Academic Entrepreneurs and Market Opportunities in Artificial Intelligence: A Problem-solving Perspective

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ABSTRACT

Founding teams rely on their prior experiences to identify market opportunities for their new ventures. Contrasting founding teams with and without academic founders, we argue that academic entrepreneurs' problem-formulation and solving approach helps them think at a higher level of abstraction and solve foundational problems, which leads to the development of technology that generates more market opportunities for their new ventures. We use a sample of 1,023 new ventures in the Artificial Intelligence field and find support for our prediction that teams with academic entrepreneurs pursue more market opportunities. We find a similar relationship for doctorates but this relationship weakens with time spent in the industry. Lastly, the number of market opportunities positively relates to new venture financing, which underscores the importance of our study.

1. INTRODUCTION

Technology-based start-ups can generate various market opportunities that require the founding team to choose which opportunities to initially pursue and develop (Gruber, MacMillan & Thompson, 2008; Shermon & Moeen, 2022). Founding teams naturally draw upon their pre-founding experiences (Agarwal, Echambadi, Franco & Sarkar, 2004; Bercovitz & Feldman, 2006; Bayus & Agarwal, 2007; Agarwal & Shah, 2014; Roche, 2022), including when pursuing options for market opportunities (Beckman, 2006; Gruber, 2010). For example, prior entrepreneurial experience combined with managerial or marketing experience, might shape the set of opportunities (Gruber, MacMillan & Thompson, 2012). Likewise, when one of the founding team members had an experience that no other member had, the new venture was more likely to build on this unique experience and enter the corresponding geographic or product market (Fern, Cardinal & O'Neill, 2012).

While prior work has focused on the association between business experience and market opportunities, little is known about the effects of academics being on the founding team. Academics leading the development and commercialization of technologies is common for technology-based new ventures (e.g., O'Shea, Allen, Chevalier & Roche, 2005; Bercovitz & Feldman, 2006, 2008; Shah & Cox Pahnke, 2014; Moeen, 2017; Roche, 2022). Academia has strong influences on individuals' skills and knowledge, that differ substantially from the ones that accrue from non-academic experience within the industry (Agarwal & Ohyama, 2013; Agarwal & Shah, 2014; Roche, Conti & Rothaermel, 2020). These differences may have a profound effect on the founding teams' ability to generate technologies that are applicable across the market opportunities they want to pursue. We, therefore, ask to what extent will these differences that emerge between academic and non-academic experiences influence the number of market opportunities a new venture might initially pursue.

In response, this paper theorizes that the inclusion of academic entrepreneurs on the founding team increases the number of market opportunities generated by a new venture. This increase likely originates from academics' approach towards problem-formulation and problem-solving, which is distinct from non-academics' approach. Drawing on the problem-solving perspective of the firm

(Nickerson & Zenger, 2004), and relying on in-depth interviews with academics, employees, and entrepreneurs, we posit that the academic context presents unique features in terms of goals, incentives, and opportunity costs that influence academics to regularly engage in high-construal (or highly abstracted) thinking in their domain (Cummings & Nickerson, 2021; Park & Baer, 2022). Cognition at high levels of abstraction enables more comprehensive problem formulation, which leads to the creation of more comprehensive (or general) technologies that are applicable across many domains and can therefore be associated with many markets (Levinthal, 2017). Conversely, cognition at low levels of abstraction enables narrower-scoped problem formulation and leads to more targeted applicability of the resulting technologies created. We thus expect that conditional on selecting into entrepreneurship, teams with an academic entrepreneur will pursue more market opportunities than those without an academic entrepreneur.

As the academic journey starts with the attainment of a PhD degree, doctoral training itself may be a source of differences in problem formulation and solving and may leave imprints on PhD holders' mindset (Stinchcombe, 1995; Beckman & Burton, 2007; Chen, Williams & Agarwal, 2012; McEvily, Jaffee & Tortoriello, 2012). All PhD holders will benefit from the problem-formulation and solving acquired during their doctoral training and will later go on to create broader-scoped technologies in their ventures. If our theorized mechanism is supported, then we expect to observe founding teams with at least one PhD holder to be associated with more market opportunities relative to those without. Further, if PhD holders subsequently become faculty, they continue to engage in this problem formulation and solving approach, while those who transition into industry jobs are likely to also adopt the norms and practices of the industry, due to the influence of local contexts (Bercovitz & Feldman, 2006; Dokko, Wilk and Rothbard, 2009). The latter are thus less likely to continue to practice the problem formulation and solving approach acquired during their doctoral days, especially as they spend increasingly more time in industry jobs. Therefore, we further expect that teams with academic entrepreneurs will pursue more market opportunities compared to teams with PhD holders who worked in the industry before transitioning into entrepreneurship. Last, we expect the association between PhD holders who worked in the industry and the number of market opportunities to attenuate with the amount of time they spent in the industry.[1]

We test our hypotheses on 1,023 new ventures within the field of artificial intelligence (AI). This context is appropriate because, like an industry in its early stage, an emerging field exhibits a higher incidence of academic entrepreneurship as compared to more established industries (Klepper, 1996; Zucker, Darby & Armstrong, 1998; Shane, 2001; Stuart & Sorenson, 2003a, 2003b). We find that founding teams with at least one academic founder generate technologies that have 13 percent more market opportunities than those without. The result is robust to accounting for other potential explanatory factors like the new venture's age, the team's prior functional experiences, the team's potential ability (proxied by past education), the social media prominence of the venture, the new venture's patented inventions and the support of the university's technology transfer office (TTO). Further, we also find that the presence of a non-academic team member with a PhD is positively associated with a higher number of market opportunities, but this association is attenuated with the number of years the individual spent in the industry. Consistent with our expectations, we find that the number of market opportunities is higher among teams with PhDs who subsequently join academia (before founding a new venture) relative to those who do not. Moreover, bolstering our hypothesized mechanism that academics' problem-formulation and solving approach leads to the development of general technologies, we find that teams with an academic entrepreneur generate inventions that apply to more domains, which correlate with more market opportunities. In supplementary analyses, we find evidence that the number of market opportunities is positively associated with a higher firm valuation and a higher likelihood of future liquidity events.

Our theorization highlights the relationship between entrepreneurs' problem formulation and solving approach and market opportunities pursued by their new ventures. Much of past work within entrepreneurship has focused on how prior experiences shape the knowledge of founders by offering them direct access to market knowledge (Gruber, MacMillan & Thompson, 2008; Gruber, MacMillan

[1] PhD holders who found their new venture immediately after graduation will not experience attenuation.

& Thompson, 2012; Gruber, 2010; Fern et al., 2012; Shermon & Moeen, 2022). We bring a new perspective to this literature by showing that prior experiences also shape founders' problem-formulation and solving approaches, expanding or constraining the scope of the technologies they created, and hence the market opportunities they can envision for their new venture.

While past research on academic entrepreneurship has compared and contrasted the academic context with the context of the firm (e.g., Sauermann & Stephan, 2013; Perkmann, McKelvey & Philips, 2019; Perkmann et al., 2021), this study is one of the first to unpack how contexts shape the problem-formulation and solving approach undertaken by entrepreneurs originating from these differing contexts. We further contribute to the academic entrepreneurship literature (e.g., Feldman et al., 2002; Jensen and Thursby, 2001; Katila and Shane, 2005; Lowe and Ziedonis, 2006; Nerkar and Shane, 2003; Bercovitz & Feldman, 2006, 2008; Agarwal & Ohyama, 2013; Perkmann et al. 2013; Shah & Cox Pahnke, 2014; Roche et al., 2020; Roche, 2022) by demonstrating the importance of doctoral training. Our results provide evidence that doctoral training is a plausible means through which individuals acquire a distinct cognitive framing. This indicates that prior literature on academic entrepreneurship, which has largely focused on the lack of complementary assets like operational know-how and marketing knowledge and the role played by TTOs in providing these services (e.g., Bercovitz et al., 2001; Clarysse, et al., 2005; Bercovitz & Feldman, 2006, 2008; Clarysse, Tartari & Salter, 2011), may have underestimated the role played by doctoral training in shaping new ventures' outcomes. Indeed, recent work has shown there is a close transfer of knowledge between professors and students during doctoral training, which has significant effects on new ventures' knowledge creation and performance outcomes (Roche, 2022); our findings add to this emerging literature.

To date, prior work on academic entrepreneurship has documented academic entrepreneurs' strengths—their tacit and foundational knowledge—, as well as their weaknesses—the lack of market knowledge and complementary assets. Our study reveals that despite these limitations, the academic approach to entrepreneurship, which is rooted in a distinct problem-formulation and problem-solving approach, may offer some benefits that were previously overlooked.

2. THEORETICAL BACKGROUND

Prior literature has examined how entrepreneurs' pre-entry experiences shape the outcomes of the ventures they found. Founders are often imprinted with the knowledge and processes of their prior jobs; these effects can persist in the long term and often shape their subsequent entrepreneurial efforts (Burton & Beckman, 2007; Beckman & Burton, 2008; Chen, Williams & Agarwal, 2012; McEvily et al., 2012). For instance, through their pre-entry experiences, founders accumulate human and social capital, which in turn influence various new ventures' outcomes such as growth and survival (e.g., Bayus & Agarwal, 2007; Burton & Beckman, 2007; Beckman & Burton, 2008; Gruber et al., 2012; Honoré, 2022). Further, entrepreneurs often rely on their prior knowledge, such as entrepreneurial and business experience (Gruber et al., 2010; 2012), as well as domain-specific knowledge (Fern et al., 2012; Shermon & Moeen, 2022), to identify market opportunities and decide on market orientation for their new ventures. Nevertheless, identifying and exploiting distant market opportunities remains one of the challenging yet central goals of a new venture (Shane, 2000).

In emerging technological fields, academic entrepreneurs represent a key actor in the entrepreneurial landscape (e.g., Agarwal & Shah, 2014; Moeen and Agarwal, 2017; Gofman and Jin, 2022). Academics' primary activity consists of conducting scientific research, the goal of which is to broaden the understanding of phenomena without any specific market application or monetization in mind (e.g., Stokes, 1997; Agarwal & Ohyama, 2013). Academics' focus on scientific research provides them with foundational knowledge that often serves as the knowledge source for their new ventures (Zucker *et al.* 1998; Lockett, et al., 2005; Mowery, 2005). Most often, academics directly extract their new venture ideas from decades of research (Jensen & Thursby, 2001; Feldman et al., 2002; Nerkar & Shane, 2003; Katila & Shane, 2005; Lowe & Ziedonis, 2006; Clarysse, Wright & Van de Velde, 2011). They are often helped by networks and complementary assets provided by other actors such as universities' technology transfer offices. Past literature, however, says little regarding the academic entrepreneurs' pursuit of market opportunities in comparison to non-academic entrepreneurs' new ventures.

Some of the differences between academics and non-academics stem from innate or intrinsic differences that influence their career selection. Future and current academics have an inherent passion for scientific discoveries, which sets them apart from non-academics (Stephan, 1996; Agarwal & Ohyama, 2013; Roach and Sauermann, 2015). They are curious and exhibit a taste for science. We argue that over and above these selection-driven differences, the unique features of the academic context significantly shape and amplify the differences between academics' and non-academics' problem-formulation and solving approaches. These distinct approaches shape the kinds of technologies developed by teams with academics vs. non-academics, and subsequently, the associated number of market opportunities for these technologies. Using organizational context as the backdrop of these differences, we develop a theoretical framework based on an underexplored channel through which pre-entry experience shapes the differences in these technologies: the problem-formulation and solving approach of academic versus non-academic entrepreneurs.

3. THEORY AND HYPOTHESES

While the literature on academic entrepreneurship has delved deep into '*what*' entrepreneurs know, it has arguably been less focused on '*know-how*', that is, how academics' approach to formulating and solving problems shapes what they create, and how this differs from the approach of non-academics. Yet, recent literature has highlighted that the problem-formulation and solving approach are important drivers of knowledge creation within the firm (Nickerson & Zenger, 2004; Hsieh, Nickerson & Zenger, 2007; Nickerson, Yen & Mahoney, 2012; Baer, Dirks and Nickerson, 2013). For example, Nickerson & Zenger (2004:p618) state: "the manager [or entrepreneur] must choose valuable problems—those which, if successfully solved, yield desirable knowledge or capability." In this paper, we examine how differences in pre-entry experiences may differentially shape problem-formulation and solving approaches that individuals carry over to their new ventures. These different processes are likely to guide the entrepreneurs' actions and strategic decisions (Felin & Zenger, 2009) and thus, expand or limit the market opportunities the new venture pursues.

We argue that relative to non-academic entrepreneurs, academic entrepreneurs, faculty who start a new venture, are more likely to adopt a more abstracted process of problem-formulation and solution due to their doctoral training and prior work in scientific research (Cummings & Nickerson, 2021; Park & Baer, 2022). At a micro level, this reasoning is consistent with the development of cognition as explained by the construal-level theory (e.g., Trope & Liberman, 2010). Higher levels of abstraction (or construal) of academic entrepreneurs lead to the development of technologies that generate more market opportunities than non-academic entrepreneurs, whose prior experiences constrain them to a more demand-oriented cognitive approach and heuristic method (Camuffo, Cordova, Gambardella & Spina, 2020; Shermon & Moeen, 2022), and limit the scope of the technologies they create. That is, conditional on creating a new venture, academic entrepreneurs' problem-formulating and solving perspective influences their pursuit of market opportunities.

Relying on the theoretical grounding of the problem-formulating solving perspective and on ten hours of field interviews with faculty, employees, and entrepreneurs,[2] we unpack the reasons behind this difference. We posit that this difference originates from the features of the organizational context and the doctoral training.

3.1 Problem formulation and solving in academia: The role of goals and incentives

The distinct feature of the academic context that sets it apart from a firm-based context is its research and exploration-oriented focus (Stephan, 1996), which is likely to lead to and reinforce a distinct problem-formulation approach. Academics mainly conduct scientific research with the goal of "the priority of discovery" (Merton, 1957; Stephan, 1996) for the knowledge they create in an organizational environment, that differs markedly from the industry (e.g., Perkman, McKelvey & Philips, 2019). Over their careers, academics develop an understanding of which specific research problems are more important to the scholarly community and can garner more attention and recognition from their peers such as through higher citations; this is an important form of reward in academia (Merton, 1973). Academics who focus on foundational questions that are relevant to a wide number of domains are

[2] We interviewed individuals belonging to the following groups: (1) current faculties (associate and full professors) in academic positions without new venture experience, (2) founders who founded or joined new ventures as a faculty, (3) founders who do not have PhDs and (4) founders who have trained in PhD programs but do not have work experience in academia as a faculty member. All the persons we interviewed worked in AI, whether in AI-based firms, startups or in their research. All had an engineering background and graduated from Computer Science or Computer Engineering departments for their undergraduate or more advanced degrees.

likely to fetch more recognition since their work is likely to be relevant to many more domains. This is revealed in one of our conversations with a faculty, who is also an academic entrepreneur:

> "*It comes down to what kind of knowledge are you trying to advance. Is it a very specific kind of question, which applies to a very specific industry or a domain? Or are you trying to answer a question, which would be more broadly applicable? More broadly means it's more foundational. Because it's broad other things can be built on top of that foundation. And I think, when you're trying to do more foundational work then it'll be more influential basically, and in a university, you gain reputation by being more influential.*"

He further explained that he chooses not to formulate very narrow (specific) problems because often peers within other departments within the university do not have the expertise to appreciate and reward the solution of very specific problems, but do understand more general problems and solutions:

> "*And if you want to be super specific, it's hard because you don't have the domain knowledge necessary to be super specific in the university, that requires, you know, 30 years of understanding of - say how car batteries are made- and we don't have that kind of expertise in it. We don't have an automotive department. So, you have to tackle more of the foundational questions that are more general and understood by more departments.*"

Our interviews reveal that the incentives within academia are geared towards formulating problems that can reach a broad audience and potentially connect with many different domains of studies. As a result of such an incentive regime, academics are motivated to formulate general (or foundational) problems that others can build upon and cite. Several academics iterated that within the academe, such as in computer science and engineering, the fundamentality of the problem drives the formulation and selection of the problem. For example, one computer science faculty described how his research group spent over a decade chipping away at the problem of indoor localization, whereby they attempted to make global positioning systems (GPS) which then typically worked outside buildings, also work efficiently inside buildings. When he started working on it, this was a fundamental problem, as indoor GPS could potentially form the basis of future technologies based on indoor tracking and navigation. Indeed, several solutions to this problem are used today within many industries that use indoor automation, such as indoor robots. He described how his group attempted to solve it from several different angles, such as using radio frequency, Bluetooth, acoustic audio signals, fusing with motion sensors, and finally Wi-Fi. He explained it this way:

"You start with the big problem that you want to solve. Break those problems into what pieces need to be solved and you go and attack the pieces that have not been solved in the past."

These incentives within academia shape how academics formulate problems. Since the incentives are geared towards rewarding more foundational work, academics tend to acquire deep knowledge within their domains (Leahey, 2006, 2007). To make an impact within their fields, academics must learn to identify which problems are foundational[3] and offer a novel contribution to the field, versus problems that would lead to incremental augmentations of existing work. To understand this distinction, they must first understand a complete body of related work and the connections and nuances within the literature. This requires abstraction: the ability to see the forest for the trees and adopt a comprehensive view of the work that has already been done. Then, they can identify gaps in what has not been done and would be foundational (Park & Baer, 2022) and would apply to various fields.

Academics are thus geared towards thinking in terms of high levels of abstraction, that is, high construal levels (Trope & Liberman, 2010; Park & Baer, 2022) as opposed to concrete narrow terms where the 'trees' are more salient than the 'forest'. More abstract thinking promotes more comprehensive problem formulation, which enhances the scope of the solution itself, while narrow problem formulation limits the applicability of the solution: "When a problem is formulated narrowly, strategic actors essentially operate with rudimentary cognitive maps of a problem space, which limits the number of causes and potential solutions they consider. Such a limited understanding of a problem can lead to locally optimal but globally ineffective solutions" (Park & Baer, 2022:p2). Achieving an abstracted view of the problem space allows academics to bring a comprehensive problem-formulating perspective to their new ventures. The technologies that originate from such high-construal problem-formulation will be more comprehensive, have broader areas of applicability and can be linked to more market opportunities (Levinthal, 2017).

[3] Foundational knowledge is defined as "sufficiently general to provide at least partial intellectual support for a number of specific applications and for the future learning of new applications and other fundamentals" (Bieniawski, 1994).

The lack of constraints and lower opportunity costs further bolster this problem-formulation approach (Perkmann, McKelvey & Philips, 2019; Conti and Roche, 2021). Since academic research is self-driven and academics are less answerable to organizational hierarchies than industrial scientists for the choice of their projects, they face fewer constraints regarding the use of their time and the associated deliverables than industrial scientists. Relatedly, academics also face lesser constraints in how to define the scope of academic scientists' projects. As a result, academics, especially tenured faculty, can choose ambitious, far-flung ideas and tap into distant domains of knowledge because they benefit from job stability and lower opportunity costs (Conti and Roche, 2021). They can push the boundaries of their scientific approach as far as they can take their technology without worrying about monetization (Sauermann & Stephan, 2013). Their formulation of the problem itself is therefore only limited by the boundaries of their abilities, and that of science. Indeed, one faculty says

> *".. it is the way it should be. Right, like one can argue about like, say, autonomous cars, right? One can argue either way like some people believe that there's no need for cars to be autonomous, and in some ways you can agree with them. But a lot of academics will believe that cars need to be autonomous because they can be."*

The goals and incentives of academia also shape *problem-solving*. One way that academics identify fundamental research questions is to delve into *why* the technology works. When solving a problem, they adopt a similar approach. Academics rely on sciences rather than on practical considerations and heuristics.[4] This approach originates from their propensity to think at high construal levels. Indeed, Wilson, Crisp & Mortensen (2013:p631) state that "High-level construal leads to interpretations of actions that focus less on *how* and more on *why* an action is performed". Focusing on the *why* leads academics to view problems in terms of their characteristics; they view problems as belonging to different *classes*, where different problems can be classified in terms of their common traits and characteristics. When targeting specific problems, they aim to develop solutions that ideally apply to entire classes of problems rather than individual problems, which in turn benefit a wider

[4] By heuristics we mean the Oxford Language Dictionary definition of "proceeding to a solution by trial and error or by rules that are only loosely defined". These approaches are geared towards achieving a short-term goal but are not guaranteed to be replicable, generalizable over many similar problems. They are more 'one off' solutions.

community of researchers. Developing general solutions can therefore help academics receive more recognition for their work.

Several faculty members stated that they develop algorithms based on solid mathematical foundations that are generalizable to classes of problems, rather than one-off solutions that address one specific need and cannot be applied to a different problem. They explained that they rely on mathematical proofs to verify the accuracy of their algorithms; this approach of 'formal verification' (using mathematical proofs to verify accuracy) is not used in many firms. At the center of their research process lie the answers to *why* the technology works. One faculty noted the difference he observed between academia and industry in that regard:

> *"So just to give an example, we are developing some algorithms for doing some verification. And then we realize that we, the algorithms people in academia, always relied on models. Someone writes down a mathematical model. But then we talk to industry and the reaction was ….* [shrugs]. *Well they often don't have models, right? Or they have a partial model. So, they formulated this problem where you have a partial model and the rest of it is just some code for which you would not be able to write down the model."*

Another interviewee (PhD holder turned entrepreneur) who received his PhD in applied computer science reiterated similar ideas and stated that he and his colleagues go about solving problems in a systematic way starting with prior literature whose theoretical models may have been developed a hundred years ago.

To summarize, the goals and incentives within academia are conducive to individuals adopting a distinct approach to formulating and solving problems. Their formulation of more general problems leads to the development of more comprehensive technologies. Their problem-solving approach allows them to develop solutions that can solve classes of problems rather than one problem at a time. The lack of opportunity costs and fewer constraints further allow them to pursue the development of their technology as far as the bounds of science and their ability will allow. Academics thus pursue a 'science first' approach toward the development of their technologies. Our interviews revealed that academics often engage in decades of research, without engaging in monetizing, and most often academic entrepreneurs identified the ability to monetize their idea much after the creation of the core technology. All of the academic entrepreneurs we interviewed emphasized that their ideas for their new ventures had their genesis in years of explorative research.

3.2 Problem formulation and solving in the industry: The role of goals and incentives

Founders who build their careers in the industry are likely influenced by the industry's orientation towards economic growth and profitability in developing or modifying their problem-formulating and solving approaches. The incentive regime that is practiced within the industry accordingly shapes the problem formulation approaches that employees later bring to their new ventures.

Expectedly, interviewed employees suggest that they solve problems to increase productivity, which generates a rapid impact on the bottom line (stated by an employee in the context of their previous job) or they follow clear directives from the board or top managers on what features to develop depending on markets' needs (stated by the same employee in the context of their current job). Our interviews uncovered that individuals from various functional departments convene in the room together during meetings, and those from sales, marketing, and finance often weigh in on technological features of products under development. The scope of the technology is thus determined very early on by these 'people in the room'. The market's needs dictate the development of technologies within the industry; most firms pursue a "markets first" approach to their problem formulation and technology development.

When such employees found their new ventures, they retain this mindset and use this problem-formulation approach to develop technologies within the new venture. Since economic profits are top of mind, these employee-turned-non-academic entrepreneurs may often be demand-oriented, and use their new venture to target specific needs within the market (Shermon & Moeen, 2021).

In various conversations, entrepreneurs with prior experience in the industry explained that they started their entrepreneurial endeavors by focusing on the features of the market that demonstrated a well-defined "pain point" or a need that they believed they could fulfill. They then developed technology that was aimed towards tackling that specific need within that market. These interviews revealed that their approach towards the development of their technologies carries imprints from what they witness within the industry: sales, growth, and market considerations featured as prominently as the features of the technology itself. One non-academic entrepreneur described how they spent hours talking to farmers to understand the problems they faced within agribusiness. These conversations highlighted the fragmentation and information asymmetry within the agricultural market in their home country. Farmers were not connected to each other, to markets or to suppliers efficiently and comprehensively; this led them to spend disproportionately high amounts of time and effort in tracking information and coordinating through middlemen. These observations inspired the entrepreneur to develop an app that connects farmers to various parties and provides them with information pertaining to all aspects of their value chain. The entrepreneur's idea was born from the identification of the need within the market, she judged that the potential demand and market size were appropriately large, and her application was therefore targeted specifically towards solving that specific need.

The approach to solving problems within the industry differs from that within academia and will influence employees-turned-non-academic entrepreneurs. In contrast to academics who rely on sciences and general solutions, those working in the industry, facing time and profitability constraints, might at first rely on heuristics and focus on generating a solution that works and pay limited attention to the proof or the reason *why* a solution works (Ott, Eisenhardt & Bingham, 2017).[5] This heuristics-based approach is targeted toward solving a problem at a time rather than a *class* of problems and constrains individuals from adopting a scientific approach (Camuffo et al., 2020). As a result, the heuristic approach may limit the development of general technological solutions. From our interviews with first-time entrepreneurs and new venture employees, we confirm that they start with opportunities that run on heuristics based on their past experiences.

> *"So the first part is going to be like heuristic based […], but this is one component of the business. And the second component is providing agriculture news and government subsidies, and schemes relevant to your region."*

[5] While some larger technology companies do focus on long-term R&D and focus on developing algorithms rather than heuristic based approaches, on average, non-academics are focused on finding an immediate solution to a problem without caring *why* that solution works, and as a result, the solutions have inherent limited applicability.

To summarize, the incentives within the industry are geared toward developing a more demand-oriented mindset among employees. This approach originates from lower-construal thinking compared to those in academia. Prior-employees-turned-non-academic entrepreneurs adopt a 'markets first', demand-oriented approach towards developing their technology. From the inception of their ventures, these technologies are targeted and focused on solving specific needs within markets and are likely to generate fewer market opportunities.

In contrast to the industry approach, the academic problem-formulation is more likely to be comprehensive, and applicable across wider domains. Academic solutions are more general and geared towards solving more general classes of problems. Last, the lack of opportunity costs and fewer constraints allow them to push the bounds of their technology without worrying about monetization or markets. This 'science first' approach contrasts with the 'markets first' approach within the industry. As a result, we expect the technologies developed by academics to be more comprehensive, and applicable across more domains and hence allow founding teams with an academic entrepreneur to pursue more market opportunities relative to those without. Therefore, we posit that

> *Hypothesis 1: New ventures founded by a team including at least one academic entrepreneur will be associated with more market opportunities than those founded by teams that do not include an academic entrepreneur.*

3.3 Problem formulation and solving: The role of doctoral training

We next propose that if true, our argument may apply to all founders that hold PhD degrees since the problem formulation and solving approach is first initiated during the beginning of their doctoral days. Doctoral training consists of rigorous and scientific training to formulate and solve research problems. Interviews with academics revealed that faculty steer their students towards seeing the big picture and tackling the 'big problems', rather than narrow problems during their doctoral training. Academics train their doctoral students in their mold (Roche, 2022). The problem-formulation approach they develop is passed on to their students. They too are taught to adopt a high-construal approach, have a comprehensive view of the field, and find a 'gap' that they can contribute to by writing an impactful thesis.

In our conversations, one faculty described his PhD students' dissertations as 'long-term' and 'ambitiously scoped' and cited 'novelty' as his chief consideration in evaluating which problems he and his team of doctoral students should focus on. For example, one of his students is working on designing a robot to pick any fruit from any tree. This difficult problem will likely take several years and multiple scholars to solve, but if successful, the underlying technology will have opportunities across many domains. For example, the technology can be used to design a robot that can be deployed not only to pick fruit from any tree but pick items from shelves in grocery stores, warehouses, etc. Non-doctoral students such as master's students by contrast focus on short well-defined projects chosen by the faculty, where they can implement a goal quickly within a few months; by construction, these problems are typically much narrower in scope. For example, while PhD students design the algorithms and systems that form the backbone of such robots, a master's student's task would be to write a small well-defined module of code (where the parameters were set by faculty or PhD students) or test smaller parts of their algorithms.

Since doctoral students are required to tackle more foundational questions, they are trained in fundamental tools rather than specific skills that apply to a specific problem. For example, doctoral students in Computer Science and Engineering, throughout their training, will learn more foundational skills such as developing algorithms that are grounded in mathematical models, as these can be broadly applied, rather than searching for ad hoc solutions. According to one of the faculty we spoke to:

> "*I tend to push them into developing a much richer toolkit that would help them in the long-term career because they're not going to do the same thing over a career path of 40 years. So, I try to enrich the toolkit as much as I can because I know whatever they did their PhD on is not going to have much of shelf life. They're going to write, they're going to go into vast areas and having the fundamentals right and having a broad set of fundamentals is the key. […] As opposed to the industry I will show [that in academia] you don't even have to think about opportunities, just know the math, just learn the math, just learn the algorithms because this is your tool kit with which you are going to use. You start to think about what your PhD thesis looks like, from what problem are you solving? Is this a real problem at all? So, you encourage your PhD students to think in the context of the bigger problem.*"

To summarize, future academic entrepreneurs develop their problem-formulation and solving approach during their doctoral days. Doctoral training teaches students how to distill large amounts of prior work, identify foundational contributions, and formulate comprehensive problems through high-construal thinking. Students also learn to solve problems based on more general tools. Doctoral training leads students to develop a distinct problem-formulation and solving approach that is likely to generate more comprehensive technologies.

The cognitive mindset that is acquired during their days of doctoral training will shape how they frame problems later on as well. Like many other seminal influences that leave important imprints on entrepreneurs, this high construal approach towards formulating problems might have imprinting effects on doctoral students, which they will carry across different organizational boundaries (e.g., Stinchcombe,1965; Bercovitz & Feldman, 2006; Dokko et al., 2009; McEvily et al., 2012; Marquis & Tilcsik, 2013, 2016). These imprints will shape their cognitive mindset and their actions or choices even after graduation. Therefore, when these PhD holders go on to found ventures—even if they spend time within the industry before founding their new ventures—their problem-formulation and solving approach are likely to lead to the development of more general technologies relative to those that never undertook doctoral training. These technologies will apply to more domains and should be associated with more market opportunities. Therefore, we expect that

Hypothesis 2: New ventures founded by a team including at least one PhD holder will be associated with more market opportunities than those founded by teams that do not include any PhD holder.

3.4 Problem formulation and solving: The attenuation

We next propose that the influence of doctoral training attenuates over time unless individuals continue to engage in high-construal thinking. Localized influences attenuate the effects of imprinting; individuals are "influenced by both social learning before an individual joining the organization, and subsequently by the individual's exposure to relevant peer behaviors within the organizational subunit" (Bercovitz & Feldman, 2006). When PhD holders become faculty, they continue to engage in the problem-formulation and solving approach that they learned during doctoral training. They hone their high-construal thinking skills through collaboration with other academics.

If they leave academia, however, and acquire experiences within the industry, they have less opportunity to do the above. While PhD holders initially bring their distinct problem-formulation approach to the firm they join, over time, they likely adapt to the norms, practices, and orientation of their industry-peers. Indeed, Dokko et al. (2009:p55) note that "cognitive models that employees hold can be challenged and replaced with scripts and schema that are more congruent with the new environment (Bartunek & Moch, 1987)" and "the current firm replaces the profession or industry as the salient institutional referent". Since firms outside of academia are more likely to adopt a low-construal and demand-oriented approach to problem formulation and solution, we expect PhD holders to adopt more of the latter approach over time. That is, the influence of doctoral training attenuates with time spent in an organization where the high-construal approach is not practiced.

Thus, in the context of new ventures, we expect to find the imprinting effects of high-construal problem formulation to be most prominent among academic entrepreneurs (i.e., PhD holders who stayed and worked in academia). For PhD holders who found jobs in the industry, the influence of high-construal training attenuates with time spent in the industry. Therefore, we expect that

Hypothesis 3a: Teams with an academic entrepreneur will pursue more market opportunities compared to teams with a non-academic PhD holder.
Hypothesis 3b: The relationship between having a non-academic PhD holder and the number of market opportunities will be negatively moderated by PhD holder's time spent within the industry.

4. CONTEXT: AI

Artificial Intelligence (AI) was coined as a scientific field in 1955 when John McCarthy, a professor in mathematics turned computer scientist, started a summer school, gathering other academics interested in this fledging field (McCarthy et al., 1955). The summer schools offered a promising starting point as McCarthy himself and many of the attendants created the first AI labs in their respective institutions, Stanford, MIT, and Carnegie Melon University (Wooldridge, 2020). In addition to these first AI labs, academic researchers from cognitive science, logic, economics, and mathematics developed the first theoretical models used in AI (Wooldridge, 2020).

The AI field rose to fame several times during the 20th century but had difficulty sustaining momentum in research for a prolonged period until the second decade of the 21st century. Nevertheless, prominent academics have led the development of significant technologies over the past five decades. One of the most significant developments within AI, the utilization of machine learning including the neural network technique that leads to deep learning, found its origins in academia.

Academics developed the idea of neural networks (such as LeCun & Bengio, 1995; LeCun, et al., 1998) through the 1980s and 1990s. Many of these academics went on to start their ventures. For example, Professor Rodney Brooks from MIT instigated research into robotics (Wooldridge, 2020) and subsequently became one of the most famous academic entrepreneurs as he founded iRobot, the parent firm of Roomba the cleaning robot, and two other ventures since then (Atoji Keen, 2013; Feldman, 2020). Later on, key industry players such as Meta, Alphabet, and Amazon became more important in the 2000s in the light of their ability to scale up and architect large neural networks, and train them on their huge data (Jacobides, Brusoni & Candelon, 2021). Other large firms have joined the fray. Recently Nvidia created convincing but fake pictures of people and DeepMind developed a program that defeated the world champion of Go (a complex Chinese strategy game) and later, developed a system to understand protein folding (Wooldridge, 2020).

Artificial intelligence has revolutionized various industries from manufacturing to robotics and has affected functional areas relevant to all industries such as human resources or risk management (Zhang et al., 2021). Due to its pervasiveness across industries, industrial funding has surpassed the funding by academic institutions (Zhang et al., 2021). Still, major national institutions finance university projects. For instance, the National Science Foundation (NSF), which funds new developmental research, invested $500 million in AI-related research (Media Affair, 2020), designated AI as one of its priority areas in its 2021 budget, and AI has been one of the underlying technologies under its "Big Ideas" project. In addition, the private sector relies heavily on highly educated graduates, suggesting that more funding will have to reach academia to grow the programs in computer science needed to provide human capital to the AI field. In the past 10 years, the number of new AI PhD graduates in North America who chose industry jobs continues to grow, as its share increased by 48%, from 44.4% in 2010 to 65.7% in 2019 (Zhang et al., 2021).

5. DATA AND METHODS

5.1 Sample and Data Construction

To test our hypotheses, we utilized data from various sources including Crunchbase, LinkedIn and Pitchbook. First, from Crunchbase, we collected the entire list of founding teams in the AI industry headquartered in the United States. Recent papers in entrepreneurship have identified their sample of new ventures from Crunchbase (e.g., Conti & Roche, 2021; Reese, Rieger & Engelen, 2021). Among these US-based teams in the AI industry, we retained the 3175 teams (75.2%) that had two or more members listed as founders.[6] Since Crunchbase data contains the LinkedIn address of founders, we used these addresses to collect their career history data from public LinkedIn profiles. We complemented the missing addresses by a manual search on LinkedIn based on the names of the founders as well as the organization name and the founded year (e.g., Reese, Rieger & Engelen, 2021). To retain each team in our dataset we had to be able to find the career history data for all founder members; this was not always possible. We were able to collect the career history data for 68.8% of associated founders, which resulted in 1,160 founding teams with career history data for all members. From this data, we captured their employment and educational background. Finally, we turned to Pitchbook to get funding data. Pitchbook collects detailed information on private firms and funding deals with professional investors and is becoming more commonly used in studies on entrepreneurship (e.g., Ewens, Gorbenko & Korteweg, 2022). A small number of ventures were not found in the Pitchbook database and had to be dropped from our sample. Our final sample consists of 1,023 founding teams with venture-level data as well as career history data for all members.

5.2 Dependent variable

Number of market opportunities. To measure the number of market opportunities, we obtained the number of "Verticals" that Pitchbook assigned to each team based on the applicability of their technology. According to PitchBook, "[A vertical] describes a group of companies that focus on a

[6] Following prior work on founding teams, we excluded single entrepreneurs (e.g., Beckman, 2006; Honore, 2022).

shared niche or specialized market spanning multiple industries."[7] This definition is in line with older scholarly work. For instance, Mosakowski (1991) explains as follows: "'Vertical markets' refers to specific industrial niches for computer products. The breadth of these niches varies considerably, ranging from large niches such as the health-care industry to narrow niches such as the automobile repair industry (p.119)." Compared to industry sectors, verticals often signify applicability across various industries. For example, Fintech, one of the verticals, can provide a product bridging commercial lending applications, insurance products, and financial platforms. Pitchbook's list of verticals as a measure of market opportunities has gained legitimacy and traction outside of academia as well. For example, National Science Foundation (NSF) refers to the same list of verticals provided by Pitchbook within the report prepared by the National Science Board, titled "*Science and Engineering Indicators"*. [8] We provide the complete list of verticals within our sample in Table A in the Appendix.

5.3 Independent variables

Having an academic entrepreneur (AE). We coded this dummy variable as 1 if the team has any founder joining from the university as a faculty and 0 otherwise. To identify AEs, we followed the classification procedure by Fuller & Rothaermel (2012) and examined the job titles that individuals held at universities. The titles of the jobs held at universities include professors as well as research associates.[9]

Having a PhD holder. We coded this dummy variable as 1 if the team included at least one individual who indicated that they hold a PhD degree and 0 otherwise.

Time in industry. This variable was calculated for the sample of teams that included at least one non-AE PhD holder. This measure was used in the test of H3b, to capture whether time spent in the industry attenuates the effect of holding a PhD. We took the start year of the first job spell and subtracted it from the founding year of the venture. For teams that included more than one non-AE PhD holder, we took the minimum of this value. We chose the minimum value since it is the most

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[7] Source: https://pitchbook.com/what-are-industry-verticals; Last accessed on February 6th, 2023.

[8] Pitchbook verticals can be found within the Technical appendix in NSB-2022-6, Technical Appendix (*https://ncses.nsf.gov* › pubs › nsb20204-tabs08-063). Last accessed on February 2nd, 2023

[9] As a robustness test, we expanded the definition to also include staff and post-docs as per Shane (2004), Agarwal and Shah (2014), Roche et al. (2020), among others. See section 6.2 for more details.

conservative way to test the attenuation of holding a PhD. The member who would have experienced the least amount of attenuation will be the most influential member to help the team pursue more market opportunities. This measure, therefore, gives us the lowest bound on the effect we are trying to capture.

5.4 Control variables

We also controlled for a series of founding team characteristics which could plausibly have associations with the outcome variables: team age, team size, team's average years of experience, team's average number of employers, whether the team has any female, whether any founder graduated from a top 10 university, any serial founder (has previous founding experience) or any foreign founder (has undergraduate degree from outside of United States). We also included location controls (East Coast, West Coast, and the rest).

6. RESULTS

Table 1 presents the descriptive statistics. In our sample, 64 out of 1,023 teams (6 percent of teams) have at least one academic entrepreneur. The number of verticals ranges from 0 to 9, with a mean of 3 (See Figure 1 for distribution.) The average team size is 2.53, and the average firm age is 4.80 years old. About one-fifth of new ventures have a female founder, and the average number of years of experience is 12.86. Seventy-two percent of new ventures have a founder with previous founding experience.

We also checked for observable differences across teams with AE and without. The results from the t-tests are reported in Table B of the Appendix. We see that the teams with AE are more likely to include a female founder and foreign founder, but less likely to include a serial founder. Also, the average number of past employers was lower for teams with AE. We observe a similar pattern when we estimate the likelihood of having an AE as a function of these observables. The results are reported in Table C of the Appendix. Since the teams with and without AE differed on these dimensions, we needed to control for these variables in all our models. To further understand which factors determine the likelihood of including an AE, we also used LASSO (Least Absolute Shrinkage and Selection Operator), following the approach used by Roche (2022) in her work on academic entrepreneurs. We found that all variables were important predictors of the inclusion of AE in teams. This procedure further validates the use of the control variables to address the selection bias (Belloni et al. 2014b, Conti and Guzman 2019).

We used OLS regressions to test the relationship between academic founders and the number of verticals. Table 2 shows the results of our OLS regressions. Model 1 shows support for our main hypothesis: the positive coefficient on academic founders indicates that having an academic founder is positively associated with the number of verticals. Teams with an academic founder are likely to have 0.39 more verticals (13% higher than the mean) compared to those without (β=0.39, p=0.04).

Next, we tested H2 to examine whether the doctoral training provides a similar advantage to all individuals who have gone through this training (regardless of the type of post-doctoral experience) by first examining the correlation between teams with PhD holders and market opportunity. Our results indicate that PhD holders indeed contribute to more applications (Model 2 in Table 2; β=0.41, p=0.00), supporting our argument that doctoral training is an important factor to understand the differences among entrepreneurs.

In H3a and H3b, we proposed that PhD training may foster a unique approach to problem formulation and solving, but this may not persist if individuals work outside of academia for an extended period. We first examined the role of post-doctoral work context by dividing the teams with PhD holders into those with AEs and those with non-AE (Model 3 in Table 2). Both were positively correlated with the number of market applications, consistent with our arguments on the role of PhD training. However, the magnitude of the coefficients was larger for teams with AEs (β=0.54, p=0.01) compared to those with non-AE PhDs (β=0.39, p=0.00), despite some overlap in their confidence intervals (p=0.22, one-tailed test). The magnitude of the coefficients indicates that the teams with AEs will likely generate more market opportunities than teams with non-AE PhDs. In H3b, we hypothesized that the time outside of academia will diminish the effect of PhD training. We test this by performing a subsample analysis among the non-AE PhD holders, and estimating the number of market opportunities as a function of the year of industry experience.[10] We initially did not find a linear effect of industry experience within this sample (Model 4), so we used a spline specification to capture any non-linearity. This helped us explore how the effects of industry experience on the number of market opportunities might vary as the years of experience increase. The spline splits industry experience into two separate variables: one variable measures the effect of experience between zero and the threshold (or the "knot") and the second variable measures the effect of experience above the threshold. The estimated coefficients on these variables capture the effect of experience on the number of market opportunities *within* that range of experience. We present a variety of analyses with thresholds set at 5, 10, and 15 years. The results are presented in Models 5-7 of Table 2. Across all models, we do not see the effect of industry experience below the threshold. In Model 6, we start to see the effect of industry experience in the second variable (β=-0.04, p=0.03); that is, the effect of time in the industry becomes negative once the total number of years of experience exceeds 10 years. The effect is especially strong and the estimation becomes more accurate once the threshold is set to 15 years (β=-0.07, p=0.01). This suggests that a moderate number of years in the industry after receiving a PhD does not affect the founders' ability to pursue more market opportunities; however, for those who have spent at least 10 years within the industry after obtaining their PhD, each additional year (after the ten years) that they spend within the industry is negatively associated with the number of market opportunities.

Collectively, our results suggest that the benefits of PhD training are sustained by working in academic contexts; they diminish for individuals who work in contexts outside of academia. We next examine whether the relationship between academic entrepreneurship and the breadth of market opportunities may have been driven by alternative mechanisms.

[10] PhD holders who immediately found firms after completing their degree will be coded as having zero years of industry experience, but we did not observe such individuals among our sample.

6.1 Exploring mechanisms and alternative explanations

6.1.1 Problem-formulating and solving shaping different kinds of inventions within the new venture

We theorized that the approach to framing and solving problems of academic entrepreneurs contributes to the development of comprehensive technologies with broader market applicability. If this is true, then we should see the same mechanism at work in the creation of knowledge within the firm. That is, the problem formulation and solving approach will allow them to generate more generally applicable inventions, which in turn will lead to more market opportunities.

To test this idea, we collected data on the patents produced by all new ventures in our sample from the USPTO database. In cases when they were acquired by other firms, we only tracked the patents produced by the team before the acquisition. Examining patents rather than publications offers a fair comparison across new ventures, as the number of publications might be highly skewed towards academic new ventures. First, we compared the number of patents produced by teams with and without academic entrepreneurs. We found that teams with academic entrepreneurs are likely to produce a higher number of patents. The average number of patents of teams with an academic entrepreneur is 4.2 whereas other teams have an average of 1.7 patents ($p<0.01$). Next, we captured the applicability of the inventions by measuring the generality of each patent produced by the founding team; generality is calculated as one minus the sum of the squared proportion of patents produced across different IPC classes (Trajtenberg et al., 1997; Valentini, 2012). A higher level of generality indicates that the patent is cited across various patent classes, rather than being relevant to only a few classes. High generality therefore shows that the patented invention is more likely to be applicable than others with a lower level of generality. We then aggregated the generality measure to the team level by taking the average of the measure. We first estimated the average generality of patents as a function of having an academic entrepreneur. The results are presented in Model 1 in Table 3. We find that teams with an academic entrepreneur are more likely to produce patents with high generality ($\beta=0.10$, $p=0.01$). This is consistent with our mechanism that the problem formulation and solving approach practiced by academic entrepreneurs leads to more broadly applicable technology. Next, we included this measure as a control in Model 2 in Table 3. As expected, we found that generality was positively correlated with the number of market opportunities (β=0.48, p=0.01). After accounting for generality, we still find the persistent effect of having an academic entrepreneur (β=0.32, p=0.09). This shows that the generality of inventions partially explains the relationship between having an AE and the number of market opportunities, and the rest may potentially be attributed to the difference in the problem formulation and solving approach that does not directly affect inventions.

6.1.2 Ruling out new venture prominence as a driver of market opportunities

Certain new ventures receive more spotlight whether it is from their initial success or factors unrelated to performance. Teams that include academic entrepreneurs may attract more media attention and have a higher number of verticals being assigned. To account for such influence, we used the number of Twitter followers (as of November 10, 2021) as a proxy for prominence. Model 3 in Table 3 shows that the effect of verticals persists even after controlling for the number of twitter followers (β=0.38, p=0.05).

6.1.3 Ruling out other team members as a driver of market opportunities

Previous research has suggested that the prior experience of team members, such as a background in marketing or management, or being a serial founder may influence the markets they target (Gruber et al., 2012). All of our regressions already controlled for being a serial founder. To examine whether the other factors changed our results we controlled for whether a team had any founder (other than the AE) with a marketing or management background. The results, presented in Model 4 of Table 3, indicate that our main finding remains unchanged after controlling for these factors. Also, in Model 5 of Table 3, we did not find any interaction effect between these variables and our main variable (*Has an AE*). Additionally, we could not observe a statistically significant relationship between having a founder with a marketing or management background and the number of verticals. One explanation for these results is that in the early stages of an industry cycle—as the field of AI currently stands—the development of technology is a more significant factor in determining the markets that ventures can target, compared to the experience of marketing or management.

6.1.4 Ruling out the choice of specific verticals

We investigated whether teams with or without AEs may target different verticals based on their prior work experience. For instance, teams without AEs may prioritize profit-driven markets and cater to certain fast-growth markets, whereas teams with AEs may focus on scientific developments. We analyzed this by compiling data on the top ten most common verticals for each team type. Our findings, presented in Table D of the Appendix, indicate that the majority of the top 10 verticals (7 out of 10) were the same for both team types, suggesting that teams with AE and non-AE did not target radically different market opportunities. There were a few differences outside of the top 7. We found that teams with AEs were more likely to target autonomous cars (top 26 among non-AE teams), while teams without AEs were more inclined towards marketing technology (not observed among teams with AEs). Yet overall, it is difficult to attribute our results solely to the differences in the choice of verticals across the teams with and without AEs.

6.1.5. Ruling out universities' involvement in new ventures

Past literature has documented that academics often draw upon university resources to make up for assets they lack, such as network connections and marketing capabilities (e.g., Shane, 2001; Bercovitz et al., 2006, 2008). Therefore, we further investigated if university involvement explains the generation of more market opportunities. We first manually checked each team with AE to confirm whether they were spin-offs from universities. An extensive web search on universities' websites, that of their TTOs, and new ventures websites identified 14 such cases. When we excluded these teams from our analysis, we found that our results were robust. The results are reported in Model 6 in Table 3. Second, we looked for instances of universities listed as co-assignees in patents filed by teams with AEs in our sample, but none were found. Finally, we checked if the AEs had any patenting activity before starting their ventures and found only one such case. Excluding this team did not alter our results. The results are reported in Model 7 in Table 3. Our results are consistent with prior work that suggests that TTOs play a more reduced role in modern new ventures (Clarysse, Tartari & Salter, 2011).

6.2 Robustness checks

We conducted the following robustness checks. First, to account for the fact that our dependent variable is a count variable, we re-ran our analyses using a Poisson model. Our main result was robust to using this model, as well as the additional mechanism tests that we described above. The results are reported in Table E of the Appendix. Second, since our theory relied on the comparison between the organizational context of academia and industry as being important in driving the problem formulation and solving approach of individuals, we excluded teams where all individuals did not have any prior experience before founding the team (i.e., those who joined right after completing their academic degree). We identified six teams whose founding teams consisted of such individuals. Our results were replicated after excluding these teams (Model 8 in Table 3).

Lastly, our definition of AE consists of only faculty entrepreneurs; however, some scholars have used a broader definition where they included staff and post-docs (e.g., Shane, 2004; Roche et al., 2020). Therefore, we checked if our results held using this broader definition. Using this definition, 7.9% of our sample was coded as academic entrepreneurs. We found that our results are robust to this definition and are reported in Model 9 in Table 3.

6.3 Supplementary Analysis: Number of market opportunities and new venture outcomes

We theorized that teams with academic entrepreneurs will generate more market opportunities relative to teams without academic founders and found results consistent with this argument. To examine whether this mattered for the quality of ventures created, we took one step further and examined whether more market opportunities led to favorable funding outcomes. Past research has shown that new ventures that identify more than one market opportunity are likely to drive higher sales revenue (Gruber, MacMillan & Thompson, 2008). Having a larger choice set in targeting markets will help entrepreneurs identify more promising solutions to their target problems, find the ideal application set for their developed technology and provide the founders with access to far-flung resources and team members. Hence, based on prior literature we expected that the teams with a higher number of market opportunities will receive a higher valuation and experience a higher likelihood of having liquidity events, which are commonly used measures to capture the success of ventures (e.g., Chatterji, 2009).

Both measures were acquired through Pitchbook. Note that we were able to find valuation data for only a subsample of teams (65%). In our sample, only two teams had experienced IPOs; the most common liquidity events, therefore, are acquisitions by other firms.

We used OLS regression to estimate the relationship between the number of applications and the valuation of the venture. Since liquidity events are right-censored, we used a survival analysis (Cox hazard model) using the time to having a liquidity event. The results are reported in Table F of the Appendix. We find that the number of verticals is positively associated with both measures. Having one more vertical is associated with a 12% increase in valuation (Model 1), and teams with more verticals are also more likely to have a liquidity event (Model 2). Since having an AE is associated with 0.39 more verticals (Model 1 in Table 2), this effect is equivalent to a 4.68% increase in terms of valuation.

6.4 Empirical boundary conditions

We reported robustness tests and alternative-explanation tests in the previous sections. However, the empirical results can only be interpreted as correlational and not causal. As we mentioned earlier, there are selection effects that our analyses do not disentangle. Individuals who select into academia may be qualitatively different in ability and preferences, from those who do not; teams that include academics may be qualitatively different from those who do not. Still, we believe that conditional on selection into academia and subsequent selection into entrepreneurship, this paper highlights a treatment effect of doctoral training and the academic context that influences the number of market opportunities founders pursue in their new venture. That the academic context has unique features has been established in past literature (eg. Perkmann et al. 2013; Sauermann & Stephan, 2013; Perkman, McKelvey & Philips, 2019; Conti & Roche, 2021; Perkmann et al., 2021). Our tests of alternative explanations, along with the interviews we conducted, strongly suggest a treatment effect over and above the selection of certain individuals into academia. They are further bolstered by the testimonies of interviewees who did not become academics.

Our interviewees who did not become faculty brought up the advantages they perceive graduates and academics to obtain during their training and academic positions. One interviewee who is a PhD dropout turned entrepreneur highlighted several ways his graduate experience differed from that of his undergraduate experience. For instance, he stated that in graduate school, students learn how to present abstract concepts and become very good presenters of abstract ideas over time but colleagues with only undergraduate degrees lack similar skills. Another interviewee sees many similarities between being an entrepreneur and an academic. He stated that academics and entrepreneurs need to be good at "storytelling" and thinks that academics have an advantage because they practice "storytelling" for years, to be published in the best journals, and to network with other inquisitive minds at conferences and university events.

The points these non-academic highlighted are crucial to our study because while we would expect faculty to explain how impactful the doctoral training they offer is, and how their academic experience helps them, we would not necessarily expect non-academics to pick up on the value of, or the treatment effect of, doctoral training or academia. Individuals who would inherently be good presenters or networkers are not likely to pick academia as their first career path. Since these two interviewees perceive academics to be good presenters and storytellers of abstract ideas, this suggests that even non-academic entrepreneurs perceive a treatment effect to be playing out. Overall, this anecdotal evidence suggests that PhD holders and academics learn ropes that others do not during their training and position.

The generalizability of our findings should be interpreted with care. AI, as an emerging field, is potentially the basis of a general-purpose technology (e.g., Gambardella & McGahan, 2010; Gambardella and Giarratana, 2013), the features of which might be unique. Whether our findings can be replicated within other emerging fields should form the basis of future work. Moreover, we examine a field that is nascent and might produce a few new distinct industries over time. Prior research on industry life cycles have shown that the kinds of firms that enter at different stages of the industry differ; firms that enter in the early stages differ from those that enter during its growth or mature stage and firms' outcomes such as performance and survival vary widely by entry timing (Bayus & Agarwal, 2007; Ganco & Agarwal, 2009). In AI, this distinction is likely to play a critical role due to the specific nature of the industry supply chain and the peculiarities of the actors in each stage (Jacobides, Brusoni

& Candelon, 2021). Whether a greater number of market opportunities pursued by new ventures entering during the early stage of the industry leads to higher long-term survival or growth is not predictable from our results on valuation and liquidity events alone. Indeed, Gruber et al. (2008) show that firms' outcomes vary non-linearly with market opportunities and are subject to diminishing marginal returns.

Despite the boundary conditions on the generalizability of our results, we believe that this study can form the basis of more empirical research using the problem-solving perspective in other emerging fields and entrepreneurial landscapes.

7. DISCUSSION

The central insight of this paper is that academic entrepreneurs pursue more market opportunities than non-academic entrepreneurs because they develop a problem formulation and solving approach that helps them think at a higher level of abstraction, produce more comprehensive technological advancements, and envision more applications for these advancements. Delving into the origin of problem formulation and solving, we show that PhD holders, who by their training acquired high construal thinking, also pursue more market opportunities in their new venture. However, the association weakens with the time PhD holders spend in the industry, a context where low construal and demand-oriented thinking dominates.

We conducted a series of tests to probe our problem formulation and solving mechanism. We theorized that problem formulation and solving leads to more general technologies that lead to more market opportunities. Using patent-based measures, we found that teams with academic entrepreneurs developed inventions that were applicable across more domains than teams without. This finding is consistent with our posited mechanisms. We also found that the influence of having an academic entrepreneur was robust to controlling for the number and the kind of invention. We ruled out alternative mechanisms such as startup prominence, other team members' characteristics, and the choice of specific verticals. Our results are also robust to using a Poisson model and a broader definition of academic entrepreneur. Last, we find that the number of market applications positively relates to the startup's valuation and liquidity events. These tests justify the importance of our study for research and entrepreneurs.

Our paper draws attention to problem formulation and solving as an underlying driver of the relationship between founders' human capital and market opportunities. Prior work has often highlighted the benefits of specific experiences during which entrepreneurs directly acquired market knowledge (Gruber et al., 2008; Gruber et al., 2012; Gruber, 2010; Fern et al., 2011; Shermon & Moeen, 2022). Such specific experiences might limit the entrepreneur to familiar opportunities. Relying on a problem formulation and solving approach that engages entrepreneurs in high construal level thinking might be critical in pursuing more market opportunities, by expanding the entrepreneurs' beliefs regarding their firm's direction (Felin & Zenger, 2009). When entrepreneurs directly contribute to the technology creation via this approach rather than being given a technology to exploit (e.g., Shane, 2000), they let the scope of the technology guide the pursuit of market opportunities (Levinthal, 2017). Thus, our paper complements prior work by emphasizing and describing the importance of the problem formulation and solving approach in the entrepreneurship realm.

Our study also complements prior work on academic entrepreneurs. This stream of literature emphasizes that academics typically lack direct market knowledge or convenient access to it and might overcome these limitations by using resources provided by the TTOs of universities. Our findings suggest that despite such limitations, academics' distinct problem-formulation and solving approach offers previously-unidentified benefits in new ventures' pursuit of market opportunities. Importantly, the finding is robust to controlling for TTO's support. Again, this paper emphasizes an approach in contrast to prior work's focus on knowledge. We also find that doctoral training is a key driver of market opportunities, which answers various calls to examine the heterogeneity in the academic population defined beyond faculty members (e..g, Mathisen & Rasmussen, 2019; Shah & Cox Pahnke, 2014).

Our paper advances the recent conversation on the method that entrepreneurs adopt to make decisions regarding the direction their new venture can take. The scientific method, rarely adopted by the general population of entrepreneurs, presents clear advantages in decision-making over ad hoc approaches based on heuristics (Camuffo et al., 2020). Academics are at the forefront of the scientific method that they carefully learned during their doctoral training and implement in their academic career. When creating and running their new ventures, academic entrepreneurs are likely to adopt a similar method, which leads to different outcomes than the ones entrepreneurs who did not practice a scientific problem-solving method might obtain.

Our paper provides some early insights into the role of entrepreneurial firms in pursuing opportunities resulting from technological advancement in the AI field and thus, expands the recent stream of work on entrepreneurship in the field (e.g., Gofman and Jin, 2022). Academics have been producing foundational contributions to neural networks and machine learning (such as LeCun, et al., 1998; Hinton, Vinyals & Dean, 2015; LeCun, Bengio & Hinton, 2015; Schmidhuber, 2015 among many others). Recently, large incumbent firms such as Google and Meta built on these early contributions and have grown to assume an important role in the field (Jacobides, Brusoni & Candelon, 2021). Today, large incumbent firms that have end-to-end vertical integration in their AI services are present throughout the industry supply chain and are simultaneously producers and consumers of AI-powered products. Entrepreneurial firms have a key role to play as complementors to such large firms, either as upstream producers of AI, through the creation of algorithms that form the basis of machine learning, or as downstream consumers through the adoption of established machine learning tools. Therefore, how many applications they can pursue may have far-reaching consequences in the future.

The limitations of this study offer avenues for future research. Our findings are bounded to the context of Artificial Intelligence. Future work could compare academics in entrepreneurship in the AI field to other fields such as life science, which is known to prominently incubate academic entrepreneurs as well (e.g., Stuart & Ding, 2006; Roche, 2022). In the life science field where the need of complementary assets such as high-tech labs and formal university patenting are more salient, academic entrepreneurs might be more constrained in their pursuit of market opportunities. Further, the number of industry jobs for PhD holders has been on the rise in the AI field (Zhang et al., 2021).

Variations in outside options and thus opportunity costs affect the number of academic entrepreneurs. Such variation over time and across contexts likely influences the behavior of new venture. Studies using these variations will likely produce important insights for our field.

8. CONCLUSION

This study highlights the role of entrepreneurs' problem formulation and solving approach in identifying market opportunities by contrasting academic and non-academic entrepreneurs. During their training and work, academics develop a cognitive process that allows them to tackle foundational problems and pursue a line of inquiries at a higher construal level. Such an approach frees them from practical or market constraints, allows them to take their technology as far as they can, and to envision more market opportunities for the technology they develop. Using the context of an emerging field, artificial intelligence, we find that teams with academic entrepreneurs are better positioned to pursue many market opportunities than teams without. We find similar results with PhD holders who worked in the industry. However, their association with the number of market opportunities weakens with the number of years they spent in the industry. We further find that teams with academic entrepreneurs generate inventions that apply to more domains than teams without. Our findings offer important contributions to the academic entrepreneurship literature. We hope that this study will open the doors to future research in other technological contexts in which academic entrepreneurs play a role.

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Figures and Tables

Figure 1. The number of market opportunities (verticals)

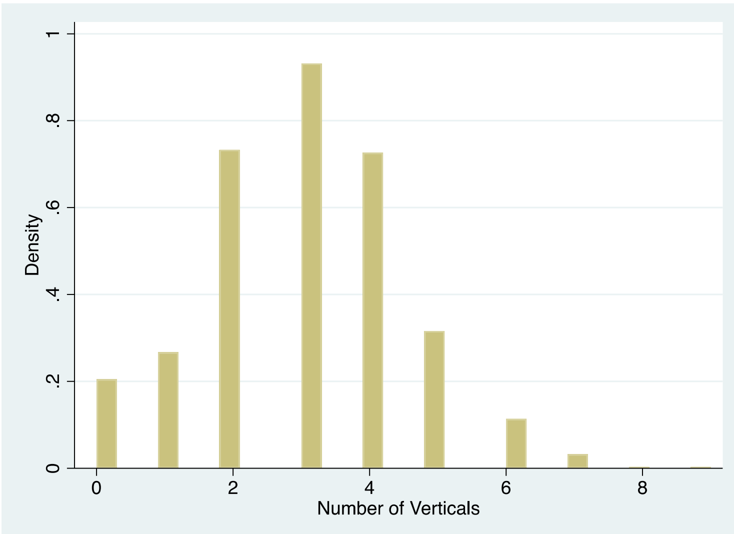

Table 1. Descriptive statistics

		Mean	S.D.	1	2	3	4	5	6	7	8	9	10
1	Number of verticals	3.00	1.49	1.00									
2	Has an academic entrepreneur	0.06	0.24	0.06	1.00								
3	Has a PhD holder	0.38	0.49	0.13	0.33	1.00							
4	Team size	2.53	0.79	0.03	0.05	0.14	1.00						
5	Firm age	4.80	2.43	0.15	0.02	0.01	0.08	1.00					
6	Has a female founder	0.23	0.42	-0.03	0.07	0.10	0.12	-0.07	1.00				
7	Average number of employers	5.96	2.27	-0.05	-0.07	-0.04	-0.01	-0.15	0.05	1.00			
8	Average experience	12.86	6.44	-0.07	0.04	0.03	-0.03	-0.07	0.03	0.49	1.00		
9	Has a serial founder	0.72	0.45	0.02	-0.10	-0.10	0.14	-0.03	-0.02	0.30	0.16	1.00	
10	Has a foreign founder	0.44	0.5	0.04	0.05	0.12	0.36	0.00	0.06	-0.06	-0.04	0.07	1.00
11	Has a founder from top 10 inst.	0.10	0.30	0.00	0.02	0.11	0.13	0.00	0.06	0.02	-0.01	0.01	0.06

Table 2. The effect of having an academic entrepreneur on the number of market opportunities (verticals)

					Among teams with non-AE PhDs		
					Threshold: 5	Threshold: 10	Threshold: 15
Dependent variable:	(1) Number of Verticals	(2) Number of Verticals	(3) Number of Verticals	(4) Number of Verticals	(5) Number of Verticals	(6) Number of Verticals	(7) Number of Verticals
Has an AE	0.39		0.54				
	[0.04]		[0.01]				
Has a PhD holder		0.41					
		[0.00]					
Has a non-AE PhD			0.39				
			[0.00]				
Has a non-AE PhD with longer industry experience							
Has a non-AE PhD with shorter industry experience							
Years of industry experience for non-AE PhDs				-0.02			
				[0.36]			
Years of industry experience for non-AE PhDs (<= threshold)					0.08	0.05	0.03
					[0.20]	[0.10]	[0.22]
Years of industry experience for non-AE PhDs (> threshold)					-0.03	-0.04	-0.07
					[0.14]	[0.03]	[0.01]
Team size	0.00	-0.02	-0.03	-0.02	0.00	0.02	0.02
	[0.98]	[0.70]	[0.69]	[0.87]	[0.99]	[0.83]	[0.82]
Firm age	0.09	0.09	0.09	0.07	0.06	0.06	0.06
	[0.00]	[0.00]	[0.00]	[0.06]	[0.08]	[0.08]	[0.09]
Has a female founder	-0.07	-0.1	-0.1	-0.33	-0.34	-0.35	-0.36
	[0.51]	[0.37]	[0.36]	[0.07]	[0.06]	[0.05]	[0.04]
Average number of employers	0.00	0.00	0.00	0.00	-0.01	-0.02	-0.02
	[0.96]	[0.96]	[1.00]	[0.98]	[0.86]	[0.71]	[0.73]
Average experience	-0.01	-0.02	-0.02	0.00	0.00	0.00	0.00
	[0.08]	[0.06]	[0.06]	[0.96]	[0.92]	[0.99]	[0.95]
Has a serial founder	0.13	0.16	0.17	-0.1	-0.06	-0.07	-0.1
	[0.24]	[0.13]	[0.12]	[0.59]	[0.72]	[0.71]	[0.60]
Has a foreign founder	0.09	0.06	0.06	0.21	0.20	0.21	0.21

	[0.40]	[0.53]	[0.54]	[0.22]	[0.24]	[0.21]	[0.21]
Has a founder from top 10 inst.	-0.01	-0.07	-0.07	0.15	0.16	0.15	0.17
	[0.93]	[0.66]	[0.67]	[0.51]	[0.49]	[0.49]	[0.45]
Constant	2.58	2.52	2.51	3.36	2.95	2.86	2.99
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Observations	1,023	1,023	1,023	323	323	323	323
R-squared	0.03	0.05	0.05	0.04	0.05	0.06	0.06

Note. P-values in brackets. All models control for location dummies.

Table 3. Mechanism tests and robustness checks

	Role of inventions		*Accounting for venture prominence*	*Ruling out the effect of other team member characteristics*		*Ruling out university involvement*		*Excluding teams with no industry experience*	*Using broader definition of AE*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable:	Average Generality of Patents	Number of Verticals	Number of Verticals	Number of Verticals	Number of Verticals	Number of Verticals	Number of Verticals	Number of Verticals	Number of Verticals
Has an AE	0.10	0.32	0.38	0.41	0.38	0.36	0.39	0.4	0.4
	[0.01]	[0.09]	[0.05]	[0.03]	[0.05]	[0.09]	[0.04]	[0.04]	[0.02]
Number of patents		0.01							
		[0.09]							
Average generality of patents		0.48							
		[0.01]							
Log number of twitter followers			0.06						
			[0.00]						
Has a founder with marketing background				0.12	0.12				
				[0.25]	[0.26]				
Has a founder with management background				-0.39	-0.05				
				[0.65]	[0.63]				
Has an AE x Has a founder with marketing background					-0.1				
					[0.84]				
Has an AE x Has a founder with management background					0.11				
					[0.77]				
Team size	0.03	-0.03	-0.01	-0.01	-0.01	-0.01	0.00	0.00	0.00
	[0.00]	[0.69]	[0.86]	[0.87]	[0.89]	[0.93]	[0.97]	[0.99]	[0.99]
Firm age	0.01	0.08	0.08	0.09	0.09	0.09	0.09	0.09	0.09
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]

Has a female founder	-0.04	-0.05	-0.08	-0.08	-0.08	-0.07	-0.07	-0.07	-0.08
	[0.07]	[0.64]	[0.50]	[0.46]	[0.45]	[0.54]	[0.53]	[0.55]	[0.49]
Average number of employers	-0.01	0.01	0.00	-0.01	-0.01	0.00	0.00	0.00	0.00
	[0.07]	[0.83]	[0.95]	[0.80]	[0.74]	[0.99]	[0.90]	[0.95]	[0.99]
Average experience	0.00	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	[0.26]	[0.05]	[0.07]	[0.07]	[0.08]	[0.08]	[0.09]	[0.09]	[0.08]
Has a serial founder	0.00	0.13	0.09	0.13	0.13	0.11	0.13	0.12	0.14
	[0.94]	[0.22]	[0.39]	[0.24]	[0.24]	[0.31]	[0.25]	[0.27]	[0.21]
Has a foreign founder	-0.02	0.09	0.11	0.09	0.09	0.09	0.08	0.08	0.08
	[0.32]	[0.35]	[0.26]	[0.40]	[0.38]	[0.39]	[0.45]	[0.42]	[0.42]
Has a founder from top 10 inst.	0.02	-0.02	0.01	0.00	0.00	0.01	-0.01	0.00	-0.04
	[0.54]	[0.88]	[0.96]	[0.99]	[1.00]	[0.96]	[0.94]	[0.98]	[0.81]
Constant	0.02	2.6	2.37	2.97	2.6	2.59	2.58	2.54	2.56
	[0.69]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Observations	1,023	1,023	1,023	1,023	1,023	1,009	1,022	1,017	1,023
R-squared	0.05	0.05	0.05	0.03	0.03	0.03	0.03	0.03	0.03

Note. P-values in brackets. All models control for location dummies. Model 6 excludes teams that were identified as spin-offs from universities. Model 7 excludes case where the AE had any patenting activity prior to starting their ventures. When we used *Having a PhD holder* in place of *Having an AE*, we found that the effects were also robust across all specifications.

APPENDIX

Table A. List of Verticals from our sample

3D Printing	Digital Health	Marketing Tech
AdTech	E-Commerce	Mobile
Advanced Manufacturing	EdTech	Mobility Tech
AgTech	Esports	Mortgage Tech
Artificial Intelligence & Machine Learning	FemTech	Nanotechnology
AudioTech	FinTech	Oil & Gas
Augmented Reality	FoodTech	Oncology
Autonomous cars	Gaming	Real Estate Technology
B2B Payments	HR Tech	Restaurant Technology
Beauty	HealthTech	Robotics and Drones
Big Data	Impact Investing	SaaS
Cannabis	Industrials	Space Technology
CleanTech	Infrastructure	Supply Chain Tech
Climate Tech	InsurTech	TMT
CloudTech & DevOps	Internet of Things	Virtual Reality
Construction Technology	LOHAS & Wellness	Wearables & Quantified Self
Cryptocurrency/Blockchain	Legal Tech	eSports
Cybersecurity	Life Sciences	
	Manufacturing	

Table B. Comparison of teams with and without AE

	Teams with AE	Teams without AE	p-value from t-test
Team size	2.67	2.51	0.14
Firm age	4.93	4.8	0.65
Has a female founder	0.33	0.22	0.04
Average number of employers	5.39	5.99	0.04
Average experience	12.8	13.8	0.25
Has a serial founder	0.56	0.73	0.00
Has a foreign founder	0.56	0.44	0.06
Has a founder from top 10 inst.	0.13	0.1	0.42

Table C. Estimating the probability of having an AE

	(1)
Dependent variable:	Has an AE
Team size	0.01
	[0.29]
Firm age	0.00
	[0.35]
Has a female	0.03
	[0.07]
Average number of employers	-0.01
	[0.02]
Average experience	0.00
	[0.00]
Has any serial founder	-0.05
	[0.01]
Has any foreigner	0.02
	[0.18]
Has any founder from top 10 institution	0.01

	[0.57]
Constant	0.05
	[0.19]
Observations	1,023
R-squared	0.03

Note: P-values in brackets.

Table D. Top 10 most common verticals

	Teams with AE		Teams without AE	
		%		%
1	Artificial Intelligence & Machine Learning	25	Artificial Intelligence & Machine Learning	23.07
2	TMT	15.38	TMT	18.07
3	Big Data	12.5	Big Data	12.23
4	SaaS	6.25	SaaS	12.09
5	HealthTech	4.81	Mobile	4.09
6	Robotics and Drones	3.85	Marketing Tech	3.15
7	Mobile	3.37	HealthTech	2.31
8	Industrials	2.88	FinTech	2.1
9	Autonomous cars	2.4	Internet of Things	1.61
10	Mobility Tech	2.4	Robotics and Drones	1.5

Table E. The effect of having an academic entrepreneur on the number of market opportunities (verticals) using Poisson model

				Among teams with non-AE PhDs			
					Threshold: 5	Threshold: 10	Threshold: 15
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	Number of Verticals	Number of Verticals	Number of Verticals	Number of Verticals	Number of Verticals	Number of Verticals	Number of Verticals
Has an AE	0.13		0.18				
	[0.08]		[0.02]				
Has a PhD holder		0.14					
		[0.00]					
Has a non-AE PhD			0.13				
			[0.00]				
Has a non-AE PhD with longer industry experience							
Has a non-AE PhD with short industry experience							
Years of industry experience for non-AE PhDs				0.00			
				[0.48]			
Years of industry experience for non-AE PhDs (<= threshold)					0.02	0.02	0.01
					[0.32]	[0.19]	[0.31]
Years of industry experience for non-AE PhDs (> threshold)					-0.01	-0.02	-0.03
					[0.24]	[0.08]	[0.03]
Team size	0.00	-0.01	-0.01	-0.01	0.00	0.01	0.01
	[0.96]	[0.73]	[0.72]	[0.88]	[0.99]	[0.87]	[0.86]
Firm age	0.03	0.03	0.03	0.02	0.02	0.02	0.02
	[0.00]	[0.00]	[0.00]	[0.14]	[0.17]	[0.17]	[0.18]
Has a female founder	-0.03	-0.03	-0.04	-0.1	-0.11	-0.11	-0.11
	[0.55]	[0.43]	[0.42]	[0.16]	[0.14]	[0.13]	[0.12]
Average number of employers	0.00	0.00	0.00	0.00	0.00	-0.01	0.00
	[0.98]	[0.98]	[0.99]	[0.98]	[0.89]	[0.77]	[0.79]
Average experience	0.00	-0.01	-0.01	0.00	0.00	0.00	0.00
	[0.14]	[0.12]	[0.11]	[0.96]	[0.94]	[0.99]	[0.95]
Has a serial founder	0.04	0.06	0.06	-0.03	-0.02	-0.02	-0.03
	[0.32]	[0.20]	[0.19]	[0.67]	[0.79]	[0.79]	[0.70]
Has a foreign founder	0.03	0.02	0.02	0.07	0.06	0.07	0.07

	[0.48]	[0.60]	[0.61]	[0.34]	[0.35]	[0.32]	[0.32]
Has a founder from top 10 inst.	0.00	-0.02	-0.02	0.05	0.05	0.05	0.06
	[0.94]	[0.72]	[0.72]	[0.61]	[0.58]	[0.59]	[0.54]
Constant	0.96	0.94	0.94	1.21	1.08	1.05	1.09
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Observations	1,023	1,023	1,023	323	323	323	323

Note. P-values in brackets. All models control for location dummies.

Table F. Number of market opportunities and new venture outcomes

	(1)	(2)
Dependent variable:	Log(Valuation)	Having a liquidity event
Number of Verticals	0.12	0.23
	[0.03]	[0.00]
Has an AE	-0.09	-0.30
	[0.76]	[0.52]
Log number of twitter followers	0.15	-0.50
	[0.00]	[0.00]
Team size	0.23	0.13
	[0.02]	[0.35]
Firm age	0.15	0.04
	[0.00]	[0.31]
Has a female founder	-0.59	-0.25
	[0.00]	[0.32]
Average number of employers	-0.12	0.00
	[0.00]	[0.98]
Average experience	0.05	0.03
	[0.00]	[0.16]
Has a serial founder	-0.04	-0.12
	[0.84]	[0.61]
Has a foreign founder	0.03	-0.27
	[0.86]	[0.23]
Has a founder from top 10 inst.	0.49	0.19
	[0.05]	[0.54]
Constant	0.78	
	[0.06]	
Observations	665	1,023
R-squared	0.18	

Note. P-values in brackets. All models control for location dummies. Model 2 was estimated using a cox hazard model. Coefficients in this model are hazard ratios and the Log Likelihood is -596.09789.