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Heterogeneous university research and firm R&D location decisions: research orientation, academic quality, and investment type

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Abstract
Universities play an important role in regional development and innovation and engage with the industry through various channels. In this paper, we examine the role of heterogeneous characteristics of university research, in particular universities' orientation towards basic or applied research and the quality of this research, in attracting firms' R&D investment. We analyze the location decisions in the United States by foreign multinational firms at the level of metropolitan areas. We contrast research and development projects and explore whether they are driven by different factors. We find that the drivers of location choice differ importantly as a consequence of the type of the focal R&D investment of the firm. Universities with an orientation towards applied scientific research and exhibiting higher academic quality of applied research attract more R&D investment focusing on development activities. In contrast, firms' investments in research activities are attracted by the academic quality of basic scientific research of local universities. Hence, increased university emphasis on academic engagement and applied research may have negative consequences for industrial research in the region.

Keywords Location choice · R&D FDI · Industry science links · Basic and applied research · Academic quality

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1 Introduction

Universities play an important role in regional development and innovation, and are increasingly expected to perform the 'third mission' of engagement in serving the economy and society, in addition to their traditional missions of teaching and research (Bozeman, 2000; Bozeman et al., 2015; Perkmann et al., 2013). The technology transfer literature has extensively studied university-industry collaboration (Belderbos et al., 2021; Bruneel et al., 2010; Lehmann & Menter, 2016; Rybnicek & Königsgruber, 2019), university patenting and licensing (Geuna & Nesta, 2006; Mazzoleni, 2006; Mowery et al., 2001), university spin-offs and entrepreneurship (Mathisen & Rasmussen, 2019; Wang et al., 2022; Zucker et al., 1998), the role of intermediaries such as technology transfer offices (Bolzani et al., 2021; O'Kane et al., 2021; Siegel et al., 2003) and incubators at universities (Cadorin et al., 2021; Rothaermel & Thursby, 2005; Youtie & Shapira, 2008).

This expanding literature has contributed important insights into how universities interact with incumbent firms or spawn new ventures. An important conclusion is that universities differ importantly in their resources and capabilities, and their academic engagement with industry and involvement in entrepreneurial activities (Grimaldi et al., 2011; Perkmann et al., 2013). Competitive and societal pressures and declining government support have provided impetus to an increased focus on academic entrepreneurship on the part of universities, and greater involvement of industry in funding university research (Siegel & Wright, 2015). An influential policy recommendation for advancing the third mission of engagement is to shift the focus of university research from basic research that is concerned with fundamental understanding to applied research that focuses on practical utility (Gibbons, 1994), although whether universities are driven away from curiosity-driven basic research toward applied research is still a subject of debate (Fini et al., 2021; Henderson et al., 1998; Mowery & Ziedonis, 2002; Perkmann et al., 2021; Thursby & Thursby, 2011). A salient unanswered question is whether heterogeneity in the characteristics of university research, in particular their orientation toward basic or applied research, has a material impact on the role universities play in economic development. In this paper, we seek to answer this question in a context of university research attracting (foreign) R&D investments to their regions.

A number of studies have found evidence for a positive association between university research and industrial R&D investments, at the regional level (Abramovsky et al., 2007; Autant-Bernard, 2001; Belderbos et al., 2014, 2017; Cantwell & Piscitello, 2005). However, it remains unclear how this association differs depending on the characteristics of academic research the university is involved in. In this paper, we focus on two important features of academic research: its applied or basic nature and its academic quality. A pertinent question is whether a focus on applied rather than basic scientific research may makes university research more directly relevant and accessible to firms. On the one hand, applied research might be more directly useful for the industry and is prescribed as a key for advancing the third mission (Gibbons, 1994; Nelson, 2003). On the other hand, given the observation that technological innovation is increasingly relying on science (Marx & Fuegi, 2020), while basic research activities conducted internally by firms are declining (Arora et al., 2018) and require a strong intellectual property protection regime (Simeth & Raffo, 2013), it is conceivable that the complementary role of basic research at universities

is important for firms. A second relevant question it is whether science that is perceived to be of high quality by other scientists will also be more valuable for corporate R&D, given the conflicting logics of science and technology (Ali & Gittelman, 2016; Gittelman & Kogut, 2003; Sauermann & Stephan, 2013). Understanding the alignment or conflict between the academic and industry logics in terms of quality standards is important for informing policy and managerial practices supporting the "third mission."

We aim to provide a nuanced answer to these questions by recognizing that firms' R&D investments are also heterogeneous in nature and objectives. We examine to what extent the influence heterogeneous university research depends on the type of R&D investments undertaken by the firms: i.e., whether the R&D investment focuses on research activities or development activities. The motivation for (multinational firms') R&D investments have generally been distinguished between market adaptation (development) and knowledge sourcing and creation (research) (Belderbos et al., 2009; Shimizutani & Todo, 2008; von Zedtwitz & Gassmann, 2002). While development activities may be expected to benefit most from applied academic research, firms' research activities may be more likely to draw on basic scientific research conducted at universities.

We examine the role of such heterogeneous academic research in attracting heterogeneous R&D investments by considering location decisions of foreign multinational firms in the United States at a fine-grained regional level of Metropolitan Statistical Areas (MSAs), which are regions delineated in terms of economic integration (Mowery & Ziedonis, 2015). Analyzing foreign firms' R&D investment location decisions has the advantage that these firms are relatively free to choose a location based on its merits, as they have no home region in the US in which they are strongly embedded that may influence such decisions. We develop geocoded academic publication data based on Clarivate's Web of Science to characterize the academic research profile of universities in each MSA across scientific domains, including the academic quality of their publications (scientific citations received), and their orientation toward basic or applied research. We take into account the varying relevance of regional academic research (Hausman, 2020) for R&D investments across industries by utilizing a concordance between science fields, technologies, and industries. Our analysis takes into account other channels through which university research can influence corporate R&D such as the supply of doctoral graduates, university patenting activities. We estimate random coefficient (mixed) logit models (Alcacer & Chung, 2007, 2014; Head et al., 1995) allowing for investor heterogeneity to analyze the location decisions for 148 research and 325 development projects across 354 MSAs during 2003–2012. We adapt a model that identifies agglomeration economies stemming from labor, supplier and customer specialization in a region (Alcacer & Chung, 2014; Glaeser & Kerr, 2009), treating academic research as an input to R&D at the firm level.

We find that an applied scientific research focus and the academic quality of this applied research of the universities in an MSA exert a positive influence on the likelihood that the MSA is chosen for R&D investments in general and for development investments in particular. In contrast, research investments are drawn to regions with a higher academic quality of basic scientific research, whereas an applied research focus and the academic quality of applied research play no role here. R&D investments are furthermore attracted by MSAs with universities specialized in the science domains relevant for the investing firm and delivering doctoral graduates with a relevant doctoral degree.

Our research contributes to the literature on university technology transfer, by providing important nuance to the debate on the relative importance of basic or applied academic research for firm innovation and the debate about the conflicting logics between science and technology (Cassiman et al., 2008; Grimaldi et al., 2011; Hausman, 2020; Perkmann et al.,

2013; Zahringer et al., 2017). We suggest that fundamental academic research strengths remain important to provide an attractive environment for more profound industrial R&D activities focusing on research rather than development. Our paper also contributes new insights to the literature on R&D investment location decisions (Alcacer & Chung, 2014; Alcacer & Delgado, 2016; Belderbos et al., 2014, 2017) related to the importance of universities and their characteristics on R&D location choice.

2 Theoretical background and hypotheses

We review the literature on the relationship between university research and corporate R&D, basic versus applied university research, the role of academic research quality, after which we develop our core hypotheses that the role of basic and applied research at universities and their quality depend on whether firms seek a location for R&D focusing on research rather than development.

2.1 University research and corporate R&D

A large body of evidence supports the important role of university research in stimulating corporate R&D and firm innovative performance (Adams, 1990; Belderbos et al., 2012; Fleming & Sorenson, 2004; Gambardella, 1992; Salter & Martin, 2001; Toole, 2012). Scientific research may yield useful applications (Brooks, 1994; Jaffe, 1989) and may transform the search and problem-solving process underlying technological innovation (Fleming & Sorenson, 2004). Besides the general provision of academic research, universities may affect firms' innovation activities through many other channels (Cohen et al., 2002; D'Este & Patel, 2007; Link & Siegel, 2005; Salter & Martin, 2001; Thursby & Thursby, 2002). They educate scientists and engineers, who may constitute the future workforce of firms, they provide experts and consultants to help firms solve particular technological problems, they serve as collaboration partners on embryonic and applied projects, and they engage in knowledge transfer through patenting and licensing activities (Belderbos et al., 2016; Cassiman et al., 2008; Hall et al., 2003; Perkmann et al., 2013).

One feature of these mechanisms through which universities contribute to firm innovation is the role played by distance. Several studies have underlined the geographically bounded nature of university-firm spillovers and the consequent necessity for firms to be located close to universities in order to fully capture the relevant benefits (Audretsch & Feldman, 2004; Mansfield, 1995, 1998). To successfully capitalize on university research, firms often need access to tacit knowledge not contained in contracts or published work; knowledge that is difficult to be transmitted across long distances (Mowery & Ziedonis, 2015; Von Hippel, 1994). Scientific knowledge related to research can be complex and difficult to codify (Von Krogh et al., 2000), which complicates effective transfer at distance. Several studies have confirmed the bounded nature of knowledge spillovers from universities (Belenzon & Schankerman, 2013; Jaffe et al., 1993) and have documented the geographically constrained mobility choices of university graduates (Berry & Glaeser, 2005; Miguélez & Moreno, 2012).

2.2 Universities' research orientation: basic versus applied scientific research

Scientific research is heterogeneous, and different types of research may vary in how valuable they are to technological innovation in firms, as well as through which mechanism their contribution unfolds. In particular, there is an important distinction between basic and applied scientific research. According to the Frascati Manual (OECD, 2002), "basic research is experimental or theoretical work undertaken primarily to acquire new knowledge of the underlying foundation of phenomena and observable facts, without any particular application or use in view." Applied research is also considered as original investigation to acquire new knowledge. It is, however, "directed primarily towards a specific practical aim or objective."

There still is considerable debate regarding what the relative merits are of basic and applied academic research for firm innovation. On the one hand, we may expect a higher added value from basic research. Fleming and Sorenson (2004) argue that basic research can provide a map for technological innovation; theoretical understanding of the problem and solution space can transform problem-solving from a relatively haphazard search process to a more directed identification of useful new combinations, leading to better solutions (Cassiman et al., 2008; Fleming & Sorenson, 2004). Although basic research is less likely to yield direct practical applications, it may lead to broader, more radical, and unexpected applications, often through a long series of follow-on research and development (Bush, 1945). For example, basic research on the CRISPR/Cas9 genetic scissors may lead to cues for cancer and inherited diseases, and basic quantum research may yield applications beyond quantum computing that may revolutionize many industries. Prior study has found that basic biomedical papers have a higher chance of being cited by patents (Ke, 2020). Furthermore, researchers with a basic research orientation or education are more likely to deliver radical and valuable technologies (Gruber et al., 2013). Studies have also observed that firms benefit from collaborating with "star scientists", i.e., elite scientists in their scientific discipline, mostly oriented towards basic research (Higgins et al., 2011; Perkmann et al., 2011; Zucker et al., 1998, 2002).

On the other hand, we might expect applied research to be more directly valuable for firm innovation, inherent to its goal towards practical use (Nelson et al., 2011; Nightingale, 1998; Rosenberg & Nelson, 1994). Applied research follows an epistemological logic that closely resembles technological development processes characterizing R&D in firms (Gittelman & Kogut, 2003; Nelson, 2003). One important point of concern about university engagement with industry is that it may drive universities away from curiosity-driven basic research toward applied research directly relevant to industry (Fini et al., 2021; Henderson et al., 1998; Mowery & Ziedonis, 2002; Perkmann et al., 2021; Thursby & Thursby, 2011). While this is still debated, it reflects a general believe that applied research is more relevant for the industry. Prior studies suggest that patents building on applied scientific research have a higher technological and economic value than patents building on basic research (Wang & Verberne, 2021). Furthermore, researchers with an applied research orientation or education are better suited for helping firms to create value from R&D (Ali & Gittelman, 2016; Baba et al., 2009; Rothaermel & Hess, 2007; Subramanian et al., 2013). Firms more readily collaborate with universities on research that is applied in nature (Godin & Gingras, 2000; Hicks & Hamilton, 1999) and studies have found that it is more advantageous for firms to work with bridging scientists, in particular "Pasteur scientist", i.e., scientists with an orientation towards applied research (Baba et al., 2009; Rothaermel & Hess, 2007;

Subramanian et al., 2013). Bikard and Marx (2020) found that geographic hubs facilitate knowledge flow from universities to industry by facilitating applied research.

2.3 Universities' academic quality of scientific research

There is also an open question regarding whether the quality standards of science and technology are well aligned. Given their different logics, science and technology may also differ in their quality standards, so it is not straightforward that research with high academic quality, i.e., being perceived to be of high quality by other scientists as reflected in forward scientific citations, will also represent high value and relevance for technological innovation. Empirical evidence is mixed and inconclusive. On the one hand, studies have shown that highly cited scientific publications are much more likely to be cited by patents (Ahmadpoor & Jones, 2017; Hicks et al., 2000; Popp, 2017; Veugelers & Wang, 2019) and that references in patents to highly cited publications have higher value (Poege et al., 2019). Highly cited academic publications authored by in-house researchers of firms have also been positively associated with innovation outcomes (Subramanian et al., 2013), and the quality of research departments has been found to stimulate collocated R&D (Abramovsky et al., 2007). On the other hand, Gittelman and Kogut (2003) found a negative association between important scientific papers (i.e., scientific papers that are highly cited by other scientific papers) and high-impact technological inventions (i.e., patents that are highly cited by other patents), and Wang and Verberne (2021) found an insignificant association between citations to scientific research and patent value.

Furthermore, Scandura and Iammarino (2022) investigated UK universities and found a negative association between academic research quality and the level of engagement with industry for departments in the basic sciences, but a positive association for those in the applied sciences. This suggests the importance of differentiating between the quality of basic and applied research when examining multinationals R&D location decisions.

2.4 Hypotheses: research versus development investments and university research

The influence of basic or applied academic research and their respective academic quality on industrial R&D is likely to depend on whether firms engage in development or research activities. This follows from the notion that R&D activities carried out by firms are also heterogeneous in tasks and objectives (Belderbos et al., 2009; Sachwald, 2008; Suzuki et al., 2017), with a salient distinction between research activities on the one hand and development activities on the other (Barge-Gil & López, 2014; Czarnitzki et al., 2010; von Zedtwitz & Gassmann, 2002).

The heterogeneity among R&D activities is particularly salient in the context of R&D internationalization. R&D activities in foreign affiliates of multinational firms can be tailored to adapt product and technologies to local consumer preferences and supporting manufacturing activities in foreign countries, focusing on development (Kuemmerle, 1997). They can also be motivated by the sourcing foreign technologies augmenting the knowledge base at home (Almeida, 1996; Cantwell & Mudambi, 2005; Florida, 1997; Zanfei, 2000) and focus on research. Shimizutani and Todo (2008) and Belderbos et al. (2009) found initial evidence that the distinction between research and development investments matters for location decisions. They observed that market size was most closely associated with development locations, while local research intensity was more closely associated with research investments.

Our conjecture is that investments in research activities are more likely to seek benefits related to high quality basic scientific research at universities, while firms' investments in development activities are more likely to seek benefits from high quality applied scientific research. Firms conducting research can seek advantages in capitalizing on the basic research performed in academia, expanding the knowledge base on which they can draw for their own innovation activities (Cockburn & Henderson, 1998; Cohen & Levinthal, 1989, 1990; Klevorick et al., 1995). Firms that are aware of new advances in relevant scientific fields are in a better position to identify promising research paths that can then translate into new inventions. This may give a first mover advantage for the introduction of new products and processes (Arora et al., 2021; Fabrizio, 2009; Rosenberg, 1990). Knowledge of basic research is also important because it provides firms with a better understanding of the overall technological landscape, which can help firms to more effectively search for new inventions and avoid wasteful experimentations (Fleming & Sorenson, 2004). In contrast, firms' development activities are most likely to benefit from applied scientific research, given the closer connection of applied scientific research to development and commercialization and the absence of such a direct connection for basic scientific research (Balconi et al., 2010). Hence, we formulate the following hypotheses:

Hypothesis 1 Firm investments in research are attracted to locations with universities' basic research, while firm investments in developed are attracted to location with universities' applied research.

Hypothesis 2 Firm investments in research are attracted to locations with a high quality of universities' basic research, while firm investments in developed are attracted to location with a high quality of universities' applied research.

3 Data, variables and empirical model

3.1 Data

We construct a dataset on the characteristics of university research at the MSA level and match it with the location decisions of foreign multinational firms' R&D investments in the United States (2003–2012) obtained from the fDi Markets database of the Financial Times Ltd. The fDi Markets database is considered to be one of the most comprehensive sources of information on cross-border greenfield investments, covering investments made by multinational firms operating across industries and countries. It is based on more than 8000 news and proprietary sources and recorded more than 120,000 worldwide cross-border greenfield investments during the period. Investments are classified into industries that can be mapped into a corresponding 3-digit NAICS sector. Investments are also categorized into different value chain activities: manufacturing, distribution, logistics, R&D, etc. The database has frequently been used in prior research (Castellani et al., 2013; Crescenzi et al., 2014; D'Agostino et al., 2013), and its validity and reliability have been confirmed independently by different researchers (Castellani et al., 2013; Crescenzi et al., 2014). We restrict our analysis to R&D investments made in the United States by firms operating in manufacturing industries. The main reason for this focus is that the use of patents is relatively rare in the service sector, such that concordances between service sectors, technologies, and science fields cannot be established well. The dataset contains 473 foreign

R&D investments undertaken by 328 firms based in a variety of countries. Among the 473 R&D investments, 148 could be classified as research investments based on and the text description accompanying each R&D investment in database. Investments are classified as research if the description of the project refers to (basic or fundamental) research, while descriptions of development investments refer to adaptation, solutions, and development. Firms based in Germany are responsible for the largest share of R&D investments (17.5%), followed by firms based in Japan (17.3%), the U.K (9.5%), France (5.5%) and South Korea (5.3%). Most R&D investments take place in the pharmaceutical and chemical industry (27.1%), followed by the computers and electronics industry (24.1%) and the transport equipment industry (16.5%).

We are interested in the role played by academic research and its characteristics in attracting R&D investments. With industry science linkages and influences of university research on corporate R&D most salient in geographic proximity, we need to define an appropriate geographical unit of analysis for our study. Such a suitable geographic unit is the Metropolitan Statistical Area (MSA) defined by the United States Office of Management and Budget (OMB) and used by several federal government agencies for statistical purposes (Nussle, 2008). Each MSA contains a core urban area with at least 50,000 inhabitants. It consists of one central county plus adjacent counties with a high degree of economic integration with the central county, as measured through worker commuting ties. After each decennial census realized by the Census Bureau, the OMB revises the list of current MSAs to reflect changes in the demographic composition of such areas. Given that investments contained in our database were performed between 2003 and 2012, we use the list of MSAs released by the OMB in 2003 following the 2000 decennial census.

We identify the relationships between university research and R&D investments from variation in the volume, type and quality of publications authored by university affiliated researchers across MSAs over time. We posit that an individual firm deciding on a location for a specific R&D project in a given year regards the existing state of university research in MSA regions as given. Whereas (large) domestic incumbent firms may have had an influence on university research through firm-university R&D collaborations and other interactions (Hausman, 2020), this feature will typically be not be present for foreign firms establishing an R&D unit in a region.

3.2 University research

We use publications to construct indicators of university research. We assign each academic publication retrieved from Clarivate's Web of Science (WoS) published by at least one author resident in the United States to an MSA. For each publication within WoS, the addresses of the authors are reported, which may include the state, the city and the first five digits of the zip code. We matched the zip codes to the corresponding MSA using the concordance table provided by the United States Census Bureau. For those WoS addresses that do not include zip codes, we matched on city and state names. The share of publications by resident authors in the United States that have at least one author address in an MSA is 97.1%. We take a fractional count of publications across authors in case there are co-authors based in locations other than the focal MSA or in multiple MSAs. We subsequently distinguish academic publications from publications by firms and research institutes using keyword lists (college, university) and manual validation.

To take into account the relevance of scientific research for investing firms in different manufacturing industries, we use concordance tables to match publications to technology

domains and then to industries. The first step of this matching exercise involves the assignment of each publication to its academic field based on the journal (issue) in which it is published. Drawing on a classification scheme developed by Glänzel and Schubert (2003) we distinguish 68 academic disciplines. If a publication has multiple academic disciplines, we adopt a fractional count approach. We assign publications to patent classes by using the concordance table developed by Callaert et al. (2014) that exploits the degree to which publications in a scientific discipline are relevant prior art cited in patents in a particular technology domain (International Patent Classification, IPC). To weight how relevant scientific discipline d is for IPC class t (3 digits), we use the number of citations from IPC class t to scientific discipline d, divided by the total number of publications in scientific discipline d. This establishes a science-to-technology weight $w_{d,t}$. Subsequently, we use the concordance table developed by Lybbert and Zolas (2014) that links IPC classes to industries (i.e., NAICS code). This concordance compares keywords in patent abstracts and titles with keywords from detailed descriptions of industry classifications. The resulting concordance assigns IPC class t a weight of relevance for industry i, that is, a technology-to-industry weight $w_{t,i}$. There are several alternative concordance schemes between patent classes and industry. For example, the IPC-NACE concordance developed by Schmoch et al. (2003) and the USPC-SIC concordance developed by Silverman (1999). We opt for Lybbert and Zolas (2014) because it is more recently developed concordance and using earlier concordances would require additional mapping between industries and (recent) IPCs. Finally, to weight the relevance of scientific discipline d for industry i, we multiply the two weights: $w_{d,t} \bullet w_{t,i}$.

3.3 University research orientation: basic versus applied scientific research

To characterize academic research as basic or applied, we use the CHI classification scheme, which classifies journals of the Science Citation Index (part of WoS) in one of four research levels ranging from very applied targeted research to basic research (Hamilton, 2003; Noma, 1986). The classification is based on a combination of expert knowledge and citation patterns. More specifically, it is based on the notion that applied research is more likely to cite basic research, while the reverse is much less likely to happen (Narin et al., 1976; Thursby & Thursby, 2011). Following prior studies (Brusoni & Geuna, 2003; Narin & Rozek, 1988), we distinguish between basic research (level 4 in the classification) and applied research (levels 1–3).

We matched WoS journals by journal name and ISSN code to the list of CHI classified journals. Given that the CHI index has not been updated, a number of more recently established journals could not be classified. At the paper level, however, 5,445,315 (73.42%) out of 7,416,366 publications have a CHI level assignment. Our basic versus applied academic research indicators draw on the publications that could be classified. While the absence of full coverage may lead to less precise estimates, we do not expect that this will systematically affect variations in the relative shares of basic and applies research across MSAs.

3.4 Variables

The dependent variable is a binary variable taking the value 1 if the firm choses MSA j as the location for its R&D investment and 0 otherwise. Table 1 shows the distribution of R&D investments over MSAs. About one third of the investments occurred in five MSAs: Detroit–Warren–Livonia, MI (10.6%), San Jose–Sunnyvale–Santa Clara (6.6%),

Table 1 Distribution of cross-border R&D investments over MSAs, 2003–2012

Metropolitan statistical area	Freq	Percent (%)	Metropolitan statistical area	Freq	Percent (%)
Detroit–Warren–Dearborn, MI	50	10.6	Lincoln, NE	2	0.4
San Jose–Sunnyvale–Santa Clara, CA	31	6.6	Madison, WI	2	0.4
Boston–Cambridge–Newton, MA–NH	30	6.3	Memphis, TN–MS–AR	2	0.4
New York–Newark–Jersey City, NY–NJ–PA	27	5.7	Milwaukee–Waukesha–West Allis, WI	2	0.4
Los Angeles–Long Beach–Anaheim, CA	25	5.3	Oxnard–Thousand Oaks–Ventura, CA	2	0.4
San Francisco–Oakland–Hayward, CA	24	5.1	Providence–Warwick, RI–MA	2	0.4
Philadelphia–Camden–Wilmington. PA–NJ–DE–MD	15	3.2	Riverside–San Bernardino–Ontario, CA	2	0.4
Chicago–Naperville–Elgin, IL–IN–WI	14	3.0	Rochester, MN	2	0.4
San Diego–Carlsbad, CA	14	3.0	Santa Rosa, CA	2	0.4
Ann Arbor, MI	13	2.7	Trenton, NJ	2	0.4
Atlanta–Sandy Springs–Roswell, GA	13	2.7	Tucson, AZ	2	0.4
Houston–The Woodlands–Sugar Land, TX	13	2.7	Wichita, KS	2	0.4
Dallas–Fort Worth–Arlington, TX	12	2.5	Allentown–Bethlehem–Easton, PA–NJ	1	0.2
Raleigh, NC	12	2.5	Athens–Clarke County, GA	1	0.2
Durham–Chapel Hill, NC	11	2.3	Augusta–Richmond County, GA–SC	1	0.2
Seattle–Tacoma–Bellevue, WA	9	1.9	Baton Rouge, LA	1	0.2
Cleveland–Elyria, OH	8	1.7	Bismarck, ND	1	0.2
Washington–Arlington–Alexandria. DC–VA–MD–WV	8	1.7	Burlington–South Burlington, VT	1	0.2
Phoenix–Mesa–Scottsdale, AZ	7	1.5	Canton–Massillon, OH	1	0.2
Charlotte–Concord–Gastonia, NC–SC	6	1.3	Cedar Rapids, IA	1	0.2
Albany–Schenectady–Troy, NY	5	1.1	Charleston–North Charleston, SC	1	0.2
Albuquerque, NM	5	1.1	Colorado Springs, CO	1	0.2
Miami–Fort Lauderdale–Pompano Beach. FL	5	1.1	Davenport–Moline–Rock Island, IA–IL	1	0.2
Cincinnati, OH–KY–IN	4	0.8	Fort Collins, CO	1	0.2
Columbus, OH	4	0.8	Fresno, CA	1	0.2
Minneapolis–St. Paul–Bloomington, MN–WI	4	0.8	Grand Forks, ND–MN	1	0.2
Portland–Vancouver–Hillsboro, OR–WA	4	0.8	Harrisburg–Carlisle, PA	1	0.2

Table 1 (continued)

Metropolitan statistical area	Freq	Percent (%)	Metropolitan statistical area	Freq	Percent (%)
Boulder, CO	3	0.6	Huntsville, AL	1	0.2
Bridgeport–Stamford–Norwalk, CT	3	0.6	Jacksonville, FL	1	0.2
Denver–Aurora–Lakewood, CO	3	0.6	Kalamazoo–Portage, MI	1	0.2
Grand Rapids–Wyoming, MI	3	0.6	Lakeland–Winter Haven, FL	1	0.2
Palm Bay–Melbourne–Titusville, FL	3	0.6	Lancaster, PA	1	0.2
Tampa–St. Petersburg–Clearwater, FL	3	0.6	Lansing–East Lansing, MI	1	0.2
Worcester, MA–CT	3	0.6	Lynchburg, VA	1	0.2
Akron, OH	2	0.4	Nashville–Davidson–Murfreesboro–Franklin, TN	1	0.2
Austin–Round Rock, TX	2	0.4	Oklahoma City, OK	1	0.2
Baltimore–Columbia–Towson, MD	2	0.4	Pittsburgh, PA	1	0.2
Chattanooga, TN–GA	2	0.4	Rochester, NY	1	0.2
Columbus, IN	2	0.4	Sacramento–Roseville–Arden–Arcade, CA	1	0.2
Dayton, OH	2	0.4	Salt Lake City, UT	1	0.2
Greenville–Anderson–Mauldin, SC	2	0.4	San Antonio–New Braunfels, TX	1	0.2
Hartford–West Hartford–East Hartford, CT	2	0.4	St. Louis, MO–IL	1	0.2
Indianapolis–Carmel–Anderson, IN	2	0.4	Tulsa, OK	1	0.2
Janesville–Beloit, WI	2	0.4	Utica–Rome, NY	1	0.2
Kansas City, MO–KS	2	0.4	Virginia Beach–Norfolk–Newport News, VA	1	0.2

Boston–Cambridge–Quincy (6.3%), New York–Newark–Jersey City (5.7%) and Los Angeles–Long Beach–Santa Ana (5.3%). In total, 90 MSAs out of 354 received at least one R&D investment.

Our main research interest focuses on the role that the characteristics of university research (research orientation and academic quality) play in attracting R&D investments. *Applied Share* is calculated at the industry level as the relevance-weighted (with weights $w_{d,t} \bullet w_{t,i}$) number of applied university publications in the MSA divided by the relevance-weighted total number of university publications in the MSA. As the share of applied research differs across science fields, we normalized the ratio by field. To evaluate the effect of academic quality, we construct the variable *Academic Quality: Applied* as the relevance-weighted average citation rate (in a five-year window) of applied university publications in the MSA, normalized by scientific fields. Similarly, we construct the variable *Academic Quality: Basic* as the relevance-weighted average citation rate of basic research publications.

In order to properly assess the influence of university research quality and applied vs. basic research focus, we should control for the overall volume of scientific research of universities in the MSA, to the extent that this research is relevant for the investing firm (Hausman, 2020). We adapt the methodological framework for identifying agglomeration economies developed by Glaeser and Kerr (2009), which distinguishes the mechanisms through which local characteristics attract investments from the level of agglomeration. While in the context of manufacturing investments, the benefits associated with agglomeration economies arise if locations specialize in suppliers, customers, labor, and knowledge sources that fit the needs of the investing firm (Alcacer & Chung, 2014), in the context of R&D investments, we can consider university research as a potential source of knowledge spillovers and input to firms' R&D activities. The attractiveness of an MSA is then determined by the fit between the knowledge generated by local universities and the knowledge needs of the investing firm in a particular industry. The fit variables are distinguished from the influence of the relevant *level* of agglomeration. We measure *Industry Establishments* as the number of establishments (retrieved from the United States Census Bureau) in the industry of the focal investing firm.

The *Academic Research Fit* of MSA l for industry i *is* a weighted-sum of the specialization of MSA l in scientific discipline d across scientific disciplines. More specifically, $AcademicResearchFit_{l,i} = \sum_{d=1\ldots,D} w_{d,t} \bullet w_{t,i} \bullet (\frac{P_{l,d}}{P_d})/(\frac{P_l}{P})$, where $w_{d,t} \bullet w_{t,i}$ is the abovementioned weight of relevance of scientific discipline d for industry i, and $(\frac{P_{l,d}}{P_d})/(\frac{P_l}{P})$ is the specialization of MSA l in scientific discipline d.[1] *Academic Research Fit* thus increases if the specialization across academic disciplines in an MSA matches the academic research 'needs' of the investing firm.

Focusing on the two sectors that received the largest number of R&D investments, i.e., the Chemicals and Pharmaceuticals sector and the Computers and Electronics sector, Table 2 lists the top 10 MSAs (in terms of their share of university publications) in the two sectors. The table reports the main universities located in the MSA, the *Academic Research Fit*, the *Applied Share*, and the *Academic Quality* variables, as well as the number of research and development investments the MSA received. The table shows that the distribution of R&D investments does not merely concentrate in MSAs with the highest share of relevant publications. For instance, San Francisco is the MSA that has the highest

[1] $P_{l,d}$ is the number of publications from MSA l in discipline d, P_d is the total number of publications in discipline d, P_l is the total number of publication from MSA l, and P is the total number of publications.

Table 2 Characteristics of university research in MSAs: chemical and pharmaceutical versus computers and electronics

Computers and Electronics industry		Academic Research	U.S. Publication	Applied	Academic Quality:	Academic Quality	Number of FDIs	
MSA	Main University	Fit	Share	Share	Basic	Applied	R	D
San Francisco	Berkeley	1.17	5.02%	45.09%	1.79	1.31	2	5
Boston	Harvard, MIT	1.15	11.45%	50.22%	1.79	1.21	1	1
Philadelphia	Univ. Pennsylvania	1.08	5.32%	57.14%	1.28	1.07	0	0
Baltimore	John Hopkins	1.08	4.33%	54.46%	1.30	1.16	0	0
Durham	Duke	1.06	4.12%	53.27%	1.44	1.13	1	1
New York	Columbia	1.05	10.09%	50.10%	1.26	1.11	0	2
Los Angeles	Caltech	1.05	6.29%	53.31%	1.49	1.14	3	1
Atlanta	Georgia Tech	1.02	3.11%	61.44%	1.17	0.96	0	3
Houston	Rice	1.01	5.20%	63.11%	1.28	1.10	0	2
Chicago	Univ. Chicago	1.01	5.38%	50.23%	1.22	1.02	0	1
Chemical and Pharmaceutical industry		Academic Research	U.S. Publication	Applied	Academic Quality:	Academic Quality	Number of FDIs	
MSA	Main University	Fit	Share	Basic	Applied	Quality	R	D
Chicago	Univ. Chicago	1.27	4.12%	49.01%	1.21	1.11	1	1
San Francisco	UC at Berkeley	1.19	3.23%	39.29%	1.78	1.41	4	0
Los Angeles	Caltech	1.16	4.45%	43.45%	1.51	1.20	0	1
Baltimore	John Hopkins	1.14	3.31%	57.39%	1.31	1.25	0	1
Philadelphia	Univ. Pennsylvania	1.12	3.29%	55.23%	1.29	1.15	2	1
Durham	Duke	1.11	3.11%	54.34%	1.41	1.20	1	3
Houston	Rice	1.08	4.17%	65.19%	1.26	1.12	0	1
New York	Columbia	1.08	7.31%	49.05%	1.27	1.19	2	2
Ann Arbor	Univ. Michigan	1.03	2.09%	55.24%	1.36	1.18	1	0
Boston	Harvard, MIT	1.00	7.03%	44.16%	1.81	1.37	2	5

The tables list the top 10 MSAs in terms of their share of relevantpublications, sorted by their academic research fit

Academic Research Fit for the computers and electronics industry (i.e., most specialized in academic research that is relevant to this industry). It also received the largest number of R&D investments in this industry among the top 10 MSAs. However, it is only ranked as an average MSA in terms of the share of relevant academic research of the MSA in the U.S. total. With the University of California at Berkeley as the most prominent university in the region, San Francisco has a low share of applied research and exhibits a high *Academic Quality* in both basic and applied research. In contrast, New York is one of the largest MSAs by publication share in the computers and electronics sector but does not receive many R&D investments. It has a low *Academic Research Fit* and exhibits lower *Academic Quality* in basic and applied research. In the chemical and pharmaceutical industry, Chicago has the highest *Academic Research Fit* but only received a moderate number of R&D investments in this industry. This might be due to its relatively low *Academic Quality* in basic and applied research. Boston received most R&D investments. It does not have a high degree of *Academic Research Fit*, but its university research does exhibit a high *Academic Quality*.

We use a similar approach to quantify other variables measuring agglomeration factors. Regional *Technology Fit* measures relevant R&D agglomeration based on patents of firms invented in the region and proxies the availability of relevant technological knowledge stemming from firms. Similarly, *University Patents Fit* is based on university patents and proxies the availability of relevant technological knowledge stemming from university research. *Doctorates Fit* measures the supply of relevant labor input for R&D establishments in a specific industry.

For the variables *Technology Fit* and *University Patent Fit*, we retrieved the number of patents per MSA from the USPTO data integrated in the PATSTAT database. To assign patents to different MSAs, we used inventor addresses. Using inventor addresses is preferable to using assignee addresses because firms often use the headquarters' address as the assignee address instead of the subsidiary's address where the invention was created (Deyle & Grupp, 2005). We adopted fractional counts when there were inventors located in multiple MSAs. In order to identify university patents, we examined the organization type of the patent applicant and additionally performed a keyword search similar to the exercise for identifying university publications. *Technology Fit* is the specialization of corporate patents in the MSA in IPC class t, multiplied by the technology-to-industry weight $w_{t,i}$. *University Patents Fit* is the specialization of university patents in the MSA in IPC class t, multiplied by the technology-to-industry weight $w_{t,i}$. *Doctorates Fit is* the specialization of the MSA in graduating doctorates in academic field d multiplied by the science-to-industry weight $w_{d,t}\prime \bullet w_{t,i}$. Data on the number of doctorate recipients by academic field are retrieved from the National Science Foundation and allocated to MSAs according to the university awarding them. We use a weight $w_{d,t}\prime$ based on the 10 academic fields distinguished by the NSF. Finally, the analysis controls for scientific research activities by non-university researchers. *Ratio Non-University Publications* is the ratio of the relevance-weighted number of non-university publications to the relevance-weighted number of university publications, in a particular MSA.

Prior research has suggested a range of other host region characteristics that may affect R&D location choices, and our analysis controls for these influences. Specifically, we control for geographical differences in income and purchasing power by including the variable *GDP Per Capita*, based on data collected from the Bureau of Economic Analysis. We control for different labor cost levels by including the variable *Wage Costs* (i.e., the annual average wage of an industrial engineer), using data collected from the Bureau of Labor Statistics of the United States Department of Labor. We control for the level of education,

Educational Attainment, which is the share of the MSA population with a master's degree. Data were retrieved from the United States Census Bureau. As data before 2005 were not available, we imputed missing values for the years 2003 and 2004 based on the series of university publications.[2] We control for the level of corporate taxes by including the variable *Tax*, which measures the state level corporate tax rate (from taxfoundation.org). When an MSA spans multiple states, the average of the relevant states' corporate tax levels is used. We also control for the level of *R&D tax credits*, employing data at the state level from Wilson (2009) and Falato and Sim (2014). *Population Density* is retrieved from the United States Census Bureau, as population per square mile, scaled by 1000 for ease of interpretation. The effect of *Population Density* might be nonlinear, as a densely populated location may allow for greater knowledge spillovers but a high level of density may also lead to congestion. Therefore, we include both linear and squared terms. To control for intra-firm co-location effects (Alcacer & Delgado, 2016; Castellani and Lavoratori, 2020), we construct the variable *Previous Investment* as a dummy variable taking the value 1 if the MSA already hosts an existing subsidiary of the firm, and 0 otherwise. In constructing this variable, we rely on the ORBIS database on firms' global affiliates, as well as the information on previous investment by the focal firm contained in the fDi Markets database.

All the explanatory variables are one year lagged with respect to the year of the foreign R&D investment decision to allow a response time by the investing firm. All variables except for binary variables and *Population Density* are taken in natural logarithms, which allows interpretation of the coefficients in conditional and mixed logit models in terms of average elasticities (Head et al., 1995).[3] The correlations and descriptive statistics for the variables are presented in Table 3. The correlations do not indicate multicollinearity issues.

3.5 Empirical model

In order to model the location choices, where each firm chooses one MSA among the set of 354 MSAs, we employ random coefficient conditional logit models. The conditional logit model is widely used in location choice studies (e.g., Head et al., 1995). Based on a utility maximization framework, McFadden (1974) proposed modeling expected utility in terms of choices' attributes rather than characteristics of agents making the decision. Firm characteristics that do not vary by location, such that firm or industry effects cannot be included in conditional logit models, as their value would be identical across choice such that they would drop out of the equation. This feature of the conditional logit model has led it to be regarded as inherently controlling for time-invariant firm traits such as industry (Alcacer & Chung, 2014; Li et al., 2023). Suppose investing firm f makes a location decision Y_f among L alternatives. Let U_{fl} be the expected utility of the lth choice for the firm. U_{fl} is an independent random variable with a systematic component $x'_{fl}\beta$, where x_{fl} represents a vector of characteristics of the lth choice. Then the expected utility of firm's R&D location choice is modeled in terms of the observable attributes of the choice (i.e., location; MSA) and an unobservable error term:

[2] Unlike data on doctorates, the National Science Foundation does not report the number of master's degree recipients by academic fields.

[3] The average elasticity of the probability of location choice with respect to a logarithmic transformed variable can be calculated as $(L-1)/L$ times the coefficient of the variable, where L equals the total number of location choices.

$$U_{fl} = x'_{fl}\beta + \varepsilon_{fl}$$

McFadden (1974) showed that if the L alternatives are independent and identically distributed with Type I extreme-value distribution, the probability that firm f chooses to invest in MSA l is given by the following formula:

$$\Pr\left(Y_f = l\right) = \frac{\exp\left(x'_{fl}\beta + \varepsilon_{fl}\right)}{\sum_{k=1}^{L} \exp\left(x'_{fk}\beta + \varepsilon_{fk}\right)}$$

The conditional logit model relies on the independence from irrelevant alternatives (IIA): the odds ratio between two alternatives is independent of changes in any other alternatives. This is an assumption that may not hold. A random coefficient mixed logit model generalizes the conditional logit, relaxes the IIA assumption, and allows for general unobserved heterogeneity in investor preferences (McFadden & Train, 2000). Because we have no priori expectations about whether certain coefficients have a random component or not, we allow all coefficients to be random (Basile et al., 2008; Chung & Alcacer, 2002; Revelt & Train, 1998; Train, 2009).

$$\Pr\left(Y_f = l\right) = \int \frac{\exp\left(x'_{fl}\beta + x'_{fl}\lambda_f\right)}{\sum_{k=1}^{L} \exp\left(x'_{fk}\beta + x_{fk}\prime\lambda_f\right)} g\left(\lambda_f\right) d\left(\lambda_f\right)$$

The mixed logit probability is a weighted average of the conditional logit formula evaluated, with the weights provided by the density function of the random part of the parameters: $g(\lambda_f)$. The locational choice probability has to be calculated over all possible values of λ_f. The mixed logit probability is therefore obtained by taking the integral of the multiplication of the conditional probability with the density functions describing the random nature of the coefficients. We follow the most general approach by allowing a normal distribution function (Basile et al., 2008; Belderbos et al., 2014; Chung & Alcacer, 2002); estimates are based on 100 simulation draws (Revelt & Train, 1998; Train, 2009), and we cluster error terms by firm. Since one of our research questions is if the role of local universities' research in firms' location decisions is different for research or for development investments, we estimate separate models for the two types of R&D investments (Hoetker, 2007).[4]

We note that the mixed logit model is actually a more general specification than an alternative branch of random coefficient models, the Latent Class Random Parameter model (Pacifico & Yoo, 2013; Rasciute & Downward, 2017). In the LCRP models the random nature of the influence is modelled at the class level only and the researcher has to predetermine which characteristics would determine class membership. In the mixed logit model, on the other hand, random influences are modelled and random parameters are estimated for each individual firm and there is no requirement to set predetermined firm characteristics that could cause preference heterogeneity. In addition, LRCP models require that variables entering the class membership model are constant across alternatives for the same agent (Pacifico & Yoo, 2013, p. 628), which does not hold for our focal influence: whether a firm invests in research or development can differ for the same firm

[4] We note that varying residual variations, compounded by the random component specification, prevent the direct comparison of coefficients of different mixed logit models (Allison, 2009; Hoetker, 2007).

Table 3 Descriptive statistics and correlations

	Mean	Sd	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Location Choice (DV) (1)	0.0028	0.0533																	
GDP Per Capita (2)	36,279.63	10,484.78	0.07																
Wage Costs (3)	69,809.93	9745.94	0.04	0.20															
Educational Attainment (4)	9.29%	3.90%	0.06	0.48	0.18														
Population Density (5)	0.29	0.47	0.11	0.33	0.13	0.26													
Population density Squared (6)	0.31	2.69	0.07	0.18	0.09	0.13	0.86												
Tax (7)	6.57	2.66	0.00	0.02	− 0.13	0.10	0.02	0.03											
R&D Tax Credit (8)	4.90	4.57	0.01	0.04	0.10	− 0.10	0.11	0.09	0.30										
Previous Investment (9)	0.01	0.10	0.16	0.11	0.04	0.08	0.15	0.09	0.01	0.03									
Industry Establishments (10)	27.41	135.55	0.03	0.04	− 0.03	0.07	0.05	0.01	0.01	− 0.02	0.03								
Technology Fit (11)	0.99	1.05	0.10	0.41	0.09	0.31	0.43	0.18	0.02	0.05	0.15	0.18							
Doctorates Fit (12)	0.14	0.30	0.04	0.21	0.07	0.38	0.19	0.08	0.01	− 0.02	0.06	0.07	0.25						

Table 3 (continued)

	Mean	Sd	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Academic Research Fit (13)	1.04	1.29	0.01	0.02	0.05	0.07	0.01	0.00	− 0.02	− 0.02	0.00	0.10	0.00	0.13					
Ratio non-University Pub. (14)	37.78%	32.60%	0.00	− 0.03	0.01	− 0.23	− 0.04	0.00	− 0.05	− 0.05	− 0.02	− 0.02	− 0.13	− 0.32	0.08				
University Patents Fit (15)	0.42	3.58	0.01	0.03	− 0.01	0.05	0.03	0.01	0.02	0.00	0.01	0.05	0.03	0.08	0.02	− 0.02			
Applied Share (16)	53.91%	31.62%	0.00	− 0.04	− 0.06	− 0.16	− 0.03	− 0.03	− 0.02	− 0.02	0.00	0.00	− 0.08	− 0.12	0.26	0.34	0.01		
Academic Quality: Applied (17)	0.61	0.63	0.04	0.26	0.20	0.43	0.22	0.11	0.02	0.05	0.06	0.02	0.27	0.29	0.07	− 0.25	0.02	− 0.23	
Academic Quality: Basic (18)	0.64	0.50	0.04	0.27	0.18	0.40	0.21	0.10	0.01	0.04	0.06	0.03	0.27	0.31	0.10	− 0.24	0.03	− 0.12	0.47

Means and standard deviations reported before logarithmic transformation

per investment project. We conclude that the LCRP model is less suitable for our research endeavors.

4 Results

4.1 University research and R&D location choice

Results of five mixed logit models are reported in Table 4. In the first column, we report the model estimated on the full sample of 473 investments with only the control variables. In the second column, we add a set of university characteristics except for the focal variables, i.e., *Applied Share*, *Academic Quality: Basic* and *Academic Quality: Applied*. In column three, we add these focal variables. Finally, in column four and five we report models separating research and development investments.

In model 1, all the control variables have the expected sign except for *Wage Costs*, which displays a positive effect ($\beta = 2.172$, $p = 0.004$). As pointed out by Crescenzi et al. (2014), wages may also proxy for the availability of skilled workers, and thus higher wages may be positively associated with location choice for high value-added functions such as R&D. Coefficients for *GDP Per Capita*, *Previous Investment* and *R&D Tax Credits* are all positive, while *Tax* does not seem to have an effect ($\beta = -0.121$, $p = 0.141$). The positive coefficient of *Population Density* and the negative coefficient of *Population Density Squared* suggest that firms are attracted to dense locations up to a certain point, after which congestion effects may render higher population density less attractive. The turning point of this relation is at the 95th percentile of the distribution of population density (about 3500 inhabitants per square mile). The variable *Industry Establishments*, as a general indicator of the level of agglomeration in the MSA, displays a positive and sizable coefficient ($\beta = 0.721$, $p < 0.001$), as expected. Similarly, the presence of agglomeration economies stemming from the presence of relevant technological knowledge and R&D agglomeration (*Technology Fit)* also exhibits a strong positive effect ($\beta = 0.993$, $p < 0.001$).

In model 2 university related agglomeration economies stemming from labor supply (*Doctorates Fit,* $\beta = 0.965$, $p = 0.016$) and the supply of academic knowledge (*Academic Research Fit,* $\beta = 0.891$, $p < 0.001$) both display positive effects. Patenting activities by universities (*University Patent Fit,* $\beta = 0.0786$, $p = 0.356$) and academic research by other non-university actors (*Ratio Non-University Publications,* $\beta = 0.395$, $p = 0.328$) have no additional significant influence. Results of model 3 show that a focus on applied academic research attracts R&D investments, as indicated by the sizable and significant coefficient of *Applied Share* ($\beta = 2.089$, $p = 0.004$). *Academic Quality: Applied* also positively affects the location of R&D investments ($\beta = 1.265$, $p < 0.001$), but *Academic Quality: Basic* does not have an effect ($\beta = 0.917$, $p = 0.075$).

4.2 Research versus development investments

We now examine differences in the locational drivers between research and development investments. The subsample models focusing on either research investments or development investments are presented in Table 4, columns 4 and 5. Results suggest a major heterogeneity in the role of university research depending on the type of R&D investment. For research investments *Applied Share* ($\beta = 0.959$, $p = 0.322$) is insignificant, while for

Table 4 Mixed logit estimates of the determinants of R&D investment location choices among MSAs

	Control	Basic	Full	Research	Development
GDP Per Capita	1.105	1.193	0.948	1.705	0.656
	(0.000)	(0.000)	(0.005)	(0.001)	(0.055)
Wage Costs	2.172	1.975	1.827	1.520	1.784
	(0.004)	(0.008)	(0.017)	(0.128)	(0.037)
Educational Attainment	1.269	1.174	1.133	1.318	1.066
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Population Density	0.530	0.542	0.534	0.921	0.451
	(0.029)	(0.031)	(0.059)	(0.077)	(0.160)
Population Density Squared	− 0.0706	− 0.0718	− 0.0804	− 0.240	− 0.0798
	(0.030)	(0.033)	(0.196)	(0.066)	(0.098)
Tax	− 0.121	− 0.117	− 0.0892	− 0.213	− 0.00510
	(0.141)	(0.150)	(0.299)	(0.284)	(0.958)
R&D Tax Credit	0.124	0.123	0.115	0.199	0.0511
	(0.037)	(0.038)	(0.054)	(0.059)	(0.481)
Previous Investment	2.147	2.129	2.103	2.252	2.024
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Industry Establishments	0.721	0.708	0.658	0.487	0.796
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Technology Fit	0.993	0.951	0.971	1.223	0.899
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Doctorates Fit		0.965	0.911	1.136	0.898
		(0.016)	(0.032)	(0.122)	(0.065)
Academic Research Fit		0.891	0.862	1.010	0.825
		(0.000)	(0.001)	(0.029)	(0.011)
Ratio Non-University Pubs		0.395	0.531	0.303	0.701
		(0.328)	(0.263)	(0.674)	(0.165)
University Patents Fit		0.0786	0.0729	− 0.767	0.164
		(0.356)	(0.395)	(0.269)	(0.063)
Applied Share			2.089	0.959	2.561
			(0.004)	(0.322)	(0.004)
Academic Quality: Applied			1.265	0.677	1.518
			(0.000)	(0.241)	(0.000)
Academic Quality: Basic			0.917	2.227	0.266
			(0.075)	(0.001)	(0.687)
# Investments	473	473	473	148	325
# Alternative Choices	354	354	354	354	354
Wald Chi^2	1086.61	1039.28	1175.32	364.09	739.25
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Significant random components					
Previous Investment	1.079	1.103			1.195
	(0.000)	(0.000)			(0.000)

Estimation results of mixed logit models. Robust standard errors clustered by parent firm, and corresponding *p* values in parentheses

development investments *Applied Share* has a large and strongly significant coefficient ($\beta = 2.561$, $p = 0.004$), in support of Hypothesis 1. For research investments, *Academic Quality: Basic* has a substantial positive association with location decisions ($\beta = 2.227$, $p = 0.001$) but this is not observed for *Academic Quality: Applied* ($\beta = 0.677$, $p = 0.241$). Similarly, for development investments, *Academic Quality: Applied* ($\beta = 1.518$, $p < 0.001$) has a positive and significant coefficient, while *Academic Quality: Basic* has no significant influence ($\beta = 0.266$, $p = 0.687$). These findings support Hypothesis 2. We also observe that *Academic Research Fit* has roughly similar coefficients across the two models. The variable *Doctorates Fit* loses significance in terms of *p*-value in both models, which is perhaps due to the reduced number of observations.

The effect sizes of the features of university research are economically relevant: the average elasticity of the probability of receiving R&D investments with respect to *Academic Quality: Basic* (in the research model) and *Academic Quality: Applied* (in the development model) are 2.2 and 1.5, respectively. The implied average elasticity of *Applied Share* in the development model is 2.5, and the estimated average elasticity with respect to *Academic Research Fit* are 1.0 and 0.8 for research and development investments, respectively. These are in the same order of magnitude or exceed the elasticities of *Technology Fit* or *Educational Attainment*.

4.3 Science-based versus other industries

The role of universities in attracting R&D investments may be contingent on the industry of the investing firms. Pavitt (1984) classified industries into four categories: supplier dominated, production intensive, and science based, where production intensive industries are further separated into scale intensive industries and specialized supplier industries. Pavitt's taxonomy has been widely used and proven valuable for innovation research (Archibugi, 2001; Bogliacino & Pianta, 2016). In the context of our research questions on the role of university research for firm innovation and R&D location decisions, the most important distinction is between science-based industries and the other type of industries. We examine whether the role of academic research is more pronounced in science-based industries, which include the chemicals and pharmaceuticals industry and the computers and electronics industry. Results of models distinguishing between these two groups of industries are reported in Table 5. Results indicate that, in line with expectations, for science-based industries, the *Academic Research Fit* and the quality of university research (both *Academic Quality: Basic* and *Academic Quality: Applied*) are crucial, while for the other industries a focus on applied research (i.e., *Applied Share*) is more important.

4.4 Supplementary analysis

We conducted a number of supplementary analyses to examine the robustness of our empirical results, results of which are relegated to the electronic supplementary material. We restricted estimation to foreign firms that established their first R&D investment in the MSA, such that prior R&D activities could not potentially have influenced university research characteristics. Generally, no pronounced differences with the findings reported in Table 4 were found. We also examined whether the size of the investment influences empirical results, by estimating the mixed logit model with observations weighted by an indicator of investment size. For size we use an estimate of the dollar value of the project

provided by the fDi markets database. This delivered very similar results. Similar results were also obtained when estimating models with state fixed effects included.

Finally, we examined the robustness of results to the potential presence of spatial autocorrelation. We may expect this to be a lesser concern in the context of our research for two reasons. First, the mixed logit models allow for random variations in preferences, unrestricted substitution patterns across locations, and correlations in utility (preferences) due to correlation between unobserved factors (McFadden & Train, 2000, p. 649). Hence, the estimates are robust to potential correlations in the error terms across locational choices due to these features. Second, only a minority of MSAs are located adjacent to each other, which mitigates spatial correlation. We examined the sensitivity of the results to the potential presence of spatial autocorrelation by examining models omitting MSAs where such correlation is most likely to occur: geographically adjacent or proximate MSAs. Omitting 29 MSAs with a neighboring MSA within 150 miles, results appeared robust. In addition, when we added spatial lags of a number of variables, these lags were insignificant while the estimates of the focal variable remained robust.

5 Conclusion

This paper examined the role of heterogeneous academic research in attracting industrial R&D investments, distinguishing between research investments and development investments. Our findings, which focused on investments by foreign multinational firms in metropolitan areas in the U.S., confirmed that universities play an important role in attracting R&D investments. The specialization of academic research in domains relevant for the focal R&D investment and the supply of doctoral students with relevant specialization both have a positive association with firms' R&D location decisions. We found support for our hypotheses that the role of university characteristics differs depending on whether firms invest in research or development. While an applied research orientation is generally associated with a greater attractiveness of the MSA to R&D investments, such attractiveness is not present in the case of research investments. Research activities are attracted by the academic quality of basic research, whilst development investments are attracted by the orientation towards applied research and the academic quality of applied research. We conclude that, in order to understand the role of university research in R&D location choices of firms, it is crucial to take into account both the heterogeneity in academic research and the heterogeneity in firms' R&D investments.

Our research contributes to the literature on technology transfer literature and industry-science linkages, in particular the literature on the effects of academic research on corporate innovation (Cassiman et al., 2008; Grimaldi et al., 2011; Hausman, 2020; Perkmann et al., 2013; Zahringer et al., 2017), by providing novel insights to the role of basic versus applied university research. Our finding that the heterogeneity of academic research with respect to academic quality, specialization, and basic vs. applied orientation attracts different types of R&D investments suggests a more nuanced perspective on the role of universities as a positive force in firms' R&D investments, adding to previous evidence suggesting a predominant importance of applied university research (Ali & Gittelman, 2016; Baba et al., 2009; Rothaermel & Hess, 2007; Subramanian et al., 2013). Our finding on the positive role of the academic quality of university research—including basic scientific research—for corporate R&D suggest that the logics in

Table 5 Mixed logit estimates of the determinants of R&D investment location choices among MSAs: science based industries versus other industries

	Full		Research		Development	
	Science based industry	Other industries	Science based industry	Other industries	Science based industry	Other industries
GDP Per Capita	1.223	0.826	1.218	2.547	1.228	0.382
	(0.003)	(0.051)	(0.067)	(0.013)	(0.018)	(0.404)
Wage Costs	0.883	3.015	0.972	1.993	0.833	2.443
	(0.291)	(0.002)	(0.484)	(0.225)	(0.442)	(0.030)
Educational Attainment	0.806	1.204	0.943	1.506	0.881	1.180
	(0.014)	(0.001)	(0.037)	(0.015)	(0.053)	(0.017)
Population Density	0.510	0.630	1.270	8.362	− 0.132	0.759
	(0.127)	(0.168)	(0.038)	(0.000)	(0.738)	(0.160)
Population Density Squared	− 0.115	− 0.132	− 0.186	− 6.012	0.00984	− 0.128
	(0.047)	(0.146)	(0.039)	(0.000)	(0.895)	(0.142)
Tax	− 0.0189	− 0.0763	− 0.0268	− 0.390	− 0.0716	0.0372
	(0.895)	(0.444)	(0.932)	(0.049)	(0.642)	(0.764)
R&D Tax Credit	0.107	0.0915	0.177	0.244	0.0865	0.0262
	(0.203)	(0.266)	(0.211)	(0.144)	(0.431)	(0.775)
PreviousInvestment	2.011	2.493	2.455	2.446	1.316	2.152
	(0.000)	(0.000)	(0.002)	(0.001)	(0.047)	(0.000)
Industry Establishments	0.657	0.759	0.279	1.026	0.910	0.736
	(0.000)	(0.000)	(0.127)	(0.000)	(0.000)	(0.001)
Technology Fit	0.617	0.985	0.765	1.318	0.714	0.920
	(0.044)	(0.000)	(0.069)	(0.002)	(0.067)	(0.000)
Doctorates Fit	1.250	0.876	1.638	1.235	0.539	1.033
	(0.031)	(0.085)	(0.045)	(0.346)	(0.446)	(0.121)
Academic Research Fit	1.589	0.933	1.631	1.150	1.392	0.680
	(0.026)	(0.002)	(0.176)	(0.039)	(0.187)	(0.161)

Table 5 (continued)

	Full		Research		Development	
	Science based industry	Other industries	Science based industry	Other industries	Science based industry	Other industries
Ratio Non-University Pubs	0.904	0.275	1.403	− 2.212	0.460	0.954
	(0.150)	(0.600)	(0.148)	(0.058)	(0.574)	(0.124)
University Patents Fit	− 2.421	0.0168	− 6.172	− 1.612	− 1.826	0.0786
	(0.110)	(0.900)	(0.055)	(0.026)	(0.250)	(0.528)
Applied Share	− 0.248	3.051	− 0.904	3.249	0.142	3.292
	(0.824)	(0.005)	(0.556)	(0.016)	(0.930)	(0.007)
Academic Quality: Applied	1.538	1.250	2.280	0.234	0.577	1.651
	(0.001)	(0.001)	(0.000)	(0.828)	(0.449)	(0.000)
Academic Quality: Basic	2.073	− 0.0555	2.489	1.495	1.762	− 0.443
	(0.002)	(0.940)	(0.015)	(0.252)	(0.047)	(0.579)
# R&D Investments	232	241	86	62	146	179
# Alternative Choices	354	354	354	354	354	354
Wald Ch^{i2}	565.89	639.75	292.76	231.52	498.96	468.37
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Significant Random Components						
Wage Costs		3.476				
		(0.000)				
Population Density				6.607		0.254
				(0.000)		(0.047)
Previous Investment	1.088	1.988		2.113		1.224
	(0.035)	(0.000)		(0.003)		(0.024)

Estimation results of mixed logit models. Robust standard errors clustered by parent firm, and corresponding *p* values in parentheses

industry and universities regarding quality standards and relevance may not be that different as prior studies have suggested (Ali & Gittelman, 2016; Gittelman & Kogut, 2003; Sauermann & Stephan, 2013), and are consistent with recent findings on the positive association between patent and publication quality (Poege et al., 2019). Finally, our research also contributes new insights to the literature on investment location decisions (Alcacer & Chung, 2014; Alcacer & Delgado, 2016; Belderbos et al., 2014, 2017) that has not previously examined the heterogeneous characteristics of university research in detail.

Our findings suggest that policies aiming at strengthening academic research can be an effective tool in fostering local R&D investments. Specialized strengths in academic research will attract foreign firms' R&D investments in industries that are most likely to draw on these specialized areas of academic research, strengthening a co-specialization of academic and private research. The importance of the academic quality of university research suggests that budget allocation based on academic quality through competitive research funds may have tangible benefits for host regions, while the importance of the academic quality of basic research suggests that universities should not disregard the importance of basic research excellence. The strong heterogeneity in the role of academic research characteristics depending on the type of R&D investment suggests that different profiles of universities are instrumental in facilitating different profiles of industrial R&D clusters. 'Entrepreneurial' universities with a focus on applied scientific research attract investments in development activities, while excellent research universities focusing on (high-quality) basic research attract investments in research. Hence, universities may play an important role in fostering specialized clusters of science and R&D activities across regions.

Our study is not without limitations. While we do examine different types of academic research, the quality of research, the role of doctorates, and the engagement of universities in patenting activities, future work should further disentangle the different mechanisms through which multinational firms may benefit from academic research, such as joint R&D projects, formal IP arrangements (licenses and spin-offs), conference participation, and consultancy and informal meetings (D'Este & Patel, 2007; Link & Siegel, 2005; Perkmann et al., 2013; Salter & Martin, 2001; Thursby & Thursby, 2002). Second, our analyses allowed for investor heterogeneity by distinguishing research from development investments and by estimating random coefficient models, investor heterogeneity may also stem from differences in absorptive capacity for science due to heterogeneous R&D strategies (Belderbos et al., 2017) or from other factors. Here in future research the use of latent class random parameter may be explored (Pacifico & Yoo, 2013; Rasciute & Downward, 2017) to examine researchers' priors concerning measurable firm characteristics that may drive heterogenous responses to locational characteristics. Third, a limitation of our study is that our analysis is restricted to the United States. Although our approach benefits from comparability in data and variables among the examined regions, which is often hampered in cross-country settings, future work may address whether results can be replicated in other settings. The important role played by academic research in attracting R&D investments may be partially driven by the leading position of the United States in scientific research. This may be associated with an overrepresentation of knowledge sourcing as the motivation behind foreign firms' R&D location decisions, which may not occur in other geographical settings where local market adaptation might be more important.

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Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.

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