA context, when BAs extend their industry diversification beyond low levels, they become more exposed to diverse knowledge inputs. A key premise is that knowledge search is a continuum that varies from leveraging closely related knowledge to leveraging knowledge that is completely unfamiliar (Kim et al., 2013). The entrepreneurship and innovation literatures suggest that when diverse knowledge stimuli

are strong enough, individuals become less bound by the knowledge corridor that prevented them from identifying value in distant knowledge domains (e.g., Ahuja and Katila, 2001; Gruber et al., 2013; Sirén et al., 2017). When a BA's attention is no longer channeled solely to one specific industry, the range of possibilities they will notice on the platform will increase (Barnett, 2008; Ocasio, 1997). When BAs are able to notice the “latent possibilities” or “shadow options” (Bowman and Hurry, 1993: 763) that were previously unnoticed, they can turn them into potential engines of choice (Barnett, 2008; McGrath et al., 2004). Following this logic, at medium levels of industry diversification, when BAs are exposed to increased distant knowledge stimuli, one can expect a generally positive relationship between the number of different industries represented in a BA's investment portfolio and his or her ability to identify promising investment opportunities. This logic is also supported in the entrepreneurship literature. For instance, entrepreneurs with experience in different industries identify a larger number of opportunities prior to starting their business (Gruber, 2010).

Building on this notion, we expect that at medium levels of industry diversification BAs are able to break free from core rigidities that prevent them from realizing investment opportunities that could have high potential to increase their portfolio returns. With fewer costs and better access to more diverse knowledge that they can benefit from, BAs are able to further generate fertile ground to search and select attractive investments, which is an important driver of investment returns (Matusik and Fitza, 2012). Therefore, we hypothesize a positive slope for the relationship between mid-level industry diversifiers and portfolio performance, as shown in Fig. 1.

4.1.3. High levels of portfolio industry diversification and the overdiversification effect

The benefits of further portfolio diversification into unknown industries are unlikely to be indefinite. The results from the VC field strongly suggest that some investors also diversify their portfolios to a very high extent. Matusik and Fitza (2012: 411) stated that it might be possible that “at extremely high levels of diversification, [their] hypothesized [U-shaped] relationship may break down.” We expect that for investors who go beyond medium levels of portfolio diversity, the incremental costs of further diversification into peripheral industries are greater than the incremental benefits and are thus detrimental to portfolio performance. Also, the search literature has indicated diminishing returns from increased diversification: as search breadth increases, the costs of integration exceeds the benefits of search breadth (Dahlander et al., 2016; Simon, 1997). We thus expect that the diversification-performance slope again becomes negative in this case, as seen in Fig. 1, for two reasons.

First, beyond a certain point, having diversified into the most attractive peripheral industries based on their preferences, BAs are left with the far-reaching industries, which would force them to become overly engaged in distant search once again. Similar arguments can be found in the corporate acquisition literature. For example, Singh and Montgomery (1987) recognized the growing strain on top managers when they try to manage increasingly disparate portfolios of unrelated businesses. Similarly, overdiversification causes firms to lose the ability to leverage their core competencies when choosing acquisition targets (Baysinger and Hoskisson, 1989; Di Guardo et al., 2018).

Second, recent research on BA decision making has shown that BAs develop shortcuts to cope with highly diversified investment proposals. For instance, Maxwell et al. (2011) found that BAs use elimination-by-aspect heuristics to quickly eliminate investment opportunities. However, these shortcuts may lead BAs to disregard interesting investment opportunities solely because they need to find a way to cope with the masses of information they need to process. The diversification literature has further highlighted that overextending attention causes people to spend less time on individual tasks, thus reducing the thoroughness and overall quality of their decision making (e.g., Ahuja and Novelli, 2017). This argumentation can also be found in the search literature. For instance, Simon (1997: 40) posited that “a wealth of information creates poverty of attention.” Decision makers' boundaries in terms of cognition, resources, and time thus limit the information they can access, process, and store simultaneously (Cyert and March, 1963; Simon, 1955; Williamson, 2002). In addition to their limited capacity to deal with the volume of diverse information (Hansen and Haas, 2001; Hwang et al., 2014; Simon, 1955), BAs' ability to process and interpret this information may also be limited. Therefore, we expect there to be an overdiversification effect for high-level diversifiers.

Overall, the BA context suggests that high levels of portfolio industry diversification lead to information overload, which causes portfolio returns to decline. BAs may choose their investment targets in new industries and their logics unwisely. Thus, we expect a negative slope for the relationship between high-level industry diversification and portfolio performance, as shown in Fig. 1. Based on the aforementioned arguments, we hypothesize the following:

Hypothesis 1. The relationship between business angels' portfolio industry diversification and performance is S-shaped such that the performance impact is negative for initial industry diversifiers, positive for mid-level industry diversifiers, and negative for high-level industry diversifiers.

4.2. The moderating effect of business angel's access to distant industry knowledge through co-investment networks

When making an investment decision, each BA decides individually whether to participate in an investment opportunity. If there is a strong interest among the investors, the deal is syndicated (i.e., shared among various investors). In our sample, these deal syndicates ranged from two to > 120 investors. Hence, through such deals, BAs with completely different investment focuses and industry knowledge can interact. Research on VC syndication has suggested that engaging in partnering arrangements with other investors is likely to provide a means to receive more suggestions that can be leveraged in future investment decisions (Brander et al.,

2002; Lerner, 1994; Sorenson and Stuart, 2001). Furthermore, the distant search literature has proposed (Afuah and Tucci, 2012) and empirically shown (Piezunka and Dahlander, 2015) that utilizing networks (i.e., crowdsourcing in their studies) is a key mechanism that “transforms distant search into local search” (Afuah and Tucci, 2012: 369) and thus enables firms to take advantage of the benefits of distant search without having to endure many of its costs.

In the BA context, the partners in co-investment relationships are important because they impact BAs' investment returns (Mitteness, Sudek, et al., 2012). For instance, Bonini et al. (2018) argued that BA network partnerships reduce risk because they generate valuable knowledge and a sense of assurance as more than one investor either individually or jointly conducts due diligence on every investment. However, the extent to which BAs can benefit from the knowledge of such a network strongly depends on the network's structure, each individual's position within it, and the network members' industry knowledge (e.g., Lam, 2007; Powell, 1998).

In this study, we are interested in the distant industry knowledge BAs can access through their co-investment networks. We expect that BAs can mitigate the downsides related to overdiversification by accessing the distant industry knowledge (i.e., knowledge that is dissimilar to BAs' own knowledge) from their networks. Therefore, BAs whose portfolios are more concentrated will likely be, on average, less dependent on their peers' industry knowledge (i.e., network centrality has limited value for improving the performance benefits of concentrated industry portfolios). The reason for this decreased dependence is that when BAs already have high industry expertise, network centrality and increased knowledge access may be of limited value as they have already formed extensive knowledge and competence about the focal industry domain. Thus, when BAs make their first out-of-scope investments, even if their decisions would potentially benefit from their networks' industry knowledge, they are most likely unable to use this knowledge because they are still strongly limited by their knowledge corridor. As a result, they are likely to ignore the knowledge or interpret it in a way that follows the pattern in their expertise domain, which causes them to overlook market anomalies. Furthermore, even if BAs can access their networks' industry knowledge, their ability to productively employ this newly acquired knowledge is limited due to the challenges of learning when one has limited experience (Musaji et al., 2019). Therefore, we do not expect BAs' access to distant industry knowledge through co-investment networks to have a moderating effect at low and medium levels of industry diversification. However, we expect to see the moderating effects at high levels of portfolio industry diversification, at which point the overdiversification effect sets in and access to distant industry knowledge outside investors' knowledge domains holds great value.

The general aim of network partnerships is for individuals with high task expertise to provide information, assistance, and guidance to those with less task expertise in order to reduce uncertainty and successfully complete tasks (Ibarra and Andrews, 1993; Morrison, 1993). In the BA context, Mitteness et al. (2016) argued that BAs are motivated to form interpersonal relationships with other BAs to gain information and complementary knowledge benefits to improve any shortcomings in their decision making and reduce information uncertainty. We expect the benefits to materialize when the industry diversification is high. One of the benefits of forming relationships with dissimilar others is to reduce deal uncertainty by accessing risk-reducing information (Bonini et al., 2018; Mitteness et al., 2016). At high levels of diversification, where uncertainty is also high (Landström, 1995), BAs who do not have access to other BAs' industry knowledge must reduce uncertainty by searching for industry information from various sources (e.g., industry reports, websites, conferences). However, acquiring distant knowledge in this way can be slow and cause delays in the investment process, ultimately leading to missed investment opportunities. Furthermore, it takes extra effort for a BA to verify this type of information. In contrast, when BAs hold a central position in their network, they can easily access the complementary knowledge that their peers have accumulated through investments in various industries. This complementary knowledge enables BAs who are highly diversified to make investment decisions in a timely manner (e.g., enjoy the benefits of lower valuations in earlier investment rounds) and thus avoid missing promising investment opportunities when engaged in distant search. This argument is supported by strategy research proposing that such ties function as a “scanning device” that allows firms to detect new trends and asymmetries in markets faster than those lacking such connections (Stam and Elfring, 2008: 99). In addition, accessing specialized industry knowledge through fellow investors provides a degree of information certainty as these BAs are experts in their respective domains. Networking with experts thus prevents BAs from having to invest significant resources to verify information.

Furthermore, we expect that the negative performance consequences caused by the shortcuts highly diversified BAs use can be mitigated by the benefits associated with accessing fellow BAs' distant industry knowledge. Experts, including BAs, often share common decision-making schemas, which is why experts assimilate and structure data in comparable ways (Dane and Pratt, 2007). As a consequence, the new knowledge BAs generate is readily usable because other experts have already assimilated and structured it. It follows that in the best case, highly diversified BAs need to put forth only a small amount of additional cognitive effort to make sense of new industry knowledge and integrate it with their current knowledge base. Because BAs need to process less information, the cognitive capacity needed to successfully acquire and utilize distant industry knowledge is reduced. In the best case, this culminates in a situation in which highly diversified BAs will not miss opportunities and their ability to make efficient decisions is not endangered. Taken together, we expect the negative performance effect of portfolio overdiversification to be less pronounced for higher-level diversifiers who access complementary in-depth industry knowledge through a central position within their co-investment network. Accordingly, we propose the following:

Hypothesis 2. Business angels' access to industry knowledge through network partners moderates the relationship between portfolio industry diversification and performance such that beyond medium levels of industry diversity, the relationship is more positive for business angels with higher access to industry knowledge.

5. Methods

5.1. Study context: angel investment platform

We test our hypotheses in the context of an angel investment platform. Angel investment platforms stimulate high information flow because knowledge sharing is among the strongest motivations for individual BAs to join an angel investment platform (Croce et al., 2017). The angel investment platform examined in our study is one of the largest angel organizations in Europe and has experienced steady membership growth over the past years. During our study period (December 2013 to June 2017) the number of BAs investing via the platform rose from 136 in 2013 to 353 in 2017. Thus, not all BAs started investing in 2013.

The platform itself does not make investments. Instead, each individual angel decides independently whether to participate in an investment opportunity. When a deal is submitted via the platform's website, it is pre-screened by trained staff members from the organization to ensure it meets network members' general investment criteria. These criteria include overall deal characteristics, such as stage of development (i.e., at least a functioning prototype) and size of the investment ticket. Once a deal has passed the pre-screening, it is assigned to an experienced deal leader from the network of investors who functions as the contact person for the venture, introduces the deal to the group of BAs, and leads the negotiation on behalf of his or her fellow investors. Once the deal is made, the deal leader usually takes a board seat with the venture and consolidates input from the other BAs co-invested in the deal. The angel group members hold regular in-person meetings to view live pitches, interact with other investors, and make decisions about specific investment opportunities.

In the context of angel investment platforms, individuals may have divergent motives when joining a network. Some BAs may be focused on the community aspect and only occasionally make an investment (Kerr et al., 2011). Others may be more involved in actively building a portfolio of BA investments. We concentrated our analysis on active BAs on the platform (see Mitteness et al., 2016 for a similar focus) and excluded all investors with fewer than three individual portfolio companies (Wright and Robbie, 1998) from our sample. We further excluded cases on non-equity investments (e.g., loans given in follow-on rounds), which ensured that we had comparable data for all investments in our dataset.

5.2. Dataset

Our overall dataset consists of 353 BAs who became members of the angel investment platform between December 2013 (when the platform started its business) and June 2017. Of the 353 BAs, 142 were considered active investors with at least three portfolio companies throughout the study period.² The platform's deal monitoring system allowed us to extract all relevant details for each investment round (e.g., round date, participating investors, investment amount per investor, share price at investment date, etc.). Thus, we were able to recreate each BA's portfolio and identify the first company in which a BA invested in (i.e., earliest investment round date documented in the deal monitoring system for the BA). We then followed each active investor on a bi-annual basis (i.e., twice a year, on June 30 and December 31) from his or her entry date in the network until June 2017. This procedure of measuring all variables twice per year created an unbalanced panel dataset with 846 observations for model estimation. In total, the BAs invested in 65 individual startup companies within 34 industry sectors. The main industry clusters included MedTech, HighTech, and consumer products. For the 65 startups, there was a total of 158 investment rounds (e.g., Pre-Seed, Seed, Series A) with a mean of 2.43 investment rounds per startup. In each of these 158 investment rounds, on average, 16.13 BAs syndicated to make an investment, creating > 2,600 individual BA investment decisions (i.e., avg. 16 investors per round x 158 rounds). Eight companies exited by June 2017, and six startups went bankrupt. The average deal size was €126,000 (average in Europe: €184,000; EBAN, 2017), with each investor averaging €8,250 per investment ticket. Thus, the investment size is below the average BA ticket size in Europe (average in Europe: €19,990; EBAN, 2017). In addition, 81% of the BAs in our sample broke even or had positive returns.

The strength of our dataset lies in the detailed information on the investor and deal level, including direct cash-flow information and net asset values (NAVs) on each investment, which we were able to access through the network's deal-monitoring system (we explain these measure in more detail below). This feature was crucial for our subsequent analysis because it enabled us to calculate precise and comparable measures of portfolio diversification and performance for each period.

5.3. Measures

5.3.1. Portfolio performance

One central challenge with research on BA investment performance is access to data as BAs are not required to publicly disclose their performance or investment activities. The comprehensive nature of our database allowed us to use a direct cash-flow measure of return gathered for each investment in an individual's portfolio. The deal-monitoring system reports the timing and size of each cash flow (positive and negative) twice a year as well as an evaluation of NAVs from each portfolio firm over time. The network's administration calculates NAVs twice a year, always on June 30 and December 31, based on either the investment agreements,

² We did not find any statistically significant differences between the performance of the BAs who were in our final sample and those who were not. Furthermore, our sample of platform members is similar to those used in other studies. For instance, Bonini et al. (2018) reported a sample of platform members who were, on average, 48.32 years of age (our study: 50.44) and who had invested in, on average, 6.36 portfolio companies (our study: 6.62).

capitalization table, audited financial statements, or company announcements. All valuations are prepared in line with International Private Equity and Venture Capital Valuation Guidelines (IPEVC, 2018) to ensure the valuation approach is comparable across all portfolio companies. We constructed two measures of performance: *internal rate of return* (IRR) and *capital gains multiple* (CGM). IRR is the standard performance measure in VC and private equity research (Hochberg et al., 2007; Kaplan and Schoar, 2005) and is also used to study BA performance (Capizzi, 2015; Mason and Harrison, 2002). It is an annualized figure that takes into account returns from the sale of shares, dividend payments, and the residual value of investments that have not been realized.³ However, research on BA performance has highlighted that angels tend to measure investment performance more as the capital gains they earn on each investment (Mason and Harrison, 2002). Therefore, we also used CGM on a deal-by-deal basis, computed as the ratio of the NAVs of shares at the end of each period to the NAVs of shares on the investment date.

5.3.2. Portfolio industry diversification

For our *industry diversification* measure, we used a Herfindahl-Hirschman Index (HHI), which has been used extensively in the VC literature to calculate portfolio diversification (Buchner et al., 2017; Dimov and De Clercq, 2006; Yang et al., 2014) and to proxy distant search⁴ (Kim et al., 2013; Lin and Patel, 2018). HHI is measured as follows:

$$HHI = \left(1 - \sum_{i=1}^n p_i^2 \right)$$

where p_i^2 is the percentage of portfolio investments made in industry i , and n is the total number of industries in which the investor has invested. To measure industry diversity among BA portfolios, we followed Yang et al. (2014) and first determined the number of active companies in the investment portfolio per year. For each investor, we identified the first company in which the BA invested from the platform's deal monitoring system. Then, for each of the following bi-annual periods, we added the companies that the BA invested in during the focal time period. One key consideration for our study is the industry-coding system. We followed prior studies (e.g., Matusik and Fitza, 2012; Yang et al., 2014) and chose to use Venture Economic Industry Codes (VEIC) to determine the industries of the BAs' portfolio companies. The VEIC classification has a finer-grained coding scheme for technology-intensive industries and is thus a more suitable classification for early-stage startup investments than the traditional SIC/NAICS schemes (Chang, 2004; Matusik and Fitza, 2012). We followed Matusik and Fitza (2012) and calculated portfolio industry diversification at the three-digit VEIC level. The smaller the index value, the higher the portfolio's level of specialization, with the value 0 representing specialization in one single industry. In our additional analysis, we report the results for different variants of this measure.

5.3.3. Industry knowledge access through co-investment networks

For our *industry knowledge access* measure, we followed previous research and created a weighted network variable that captures each individual's network position weighted by both portfolio industry diversification and industry relatedness within each BA's co-investment network (e.g., Allatta and Singh, 2011; Davis and Mizruchi, 1999; Gulati, 1999). We created this measure in two steps.

First, in order to map the co-investment network for each individual, we tracked all participants of every investment round via the platform's deal monitoring system. This allowed us to calculate each BA's position within his or her co-investment network (i.e., how centrally located the BA is to reach knowledge from others). This step alone, however, does not capture the extent to which the knowledge reached through other BAs is complementary to the focal BAs' knowledge.

Therefore, as a second step, we assigned each node a weight based on its value for both portfolio industry diversification and industry relatedness. Industry relatedness is based on a one-digit VEIC level and was calculated as the absolute value of the difference between two individuals' industry focus (see Mitteness et al., 2016 for a similar approach to calculating knowledge dissimilarity). Industry focus was calculated as the mode value of industries in each BA's portfolio (Matusik and Fitza, 2012). Finally, using both portfolio industry diversification and industry relatedness as factor weights, we calculated a weighted betweenness centrality measure using the *igraph* library's "estimate_betweenness" command in R. Introducing both weights allowed us to calculate the (weighted) shortest paths to the knowledge of specialized investors who are dissimilar in terms of their industry focus (Brandes, 2001).

A high *industry knowledge access* score thus indicates that a BA can reach distant knowledge from his or her co-investment network via relatively short paths. To increase interpretability and control for network size, we followed previous research (e.g., Brandes, 2001; Hochberg et al., 2007) and normalized our measure so that it lies between 0 and 1.

5.3.4. Control variables

We controlled for several factors known to affect BA investment returns. At the portfolio level, we accounted for portfolio size and its potential influence on performance based on the *portfolio volume* and *number of portfolio companies*, which were measured using the logarithm of the total amount invested and the absolute number of portfolio companies (Buchner et al., 2017). We also controlled for the *stage of development* focus of the investment portfolio by measuring the percentage of seed-stage investments in each BA's portfolio. We followed Ruhnka and Young (1987) and measured the stage of each company at the time of initial BA investment using

³ It is important to note the effect of the holding period on IRR, as illustrated by following example: a multiple of five harvested after 3 years generates a 71% IRR, but it drops to 31% if the exit occurs after 6 years.

⁴ Kim et al. (2013) used the theoretical arguments of distant search and operationalized it with a Herfindahl-type measure to capture the relationship between diversification and innovation output (see also Lin and Patel, 2018 for a similar approach).

the following five categories: seed stage, startup stage, second stage, third stage, and exit stage. As prior studies have suggested that BAs prefer to make “home turf” investments, we further controlled for each BA's *geographical focus* by creating a dummy variable that takes the value 1 if more than half of the portfolio investments were made outside the BAs country of residence.

At the individual level, we accounted for *investment experience* by measuring BAs' network tenure, measured as the time each individual had been a member of the angel investment platform in months from his or her entry date (Mitteness et al., 2016),⁵ In addition, because the BAs' knowledge came not only from their involvement in the network but also from their previous experience, we included each *investor's age* as a proxy for accumulated knowledge prior to joining the community (Greenwood and Nagel, 2009). We further controlled for the impact of each individual's activity as a deal leader (*investor activeness*) by measuring the number of times a BA had served as a deal leader for a startup.

Furthermore, because a BA's knowledge depends not only on the diversification of his or her investments during a given observation period but also on previous investments, we controlled for BA's *past diversification* (t-1) as well as for the squared and cubed term of this variable (Hashai, 2015; Matusik and Fitza, 2012).

To control for the influence of industry effects on portfolio performance, we introduced a set of dummy variables for the industry each BA invested in by taking the mode value of industries in the investment portfolio (Matusik and Fitza, 2012). Finally, to control for periodical differences in portfolio performance, we further included a set of dummies for each bi-annual period.

6. Analysis and results

6.1. Summary statistics

Table 1 presents the descriptive statistics for all variables, including the mean, median, standard deviation, and minimum and maximum values. Given the panel structure of our data, the table presents descriptive statistics of the mean values of variables across all observation periods. This approach, which is regularly used in panel data analysis (e.g., Shaver, 2011), averages the statistics to account for multiple observations in the sample. It is worth noting that the average IRR in our sample is 52.25%, with a median of 35.84%. The fact that the mean is higher than the median suggests that the distribution of returns is positively skewed, which is interesting as prior studies have shown BA returns to be negatively skewed (e.g., Mason and Harrison, 2002). In our sample, 80.62% of the BAs have positive returns. The mean (median) of portfolio industry diversification is 0.78 (0.80), suggesting that most investors attempt to diversify the industry scope of their investment portfolios. Our sample further shows that BAs' performance varies depending on the level of portfolio industry diversification. In the 25th percentile of portfolio industry diversification, the angels show a mean IRR of 46.26% (median: 24.31%). The 50th and 75th percentiles show mean IRRs of 48.57% (median: 33.29%) and 54.73% (median: 38.70%), respectively. The percentage of BAs who achieve an IRR of over 50% is 41.63% and 42.34% for the 25th and 75th percentile, respectively. On average, the angels in our sample were 50.44 years of age and had invested in 6.62 individual portfolio companies. Our sample further supports prior studies' findings on the geographical investment activity of BAs (e.g., Aernoudt, 1999; Mitteness et al., 2012a) as, on average, 82.33% of BAs have made at least 50% of their investments within their country of residence. Further, on average, 23.42% of investments were made in seed-stage companies.

6.2. Main analysis

We used generalized least squares (GLS) fixed-effects models to test our hypotheses. GLS models correct for the presence of autocorrelation and heteroscedasticity in pooled time series data (Kmenta, 1971). Using the Hausman specification test (Baltagi, 2008), we compared our fixed-effects models to random-effects models, and the fixed-effects models were preferred in all cases. An inspection of the variance inflation factors (VIFs) showed that multicollinearity is not an issue in our study. As Table 1 indicates, all VIFs are below the acceptable limit of 5 (O'Brien, 2007), confirming that multicollinearity did not influence our results. For the subsequent analysis, we standardized all variables. Table 2 reports the regression results. As baseline models, Model 1 and Model 4 contain only the control variables.

Models 2 and 5 evaluate Hypothesis 1, which proposed a sideways S-shaped relationship between BAs' portfolio industry diversification and portfolio performance. The results from Models 2 and 5 confirm that the relationship between portfolio industry diversification and portfolio performance is cubic (Model 2: $\beta = -2.33$; $p < 0.05$; Model 5: $\beta = -1.89$; $p = 0.061$). Model 2 explains 23% of the variance of portfolio performance and is a significant improvement over Model 1 ($\Delta R^2 = 2.91$, LR $\chi^2 = 31.29$, $p < 0.01$), and Model 5 explains 24% of the performance variance and is a significant improvement over Model 4 ($\Delta R^2 = 2.32$, LR $\chi^2 = 25.21$, $p < 0.01$). Interestingly, we find that investors' activeness as a deal leader has a significant negative relationship with portfolio performance (Model 2: $\beta = -0.15$; $p < 0.05$; Model 5: $\beta = -0.16$; $p < 0.01$). This means that BAs who regularly act as facilitators of investment deals experience lower portfolio returns than those who tag along.

To illustrate the nature of the main relationship between portfolio industry diversification and performance, we plot the relationship in Fig. 2a and b at the full range of its values. The plots show that the marginal performance effect of diversification first decreases with portfolio diversification and then starts to increase after the level of industry diversification exceeds 0.67 for both IRR and CGM. Ultimately, after exceeding a level of 0.91 (IRR) and 0.92 (CGM), portfolio performance starts to decrease, thus revealing a

⁵ Because fixed-effects models control for variance due to time-invariant characteristics, controlling for factors such as gender, education, or prior field of expertise is not necessary (Carpenter and Fredrickson, 2001).

Table 1
Descriptive statistics and correlation.

Variables	Mean	Median	SD	Min.	Max.	1	2	3	4	5	6	7	8	9	10	11	12	VIF
1. Internal rate of return ^b	0.52	0.36	0.71	-0.70	2.52	1.00												
2. Capital gains multiple ^{a,b}	1.53	1.20	0.72	0.29	3.53	0.98	1.00											3.28
3. Industry diversification	0.78	0.80	0.10	0.56	0.99	0.08	0.08	1.00										2.81
4. Industry knowledge access	0.01	0.00	0.06	0.00	1.00	0.11	0.11	0.11	1.00									4.33
5. Number of portfolio companies	6.62	5.00	5.63	3.00	80.00	0.11	0.11	0.71	0.67	1.00								2.31
6. Portfolio volume ^a	10.59	10.51	1.08	8.94	14.44	0.17	0.19	0.66	0.30	0.62	1.00							2.01
7. Investment experience	10.78	11.57	3.06	2.30	14.37	0.35	0.38	0.35	0.13	0.28	0.39	1.00						1.19
8. Investor age	50.44	49.00	9.44	31.00	79.00	0.05	0.03	0.05	0.07	0.11	0.17	-0.04	1.00					2.09
9. Investor activeness	0.69	0.00	2.97	0.00	30.00	0.08	0.10	0.27	0.69	0.57	0.37	0.14	0.11	1.00				1.99
10. Stage of development	0.23	0.22	0.18	0.00	0.75	-0.20	-0.22	-0.13	-0.02	-0.10	-0.26	-0.18	0.01	0.01	1.00			2.90
11. Geographic focus	0.82	33.33	10.81	66.66	100.00	-0.29	-0.33	-0.31	-0.05	-0.19	-0.37	-0.52	0.22	-0.05	0.65	1.00		2.26
12. Past diversification	0.76	0.75	0.15	0.00	0.99	0.14	0.15	0.64	0.19	0.50	0.52	0.56	0.06	-0.10	-0.28	0.20	1.00	

Notes: $N = 846$ observations from 142 BA portfolios. Descriptive statistics present the average across all observation periods. VIF = variance inflation factor.

The VIF values for diversification² and diversification³ are 3.28 and 3.54, respectively.

Values ≥ 0.05 are significant at $p < 0.05$.

^a Logarithm.

^b Variable is winsorized at the 5th and 95th percentile to reduce the effect of extreme values.

Table 2
Regression analysis.

Variables	Internal rate of return ^b			Capital gains multiple ^{a,b}		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Number of portfolio companies	0.11*** (0.04)	0.15*** (0.05)	0.19** (0.08)	0.11*** (0.04)	0.13** (0.05)	0.15* (0.09)
Portfolio volume ^a	−0.49*** (0.08)	−0.59*** (0.09)	−0.61*** (0.09)	−0.51*** (0.08)	−0.60*** (0.09)	−0.62*** (0.09)
Investment experience	−0.35*** (0.12)	−0.49*** (0.13)	−0.48*** (0.13)	−0.29** (0.12)	−0.41*** (0.13)	−0.40*** (0.13)
Investor age	2.59*** (0.42)	2.73*** (0.43)	2.66*** (0.43)	2.37*** (0.43)	2.50*** (0.44)	2.46*** (0.44)
Investor activeness	−0.16*** (0.06)	−0.15** (0.06)	−0.18*** (0.06)	−0.17*** (0.06)	−0.16*** (0.06)	−0.19*** (0.06)
Stage of development	−0.17 (0.12)	−0.26** (0.12)	−0.28** (0.12)	−0.08 (0.12)	−0.16 (0.12)	−0.18 (0.12)
Geographic focus	0.41 (0.55)	0.67 (0.55)	0.76 (0.55)	0.29 (0.56)	0.49 (0.56)	0.57 (0.56)
Past diversification	0.38*** (0.08)	0.57*** (0.18)	0.62*** (0.18)	0.41*** (0.09)	0.61*** (0.19)	0.66*** (0.19)
Past diversification ²		0.14 (0.10)	0.10 (0.10)		0.13 (0.10)	0.09 (0.10)
Past diversification ³		−0.07 (0.09)	−0.12 (0.09)		−0.08 (0.09)	−0.12 (0.09)
Diversification		−1.65 (1.20)	−3.23** (1.47)		−1.48 (1.22)	−3.11** (1.50)
Diversification ²		4.15** (1.95)	6.03*** (2.19)		3.55* (1.99)	5.43** (2.23)
Diversification ³		−2.33** (0.98)	−3.13*** (1.10)		−1.89* (1.01)	−2.63** (1.12)
Industry knowledge access			3.80 (2.48)			4.06 (2.54)
Diversification x knowledge access			−13.17* (7.12)			−14.09* (7.27)
Diversification ² x knowledge access			14.53** (6.95)			15.51** (7.09)
Diversification ³ x knowledge access			−5.12** (2.27)			−5.45** (2.31)
Industry dummies	Included	Included	Included	Included	Included	Included
Year dummies	Included	Included	Included	Included	Included	Included
Obs.	846	846	846	846	846	846
R-squared	0.20	0.23	0.24	0.21	0.24	0.25
LR χ^2		31.29***	11.54**		25.21***	12.43**
AIC ^c	1323.23	1301.93	1298.39	1353.13	1337.92	1333.48

Notes: Standardized regression coefficients are shown, with standard errors in parentheses. All two-tailed tests.

^a Logarithm.

^b Variable is winsorized at the 5th and 95th percentile to reduce the effect of extreme values.

^c AIC: Akaike's information criterion.

* $p < 0.10$.

** $p < 0.05$.

*** $p < 0.01$.

sideways S-shaped relationship between portfolio diversification and performance. The results of Models 2 and 4 as well as Fig. 2a and b fully support Hypothesis 1.

Hypothesis 2, which predicts a moderating effect of BAs' access to industry knowledge through network partners, is evaluated in Models 3 and 6 by entering the interaction terms of portfolio industry diversification and industry knowledge access as well as the interaction of the squared and cubed terms of diversification and industry knowledge access. The interaction is negative and significant in Model 3 ($\beta = -5.12$; $p < 0.05$) and Model 6 ($\beta = -5.45$; $p < 0.05$). Model 3 explains 24% of the variance and is a significant improvement over Model 2 ($\Delta R^2 = 1.05$, LR $\chi^2 = 11.54$, $p < 0.05$), and Model 6 provides a significant improvement over Model 5 ($\Delta R^2 = 1.12$, LR $\chi^2 = 12.43$, $p < 0.05$).

Fig. 3a and b illustrates the plotted marginal effects of the interaction. Following Dahlander et al. (2016), we plot the marginal effects at low (the 15th percentile) and high (85th percentile) levels of industry knowledge access using the results from Model 3 and Model 6, respectively. Two noteworthy findings emerge from these figures. First, as we stated in the hypothesis development, we did not expect industry knowledge access to moderate the relationship between industry diversification and portfolio performance at lower levels of diversification. This assumption is supported by Fig. 3a and b as both BAs with low access and high access to distant knowledge appear to suffer the same costs of initial industry diversification in their investment portfolios (the slope difference is not

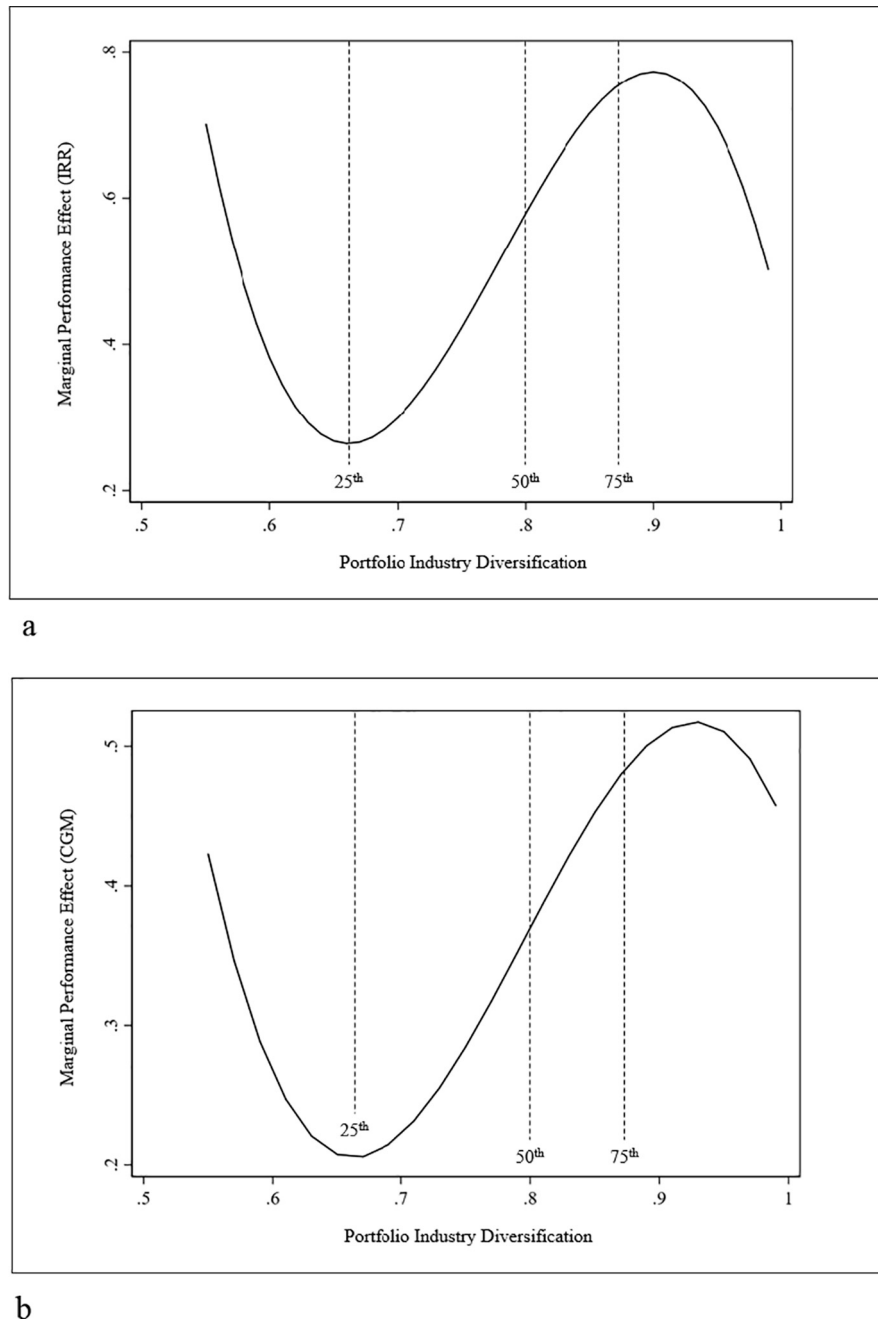


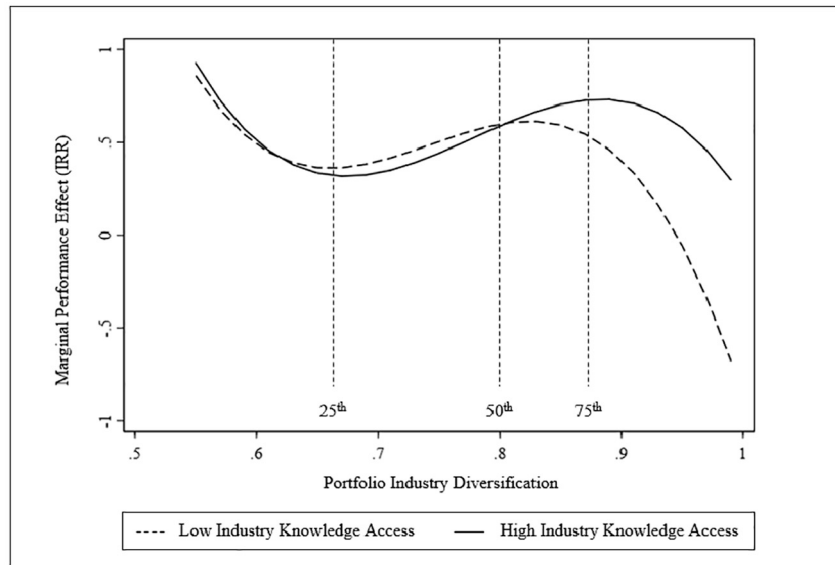
Fig. 2. a: Relationship between portfolio industry diversification and performance (IRR).
b: Relationship between portfolio industry diversification and performance (CGM).

significant). Second, as predicted in our [Hypothesis 2](#), the figures show that BAs with high knowledge access gain significant advantages from their co-investment networks at higher levels of portfolio industry diversification. When BAs have access to a diverse network of co-investors, the amount of different industries in which they can invest to optimize their portfolio returns increases. Taken together, these results support [Hypothesis 2](#). We further elaborate on these results in the discussion section.

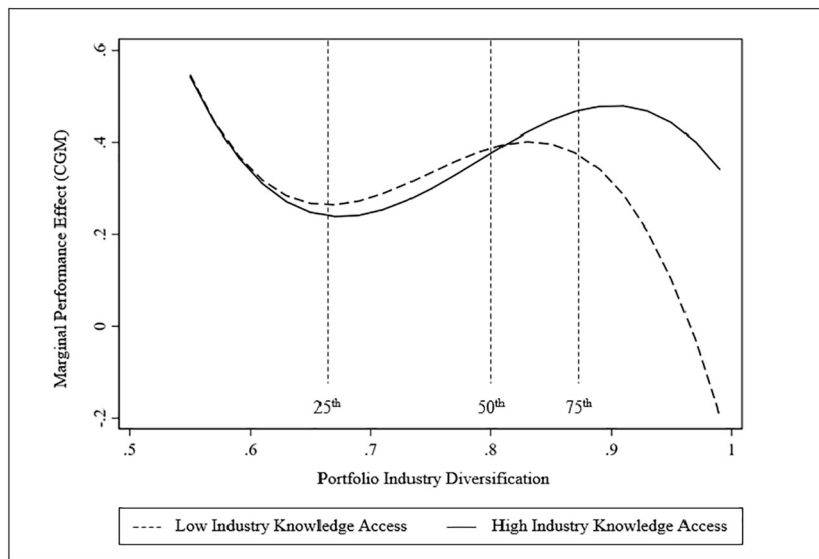
6.3. Additional analyses

To further assess the robustness of our results, we conducted several additional analyses. We report all robustness tests with IRR as the dependent variable. The results from the analyses with CGM as the dependent variable lead to the same conclusions.

First, we verified whether the nonlinear relationship found in our study is instead a biquadratic curve (W-shaped) evidenced by a



a



b

Fig. 3. a: Moderating effect of industry knowledge access on the relationship between diversification and performance (IRR).
b: Moderating effect of industry knowledge access on the relationship between diversification and performance (CGM).

significant diversification quartic term (Baù et al., 2017). Estimating Model 2 and Model 3 with a quartic term of portfolio industry diversification, which it not significant, also led to no significant improvement (Model 2: LR $\chi^2 = 3.27$, n.s.; Model 3: LR $\chi^2 = 4.00$, n.s.) over the models used in our study.

Second, following Baù et al. (2017) we split our sample into subcategories according to the three phases of our curve by taking the sample distribution of our portfolio industry diversification measure and dividing it into categories of one standard deviation below and above the sample mean. We tested the linear effect of portfolio industry diversification in those subsamples. Our main results were confirmed: diversification in the low-level sample ($HHI < 0.69$) has a negative effect, diversification in the mid-level sample ($0.69 \leq HHI \leq 0.88$) has a positive effect, and diversification in the high-level sample ($HHI > 0.88$) has a negative effect on portfolio performance. Each of these subsamples includes enough observations to conclude that our results—especially for high levels of portfolio industry diversification—are not influenced by a lack of observations to make such inferences. The first part of the curve has 264 observations, and the second and third parts of the curve have 420 and 162 observations, respectively.

Third, we checked for the potential influence of a time lag in industry knowledge access on the relationship between portfolio diversification and performance by lagging our *industry knowledge access* variable by one period (Baù et al., 2017). Adding this variable to our models did not change the main relationship. With the lagged variable, Model 3 shows that the relationship between diversification and portfolio performance remains a sideways S-shape ($\beta = -3.03$; $p < 0.01$). Introducing the lagged variable also shows that the moderating effect of industry knowledge access follows the same direction but becomes marginally significant (Diversification³: $\beta = -4.10$; $p = 0.064$). To test whether our results were influenced by the choice of our time lag, we reran all models—both the principal models and robustness analysis—with t-2 bi-annual periods as the time lag and reached the same conclusions.

Fourth, in the main analysis, the fixed effects modeling that we chose based on the Hausman test did not allow us to investigate the influence of time-invariant BA characteristics on portfolio performance. As such, we chose to investigate the influence of BA's gender on portfolio performance as gender is often found to influence investment decisions (Harrison and Mason, 2007; Sohl and Hill, 2007). We reran our models by using hierarchical linear modeling (HLM) with mixed-effects as BAs in our data are nested within syndicated investment rounds. A null model without predictors revealed that only 8% of the variance of portfolio performance (as indicated by the ICC value) resides between investment rounds and thus confirmed our approach of using fixed effects models over HLM. The results show that in the control model, gender has a significant influence on portfolio performance ($\beta = -1.64$; $p < 0.01$). However, the significance disappears when the cubed term of portfolio diversification is introduced into the model. Overall, the HLM results confirm the S-shaped relationship ($\beta = -2.06$; $p < 0.01$) but not the moderating effect of industry knowledge access ($\beta = -1.07$; $p = \text{n.s.}$). Above that, when BAs enter the network, they report their main area of expertise (e.g., marketing, finance, engineering) in the application process. We were able to collect this data for a subsample of BAs, but this variable is not significantly related to portfolio performance ($\beta = -0.01$; $p = \text{n.s.}$).

Fifth, our main analysis concentrates on active BAs and thus omits all portfolios with fewer than three investments. To test whether our portfolio cutoff influenced the hypothesized effects, we followed the approach of Yang et al. (2014) and estimated our models by omitting all portfolios with fewer than two investments. The results confirm the main relationship and moderation effect of our analysis (Diversification³: $\beta = -1.44$; $p < 0.01$; Diversification³ x Industry knowledge access: $\beta = -1.77$; $p < 0.05$).

Sixth, although HHI is a robust measure of portfolio industry diversification (e.g., Buchner et al., 2017; Dimov and De Clercq, 2006; Yang et al., 2014), it has also been criticized for not capturing the nuances of industry relatedness in a given investment portfolio (Rodan and Galunic, 2004; Wadhwa et al., 2016). To test whether the results for Hypothesis 1 were influenced by our choice of diversification measure, we constructed a new measure that captures how different the industries are from the investor's main industry as well as how different the investments are from each other (Wadhwa et al., 2016).⁶ The results for the relationship between portfolio industry diversification and performance remain unchanged (Diversification³: $\beta = -0.16$; $p < 0.05$).

Finally, using a fine-grained industry classification, such as three-level VEIC, may include a risk that the classification is too narrow to capture meaningful specialization in different industries (Gao, 2011). Therefore, we followed the approach of Gompers et al. (2008) and ran a robustness analysis by combining the 69 VEIC industries to five broader industries in accordance with the industry classification used by the angel investment platform examined in our study. The industries we constructed from the narrower definitions are (1) technology, (2) industrial, (3) consumer products, (4) internet and mobile, and (5) social impact. This alternative classification groups ventures that are similar in technology and management expertise and thus allowed us to capture specialization beyond our original industry classification. For instance, BAs specialized in blockchain technology might still have a specialized approach to investing even though their portfolios contain various industries. Running our models with HHI based on this broader industry definition led to the same conclusions in terms of the main relationship (Diversification³: $\beta = -0.40$; $p < 0.01$) and the moderating effect of industry knowledge access (Diversification³ x Industry knowledge access: $\beta = -1.31$; $p < 0.05$). Taken together, we believe these analyses demonstrated the validity of our conclusions since our results remain relatively stable across different analytical procedures and model specifications.

7. Discussion

Entrepreneurial finance research has intensively discussed the role of portfolio diversification in venture finance (Buchner et al., 2017; Cressy et al., 2014; Knill, 2009; Matusik and Fitza, 2012; Norton and Tenenbaum, 1993). While these studies have acknowledged that diversification comes with challenges, the literature on BA investing has not yet engaged in this discussion. The main reason for this lack of engagement is that the opportunity to diversify has previously been limited for individual BAs (Benjamin and Margulis, 1996; Mason and Harrison, 2002). This restriction of BA investing began to change when BAs started to form large angel investment platforms, which have enabled them to receive more deal flow and syndicate their investments, thus allowing them to make more diversified investments than previous possible (Drover et al., 2017). However, do these new opportunities pay off for individual BAs? With our research, we extend the literature on VC diversification by theoretically and empirically identifying BAs' challenges when diversifying their investments. Prior research on VC funds has found that industry diversification is generally positive (Buchner et al., 2017; Knill, 2009). Other studies have stressed the costs and benefits of diversification and have proposed a

⁶ We first calculated the normalized distance between the investor and each portfolio company based on their individual VEIC codes. Second, we built a uniqueness measure for each portfolio firm following Wadhwa et al. (2016), whereby uniqueness was calculated as the solution of each contact's Eigen equation. Third, following Rodan and Galunic (2004), we calculated portfolio industry diversification as $1/N \sum_{j=1}^N d_{ij} * \lambda u_j$, where d_{ij} is the VEIC-based distance of venture j from investor i , and j 's uniqueness score is related to all of i 's portfolio firms.

nonlinear (U-shaped) relationship between diversification and performance (Matusik and Fitza, 2012; Yang et al., 2014). Our study builds on the idea of nonlinearity in the diversification-performance relationship and adds the additional viewpoint of a potential overdiversification effect at the highest levels of industry diversification. We further theorize and empirically examine how each individual BA's engagement within his or her co-investment network may mitigate the negative effects of overdiversification.

Our findings from a longitudinal dataset of 142 members of a professional angel investment platform and their portfolio returns between 2013 and 2017 confirm our theoretical framework. Drawing upon insights from the search literature (e.g., Dosi and Marengo, 2007; March, 1991; Piezunka and Dahlander, 2015) and especially emphasizing the challenges associated with distant search for industry knowledge, we find that industry diversification has a nonlinear (sideways S-shaped) relationship with portfolio performance. Furthermore, we find evidence that angel group members' ability to access industry knowledge through their co-investment networks helps mitigate the costs related to high levels of portfolio industry diversification.

The theoretical arguments made both in the search and diversification literatures stating that diversification can have countervailing influences on performance are supported by our study. Thus, the key findings of this paper offer insights into the difficulties that BAs face when building a diversified investment portfolio. We further emphasize under what circumstances the positive effects of portfolio specialization outweigh the negative effects of portfolio diversification. As such, our study demonstrates that initial industry diversification has a negative influence on portfolio performance but that this influence turns positive at medium levels of diversification. The results supported our arguments that at low levels of diversification, one additional out-of-scope investment does not pay off. Consistent with the information processing literature, this finding emphasizes the benefits and self-reinforcing qualities associated with deep specialized knowledge. Because the costs of distant search increase with too many far-reaching investment decisions, our findings confirm the existence of an overdiversification effect at high levels of portfolio industry diversification. This effect is mainly due to individuals' cognitive limitations when trying to access, process, and store relevant information to make informed investment decisions. Thus, an important contribution of our study is that we extend prior knowledge on the limitations of accessing and processing information in BA investing.

Our study also adds insights into the network aspect of BA investing. The recent review by Drover et al. (2017) suggested that a more socialized approach to investing may be of great relevance to angel group members. Our results further demonstrate that for angel group members who are central within a network of specialized individuals, the costs of distant search and thus the negative performance effect of overdiversification are less dramatic when developing highly diverse investment portfolios. This finding supports the relevance of co-investment networks in angel investment platforms. Professional angel investment platforms allow BAs to leverage their peers' knowledge to rapidly and continuously assess, evaluate, and decide upon the most promising investment opportunities. Though consistent with our broad expectations that angel investment platforms can be valuable in general, our findings suggest that research should study how BAs build networks within these professional communities and how they use these membership platforms to improve investment performance (Drover et al., 2017; Mason et al., 2016). Furthermore, it is noteworthy to emphasize that even for those individuals who have access to fellow BAs' specific industry knowledge, the diversification-performance effect is still negative. This finding indicates that BA networks may not provide enough distant knowledge to fully mitigate the overdiversification effect. The search literature has suggested that individuals need to be "communication stars" who excel at maintaining external and internal information sources to reach this goal (Allen, 1984; Dahlander et al., 2016).

Aside from a handful of studies (e.g., Capizzi, 2015; Mason and Harrison, 2002; Riding, 2008; Wiltbank, 2005), previous research has not examined BA investment returns much. Our study not only reports the portfolio returns of 142 members of a professional angel investment platform but also points toward measures that allow BAs to structure their portfolios and influence their investment returns. Although our results suggest that portfolio returns may vary across different levels of diversification, the proportion of BAs who, on average across all levels of portfolio industry diversification, achieved an IRR over 50% was 43.26% in our sample and thus much higher than the 23% reported by Mason and Harrison (2002) for a sample of independent BAs. This finding is noteworthy because it suggests that BA investing should be considered a diversifiable asset class and that building a moderately diversified portfolio may allow angels to achieve superior returns after all.

Although not the core focus of this study, our paper also provides first insights into the role of deal leaders in angel organizations. The results of our analysis indicate that despite deal leaders being more experienced BA investors—both in terms of number of investments and tenure with their networks—deal leaders experience lower overall portfolio performance. A reason for this finding might be that investors are often asked to function as deal leaders on transactions for which they have the most industry experience or "paper fit" to the investment opportunity. Accordingly, deal leaders might sense a social obligation toward their communities or fellow investors to participate in investment opportunities that they would not have selected otherwise. As we learned from the collaboration with the platform, the deal-leader role often leads to a subsequent board appointment, which may be time consuming. Also, Jackson et al. (2012) found that despite active engagement being positively related to investment returns, increasing the number of investments while intensively assisting portfolio companies is negatively associated with portfolio returns. In line with our findings, these arguments suggest that BAs who act as deal leaders may face multiple agency problems (Kaplan and Strömberg, 2004) that aggravate their cognitive overload and decrease their ability to make informed investment decisions. As deal leaders are important actors in angel investment platforms and act as gatekeepers (Paul and Whittam, 2010), we encourage further studies to examine their role and behavior in these platforms in further detail.

7.1. Practical implications

Understanding the extent to which portfolio industry diversification influences the returns of BA investing via angel investment platforms is essential for individual BAs and operators of angel investment platforms. Our results indicate that BAs should build their

portfolios with caution because high levels of industry diversity can potentially lead to reduced portfolio performance. To circumvent a “spray and pray” approach to portfolio diversification, our results show that BAs may benefit from their co-investment networks to mitigate the overdiversification effect. BAs who have access to industry knowledge through a central position within a network of industry specialists tend to do much better at higher levels of portfolio industry diversification. As such, angel investment platforms should examine how they can best facilitate the exchange of industry knowledge among their members. Co-investment networks, especially those that are built with dissimilar peers, need to be promoted so investors can achieve higher returns from increasingly diversified portfolios. Because diversification may be a new portfolio strategy arising from angel investment platforms, we encourage the operators of these platforms to utilize their legitimacy to educate BAs about the costs and benefits of portfolio industry diversification.

7.2. Limitations and future research

This study has certain limitations that provide potential avenues for future research. A central assumption in the BA literature (e.g., Mitteness et al., 2016) as well as in our study is that BAs actively engage in knowledge exchange. While this assumption is often true, in some cases, especially with novice BAs, investors might rely more heavily on (i.e., mirror) the most prominent and experienced investors to make their investment decisions and thus restrict their involvement in active knowledge exchange. Therefore, it would be interesting to examine the actual exchange of knowledge that takes place among BAs. Furthermore, we acknowledge that a variety of factors beyond diversification and industry knowledge that we could not completely account for in our study may affect BA performance. Despite our best efforts to control for established factors in our models, future research could extend our work by explicitly considering other potential drivers of BA investment returns. Although we ran additional tests to include the effect of BAs' main area of expertise, we were not able to account for BAs' experience across all relevant industries. Furthermore, our measure of industry knowledge access weights the knowledge of BAs' networks with portfolio specialization. We encourage future studies to consider other forms of experience or education as potential weights when measuring industry knowledge access in BA co-investment networks. Also, we did not have information regarding the applicability of BAs' experience in different industries. It might be that experience gained from one industry or one technology (e.g., artificial intelligence) is not only applicable in one industry but can also help BAs choose their investment targets more wisely across larger pools of industries. Thus, our findings should be viewed in light of this shortcoming, and future research investigating BA portfolio diversification should make an effort to control for these aspects to a larger extent. Future studies should also investigate whether our results are generalizable to other similar contexts, such as VC firms. Finally, we limit our study to industry diversification. Despite our choice to focus on portfolio industry diversification, our theoretical reasoning could also be used to study other types of diversification, such as geographic diversification or stage diversification.

8. Conclusion

The angel market has dramatically changed in recent years. Instead of acting alone, BAs are forming investment syndicates through angel investment platforms. Although angel investment platforms have changed the way BAs approach strategic portfolio decisions, the literature lacks an empirical understanding of their performance effects. The results presented in this paper suggest that portfolio industry diversification is beneficial to BA portfolio performance at medium levels of portfolio diversification but harmful at initial and high levels of portfolio diversification. Although BAs may benefit from diversifying their portfolios to a certain extent, the costs of distant search outweigh the benefits after a certain threshold. Our analysis supports the notion that it is important for angel group members to develop a central network position to access fellow investors' specific industry knowledge and thus mitigate the negative consequences of overdiversification. Given this emerging phenomenon, our research highlights the importance of knowledge relationships and knowledge transfer among BAs. Overall, our hope is that this study will encourage future research on BA syndication and the ways BAs develop and diversify investment portfolios.

CRedit authorship contribution statement

Torben Antretter: Conceptualization, Data curation, Formal analysis, Methodology, Project administration, Visualization, Writing - original draft, Writing - review & editing. **Charlotta Sirén:** Conceptualization, Methodology, Formal analysis, Visualization, Writing - original draft, Writing - review & editing. **Dietmar Grichnik:** Conceptualization, Project administration, Supervision, Writing - review & editing. **Joakim Wincent:** Conceptualization, Methodology, Formal analysis, Writing - original draft, Writing - review & editing.

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