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Attraction or repulsion? Testing coagglomeration of innovation between firm and university

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ATTRACTION OR REPULSION?

TESTING COAGGLOMERATION OF INNOVATION
BETWEEN FIRM AND UNIVERSITY

Simon Rudkin, Ming He, and Yang Chen

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Simon Rudkin, Ming He, and Yang Chen

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ABSTRACT

Agglomeration theory supports and existing findings confirm the geographical proximity of similar firms and spatial attraction of firms to universities. In addition to that, we are able to identify whether universities as one type of innovative units are attracted by firm-type innovators and the size of such attraction. Testing the bidirectional spatial innovation linkage contributes to the debate on firm- or university-led innovation. Using a large patent dataset from Shenzhen, the first innovation-led city in the People's Republic of China, and employing a spatial point process analysis technique, underutilized in the literature that allows the bidirectional testing of coagglomeration, we find varying attraction distances between the same type of innovative units and across university-firm innovation pairs. Attractions are not only limited to identical technology fields but also generate coagglomerations across different technology fields of firms and universities. We find the attraction from firms to universities is more than that from universities to firms. Support is offered to the integration of firms into the university-led innovation clusters in science parks; firm innovation in patent fields like human necessities, physics, and electrical deserve more policy focus to benefit university research and innovation.

Keywords: agglomeration, innovation, patents, spatial distribution, universities

JEL codes: O31, R11, R12

I. INTRODUCTION

In an ever automating and technology-driven world, the university–firm innovation linkage attracts clear academic, industry, and policy attention. The earlier literature suggests that firms benefit from academic knowledge and the attraction forces might be localized (Jaffe 1989; Jaffe, Trajtenberg, and Henderson 1993; Rosa and Mohnen 2008). Recent findings confirm that geographical proximity is more relevant for collaboration between firms and universities, than for the purely academic sector (Abramovsky, Harrison, and Simpson 2007; Abramovsky and Simpson 2011). From the policy perspective, governments in the United States, the United Kingdom, and many other countries emphasize the interaction between business and academic institutions (Branstetter and Ogura 2005; Griffith, Harrison, and Van Reenen 2006). The Government of the People’s Republic of China (PRC) has also paid increasing attention to innovation-led economic transition and policy highlights the role of geographic innovative clusters with close interaction between research institution and business in improving innovation performance.

To explore the spatial innovation linkage (attraction versus dispersion) of university and firm, we employ a new relative spatial measure on the most detailed patent data including different types of organizations—firms and academic institutions. The use of a bivariate M function (Marcon et al. 2015) directly incorporates the point data and avoids the concern with regard to the modifiable areal unit problem. With a focus on Shenzhen—the most innovative urban area in the PRC, we provide evidence about the distance up to which patent applications from universities and firms cluster together.¹ We find that (i) among a range of patent technologies, not all patent technologies in academic institutions colocate with firm patents, nor are all firm patent types universally attracted to innovation from universities; and (ii) that there are many pairs of fields over which significant attraction occurs, echoing the coagglomeration message of Forman, Goldfarb, and Greenstein (2016) and others. Variation across patent technologies sparks broader discussion of organization for new industrial or science parks.

A vast body of research documents spatial agglomeration of production activities of firms and industries across various levels of spatial units such as states, cities and counties (Ellison and Glaeser 1997; Ellison, Glaeser, and Kerr 2010; Kerr and Kominers 2015; Klaus Desmet 2017).² However, there is a paucity of studies that examine the spatial innovation distribution of organizations with different institutional backgrounds, in particular, within a single urban area. This paper is an example of such, with its attention on firms and universities. Difficulty studying such arises from two aspects: methods and data availability (Kerr and Kominers 2015, Marcon and Puech 2017). We meet these difficulties with a microlevel patent database capturing the location of each patenting organization, and a relative bivariate analysis that gives a complete picture of coagglomeration patterns of patents across universities and firms in eight technology categories. The relative index M statistic provides nonsymmetric estimations; different results are derived when firms are the reference and universities are the neighbors compared to when universities are the reference and firms are the neighbors. Relative to the distance-based spatial measures by Duranton and Overman (2005, 2008), this approach offers a unique opportunity to show that the colocalization of firm innovation relative to academic institution and that of university innovation relative to business are directional.

¹ Shenzhen was appointed the PRC’s first special economic zone since 1980 that grew fast in the manufacturing sector during the 1990s and the 2000s before transforming itself into a vibrant innovation hub and home to entrepreneurs, innovators, and tech firms.

² Also see good reviews by Duranton and Puga (2004) and Rosenthal and Strange (2004).

Our contribution is made in two key dimensions at a critical period (the 12th Five-Year Plan, 2011–2015) in the PRC’s development. First, we demonstrate that there are varied distance horizons over which university and firm innovations attract and repel each other; often repulsion occurring over shorter distances. Second, we are able to demonstrate that the attraction of university innovation to firms is stronger than that of firm innovation to universities. This asymmetric coagglomeration pattern recognizes a bidirectional relationship not modeled in the literature. Third, we show that proximity to university is important for firms to access research ideas. Advances in internet communication might be expected to reduce the strength of geographic agglomeration. However, the data do not show this to be happening during the 12th Five-Year Plan period. Data for this paper specifically address the 12th Five-Year Plan period (2011–2015), a time when policy was particularly focused on enabling innovation to cement the industrial development of previous decades.³ Our results align with a growing importance of coagglomeration across patent technology fields, and an increased recognition of the importance of universities as an innovative force.

The remainder of the paper begins with a look at current understandings of agglomeration, innovation, and the role that universities play within the process in section II. Our dataset and context in Shenzhen are discussed in section III, with section IV providing a foundation for the empirical approach. Our colocalization results are presented in section V, with a brief policy discussion provided in section VI. Finally, section VII concludes.

II. BACKGROUND AND LITERATURE

A. The Background of Shenzhen

The city of Shenzhen is located in the southern Guangdong province and was the first special economic zone created during the PRC’s economic reform and opening in 1978. It has 923.25 square kilometers (km²) of built-up area as of 2016 and a permanent population of 13.02 million. As of 2016, Shenzhen comprised nine administrative districts and one new district.⁴ With its rapid economic development and transition, Shenzhen was designated as the first national-level innovation-led city by the National Development and Reform Commission in 2008. It is expected to evolve to meet the definition of an internationally competitive innovative city by 2020.

Against this backdrop, there has been wide policy debate and academic interest in the mechanism to promote development of a “regional innovation system” that integrates industrial clusters and higher education institutes. In addition to providing financial incentives and public resources to foster collaboration between firms and universities, the Shenzhen government built the Shenzhen Virtual University Park (SZVUP) in 1999 in the model of one campus for multiple universities. Sixty prestigious universities and research institutes from home and abroad are located within the SZVUP.⁵ A total of 1,265 high-technology enterprises are incubated within the park. In 2002, SZVUP was given the distinction of being a national university science park having a total area reaching more than 480,000 square meters. As a vehicle to facilitate innovation and a common service platform, SZVUP has gradually developed into a cluster of high-technology small and medium-

³ The State Council of the People’s Republic of China issued the National Patent Development Strategy since 2010. See the report from http://www.sipo.gov.cn/gk/gzyd/201111/t20111128_633501.html.

⁴ They are Futian, Luohu, Nanshan, Yantian, Bao’an, Longgang, Pingshan, Longhua, Guangming, and Dapeng new district.

⁵ There are 44 mainland universities; six universities from Hong Kong, China; seven international universities; and three research institutes such as Chinese Academy of Sciences, academician’s center Chinese Academy of Engineering, and Graduate School of Chinese Academy of Social Sciences.

sized enterprises, high-caliber talents with distinctive specializations, prestigious universities, and research institutes.

In 2002, the Shenzhen government also established the University Town of Shenzhen (UTS) in Nanshan district to enhance the role of higher education in facilitating regional innovation and development. UTS is 10 km away from the original 1999 Shenzhen High-Tech Industrial Park. In the recent 2009–2015 masterplan for Shenzhen High-Tech Industrial Park, the planning area of the whole park totals 185.58 km². Fourteen smaller industrial parks are also located across the whole Shenzhen city. The mean planning area of these industrial parks is 13.26 km, with the smallest one (Liuxiandong industrial park) covering 2 km², and the largest (Pingshan industrial park) being 41.3 km².⁶ With a wide range of preferential land, fiscal, personnel, and financial policies, Shenzhen High-Tech Industrial Park has attracted a batch of high-quality innovation enterprises such as ZTE, Huawei, Tencent, Mindray, and Langke. As of June 2018, the total number of high-technology firms in Shenzhen reached 17,353, more than 10 times the number in 2009.⁷ These firms are mainly in the fields of electronics and information technology, biotechnology and new medicine, aerospace, new material, high-tech service, new energy, resource and environmental technology, and advanced manufacturing and automation.

As the first city in the PRC to propose the idea of a “regional innovation system,” first coining the term in 2004, the technique adopted by the Shenzhen government has attracted attention from industry and academia. Rigid planning techniques in the earlier stages were characterized by salient policy intervention and premeditation. Recent policy since 2010 has been more resilient, which permits and supports spontaneous location choice and clustering of business and universities within and outside the industrial parks, the university towns, and the national university park. In so doing, it enables the organic development of a multicenter innovative industrial belt and innovation network (Zhang, Liu, and Li 2017). Against this backdrop, we explore whether innovation in business and universities across different technology fields coagglomerate and, if so, over which distance they coagglomerate.

B. Industrial Agglomeration and Coagglomeration

The tendency for industries to cluster in some areas has fascinated economists, geographers, and caught the imagination of policy makers (Duranton and Overman 2008, Ottaviano and Puga 1998). The success of Silicon Valley is a good example seen by many as the magical driver for regional development. Theories of agglomeration since Marshall's (1890) principles disclose three main causes: sharing of intermediate goods supply, knowledge flow, and sharing of a common labor market (Carlino and Kerr 2015; Ellison, Glaeser, and Kerr 2010; Rosenthal and Strange 2004). The first channel is also termed as the input-output linkage and describes how the spatial concentration allows division of overall production processes to multiple subsidiary industries. With constant demand from diverse final goods producers, clustering facilitates the bearing of fixed costs for specialized machinery that is used to produce intermediate inputs (Koh and Riedel 2014). The second channel refers to the spillover of knowledge, ideas, and skills. The power of knowledge spillovers receives a large fraction of attention in the literature (Audretsch and Feldman 1996; Azoulay, Graff Zivin, and Wang 2010; Jaffe, Trajtenberg, and Henderson 1993; Kerr and Kominsers 2015; Moretti 2004). Third, spatial clustering of economic activities brings a variety of employment opportunities providing a pooled market for skill

⁶ The data is from Shenzhen High-technology Industrial Park Development Planning (2009–2015) http://www.sz.gov.cn/zfgb/2009/gb665/200908/t20090825_1161918.htm.

⁷ The list of high-technology enterprises is provided by Shenzhen High Technology Industrial Park Management Commission <http://stic.sz.gov.cn/zxbs/bszn/gqrd/>.

which improves matching between workers and employers. Such pooling also facilitates risk sharing among firms against idiosyncratic shocks.

As the key feature of economic geography, a vast body of studies documents the pattern of agglomeration of specific industries and the coagglomeration of linked industries in many regions and countries (Duranton and Overman 2005, 2008; Ellison, Glaeser, and Kerr 2010). This literature establishes the importance of clustering for firm and worker productivity (Graham et al. 2010; He, Chen, and Schramm 2018; Lin, Li, and Yang 2011). There are, in general, two ways to measure agglomeration. To assess the geographic distribution of activity in a given territory, a set of early papers identified such pattern using concentration indices such as the Herfindahl–Hirshman Index (HHI), the Gini Index, and the Ellison and Glaeser Index (EGI). HHI and Gini Indices compare the employment pattern of one industry with that in the aggregate; EGI compares the concentration of industries in a jurisdictional unit with the jurisdiction's overall plant activity controlling for the industry's plant size distribution. These three indices are sensitive to the spatial aggregation of the geographical units used for the calculation (Duranton and Overman 2005, Kerr and Kominers 2015). The second approach calculates industrial agglomeration patterns based on spatial point analysis considering the bilateral plant distances and determines whether the industry's location pattern significantly deviates from randomness. Using the second approach Duranton and Overman (2005, 2008); Marcon et al. (2015); Mori and Smith (2015) remove the zoning of space, providing concentration information at all scales and solve the Modifiable Areal Unit Problem (Arbia 2001, Marcon and Puech 2003). Following the spatial point analysis approach, Billings and Johnson (2016) compare the bivariate distributions of two industries using the Wasserstein metric. They use the Wasserstein distance between two industries and a counterfactual of general industry concentration to construct an index interpreted as the probability of correctly rejecting the null hypothesis that a given industry colocates with a randomly located industry. Their index is nonsymmetric in measuring spatial similarity. They have no measure of the distance between establishments and cannot conclude anything about the size of clustering. Robustness to the modified area unit problem is of importance to the study of innovation where locations have roots in established provision, so we follow the second approach.

C. Coagglomeration of Industry and University Innovation

Compared with the existing literature that focuses on industrial clusters, discussion of localized individual innovation connections are limited; notable exemptions are Forman, Goldfarb, and Greenstein (2016) and Kerr and Kominers (2015). Forman, Goldfarb, and Greenstein (2016) compare the number of information and communication technology patents in the Bay Area with that in the other top 20 cities in the United States; clear evidence of agglomeration of invention emerges. A similar way is adopted to identify that the non-information and communication technology patents in the Bay Area have also surpassed levels in the other 20 cities confirming the coagglomeration. Using patent citation data, Kerr and Kominers (2015) calculate the differences in the lengths of maximal radii across technology groups. The clustering of innovative units could be driven by similar forces as that of production units and the interaction between individual innovative units generates a defined distance over which attraction or repulsion forces operate. Herein, we take motivation to identify the lengths over which coagglomerative forces operate between different types of innovative units across patent technology fields.

The microinteraction between university and industry in its various forms is seen as a critical tool for regional development, as it provides business with scientific knowledge, graduates, and intermediate innovative inputs (Breschi and Lissoni 2001, Feldman and Desrochers 2003). These linkages allow firms to benefit from specialized technical and personnel support, as well as offering

access to platforms, labs, and facilities that are indispensable to business research and development (R&D) activity (Grossman, Reid, and Morgan 2001; Mowery et al. 2015). The knowledge spillover from universities to firms coincide with the development of innovation systems in the sense that firms' location decisions are strongly influenced by the potential benefit from these positive externalities (Anselin, Varga, and Acs 2000; Bramwell and Wolfe 2008). Despite the benefits received by firms to coagglomerate with universities, Abramovsky and Simpson (2011) show that the scale of R&D and production facilities in some industries such as chemicals, vehicles, and machinery could lead firms to locate outside urban areas and further away from university research still typically found in the city center.

Un and Asakawa (2015) also argue for the presence of both centripetal and centrifugal forces between industry and universities from a value chain perspective. They point out that universities are the upstream part of the value chain of the firm in terms of R&D collaboration while they are distant from the focal firm in terms of contextual knowledge distance. Universities focus on teaching and doing research. Some output in pursuit of these goals may overlap with the interests of firms, but universities' main operation is distinct from the firm. Universities have a complex interrelationship in which they compete more with other universities for students, faculty, and research funding but simultaneously, they cooperate in the creation and dissemination of knowledge. The incentives of higher education administrator and focus of faculty in universities differ significantly from those of entrepreneurs and their employees in the firm (Czarnitzki, Hussinger, and Schneider 2011). Colombelli and Quatraro (2018) find that the degree of relatedness and differentiation across technological domains may shape new firm formation at the regional level, but hardly discuss how technological linkage affects the spatial connection of individual innovative units. Considering both attraction (centripetal) and repulsion (centrifugal) forces, we are concerned with whether firms coagglomerate with universities, and if they do, how large is the size of clustering.

Though evidence of knowledge spillovers from universities to firms has been found (Acosta Coronado, and Flores 2011; Leten, Landoni, and Van Looy 2014; Liu 2015), the related question of “whether universities are equally attracted by firms, and if yes, how large is the size of clustering” is underinvestigated in the literature. The spatial linkage of universities to firms might be attributed to the widely observed funding opportunities. For example, Blumenthal et al. (1986) has found that universities receive funding from nearly one-half of all biotechnology companies to support their research; and these investments yield substantial benefits to involved firms, though government remains the principal source of support for university research. Universities can also benefit from the interaction with industry as it inspires new research directions for faculty and provides internship or placement for students (de Wit-de Vries et al. 2018, Deste and Perkmann 2011). In addition to funding, there is an increasing call for higher-education institutes to transfer technology and research findings from the ivory tower to the market through joint publication, contract research, consulting, patent licensing, joint ventures or spin-off creation (Schaeffer, Öcalan-Özel, and Pénin 2018; Grimpe and Fier 2010). The potential benefits and the emerging call to commercialize university research attract universities to industry. There remains an extent to which industrial funding and academic entrepreneurship might have a negative effect on research productivity measured by the quantity and quality of publications or work as a peril of the “culture of open science” (Banal-Estañol, Jofre-Bonet, and Lawson 2015; Backs, Günther, and Stummer 2019; Hottenrott and Lawson 2017). These forces might push universities to locate further away from industry and instead interact more with universities and other institutes. To study whether universities are also attracted by firms, and the scope of attraction or repulsion, we use the bivariate intertype function rather than the univariate intratype function to identify colocalization of two types of entities, firms, and universities.

III. DATA

A. Patent Data

Our data are taken from the China National Intellectual Property Administration including patent applications from 1999 to 2016. To address the specific question of coagglomeration of innovation between firm and university, we only incorporate patent data for the city of Shenzhen mapped in Figure 2 focusing on the 12th Five-Year Plan period from 2011 to 2015. Within the dataset there are more than 150,000 applications, of which 73% were made by firms. The dominance of industry-led innovation is unsurprising. Depicting the breakdown of patents by applicant type, Figure 1 shows how individual applications had grown through the first 15 years of the century. The patent applications started to take off since the outline of the Medium- and Long-Term National Science and Technology Development Plan was issued. Numbers from universities and research institutes are notably lower, but a broad upward trend is discernible at the base of the bar chart. After a slight stagnation in 2010, our period coincides with a rapid increase in the number of patents applied for. This is also a period of acceleration for university innovation, but is a mixed period for research institute patent applications. The patterns illustrated are in line with the aims of the 5-year plan.

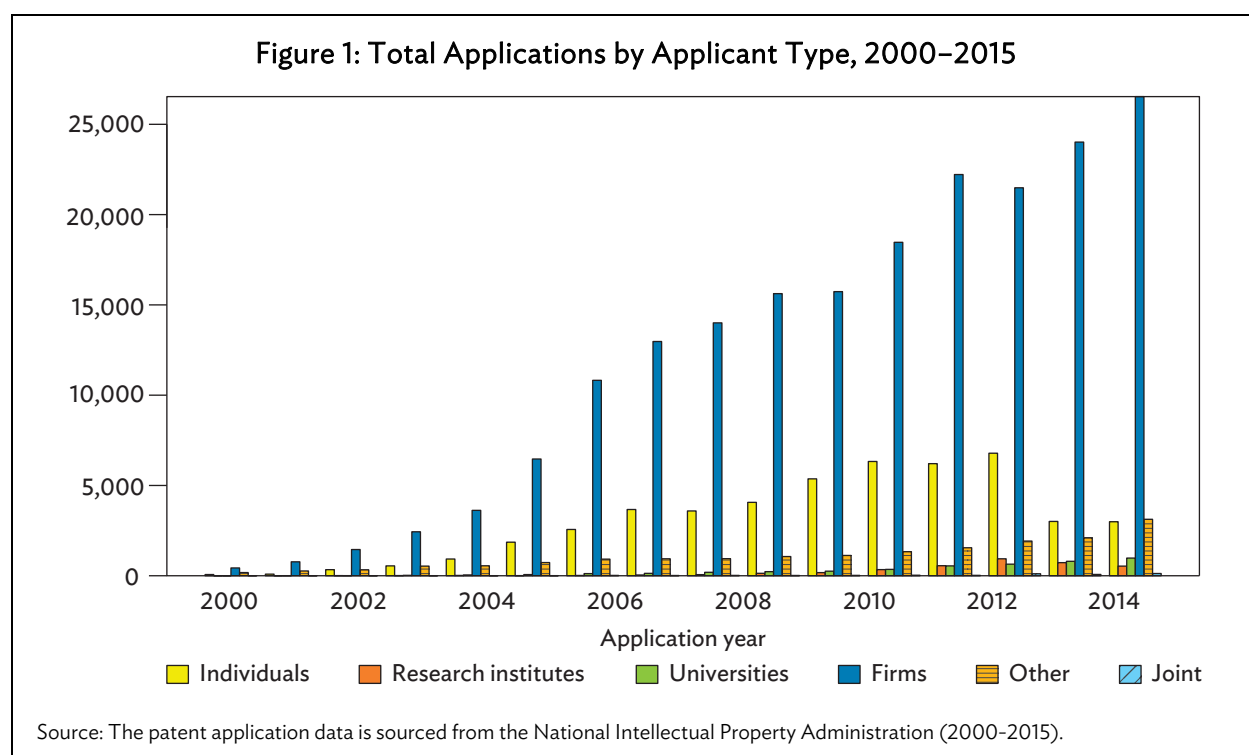


Table 1 details the eight fields of patent technologies that are studied within the paper and the six main applicant types. Joint patent applications are kept separate from the study of the relationships between universities and firms, as our aim is to understand the effect of applications generated by the two individual types across space; joint applications will necessarily be located at the same point as either the firm or the university and so, would not give a true spatial representation of the relationship. With so few joint applications, it is not expected that this exclusion will have any effect, and robustness checks on patent type A, human necessities, confirm this expectation in that field. Inclusion of patents lodged by individuals, research institutes and others within the sample provides the M function with further possible locations over which to randomize the distribution of points.

Table 1: Patent Applications by Applicant Type and Field, 2011–2015

Patent Field Type	Applicant Type						Total
	Ind	RI	Uni	Firm	Other	Joint	
Human necessities (A)	768	578	259	4,328	2,223	101	8,257
Operations and transport (B)	1,810	195	263	6,300	1,578	27	10,173
Chemistry and metallurgy (C)	2,884	490	576	4,798	699	87	9,534
Textiles and paper (D)	18	6	12	192	69	1	298
Fixed construction (E)	234	8	45	999	478	7	1,771
Mechanical engineering (F)	2,439	10	47	3,208	943	42	6,689
Physics (G)	8,719	1,293	1,217	34,976	2,096	68	48,369
Electrical (H)	8,449	513	901	57,916	1,934	24	69,737
Total	25,321	3,093	3,320	112,717	10,020	357	154,828

Notes: Field provides the main field of the patent as classified within the application. The six applicant types are individual (Ind), research institute (RI), universities (Uni), firms, others, and joint.

Source: The patent application data is sourced from the National Intellectual Property Administration (2011–2015).

B. Mapping Innovation

Each application contains detailed address information which permits geolocation to a high degree of accuracy using Amap API; such information further enabling the use of spatial distribution methods within this paper. Many complexities have been documented in the geocoding process, but increasingly, applications and scripts have been created to overcome these (Li et al. 2018). To provide an understanding of the geography of the dataset, we separately map the innovation across the eight patent fields for universities and firms. Figure 2 provides the Shenzhen area map with its component counties. As is typical for cities in the PRC, universities cluster in downtown areas, while firm innovations form clusters more spread out across the map.

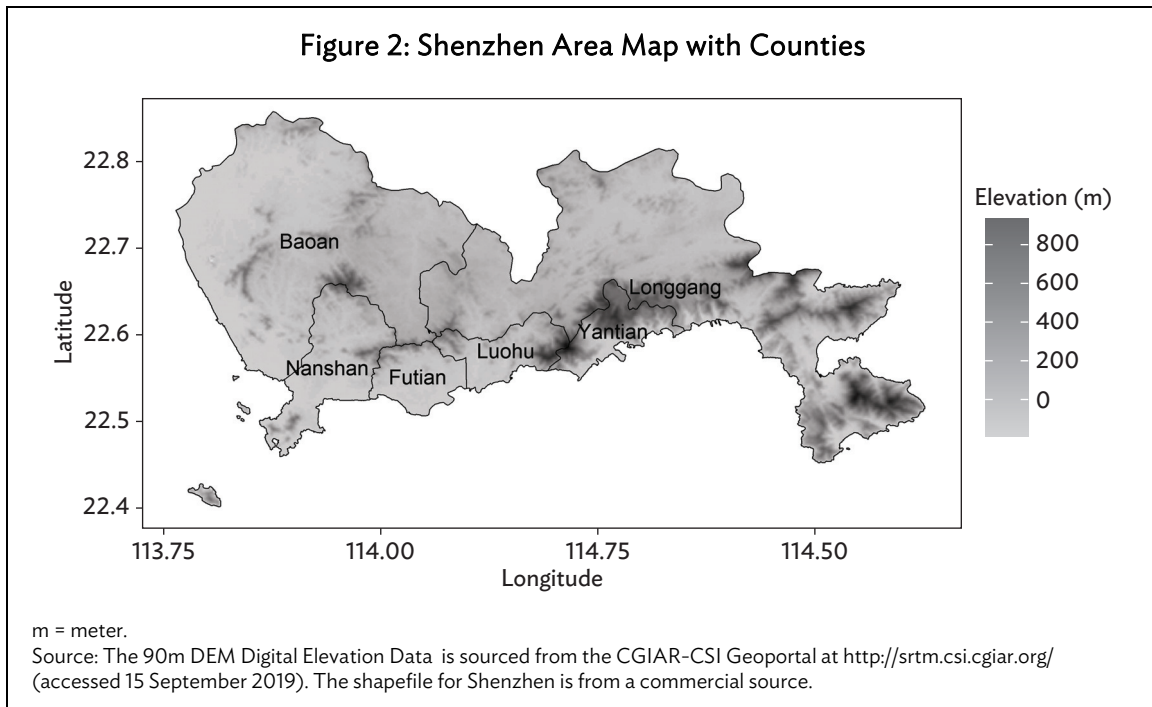
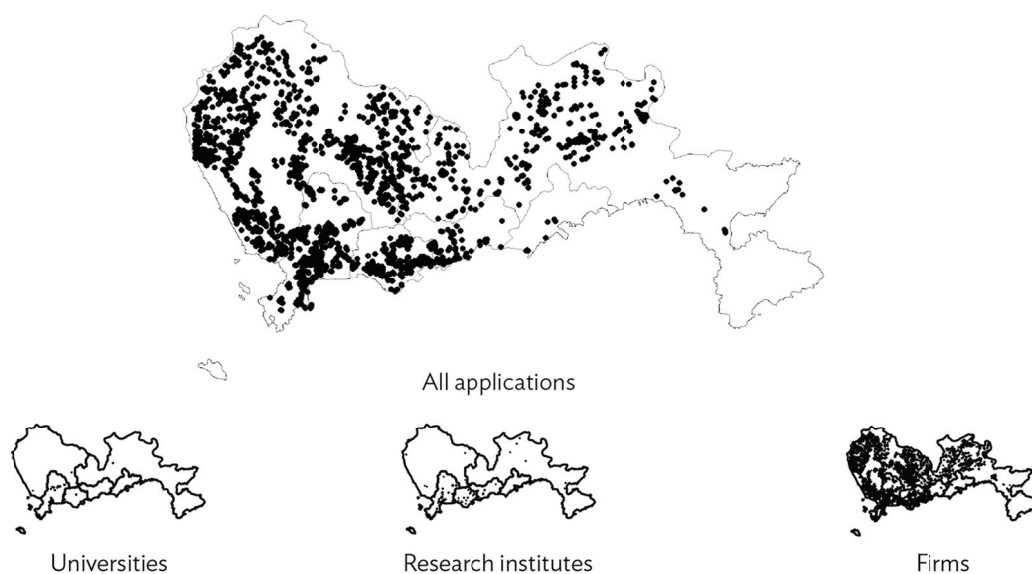


Figure 3 plots the locations provided for the patent applications between 2011 and 2015 with the lower figures breaking down the set into universities, research institutes, and firms for whom the localization is being studied. Universities are concentrated in Nanshan district to the southwest of the map, with small pockets of innovation then appearing in the central Futian and to the northeast in Longgang. Where universities are identified, there are often several points in close proximity to create more solid-looking masses compared to the research institutes, which are more spread out through the region. Compared to universities, there are many more research institutes and we can see that they reach into the southeast of the map where no universities, and only a few firms, are located. The dominance of firms is seen once again by the darkness of their map. Firms do appear clustered within the Nanshan district, but we also see agglomerations in other districts or counties to correspond with the population centers therein.

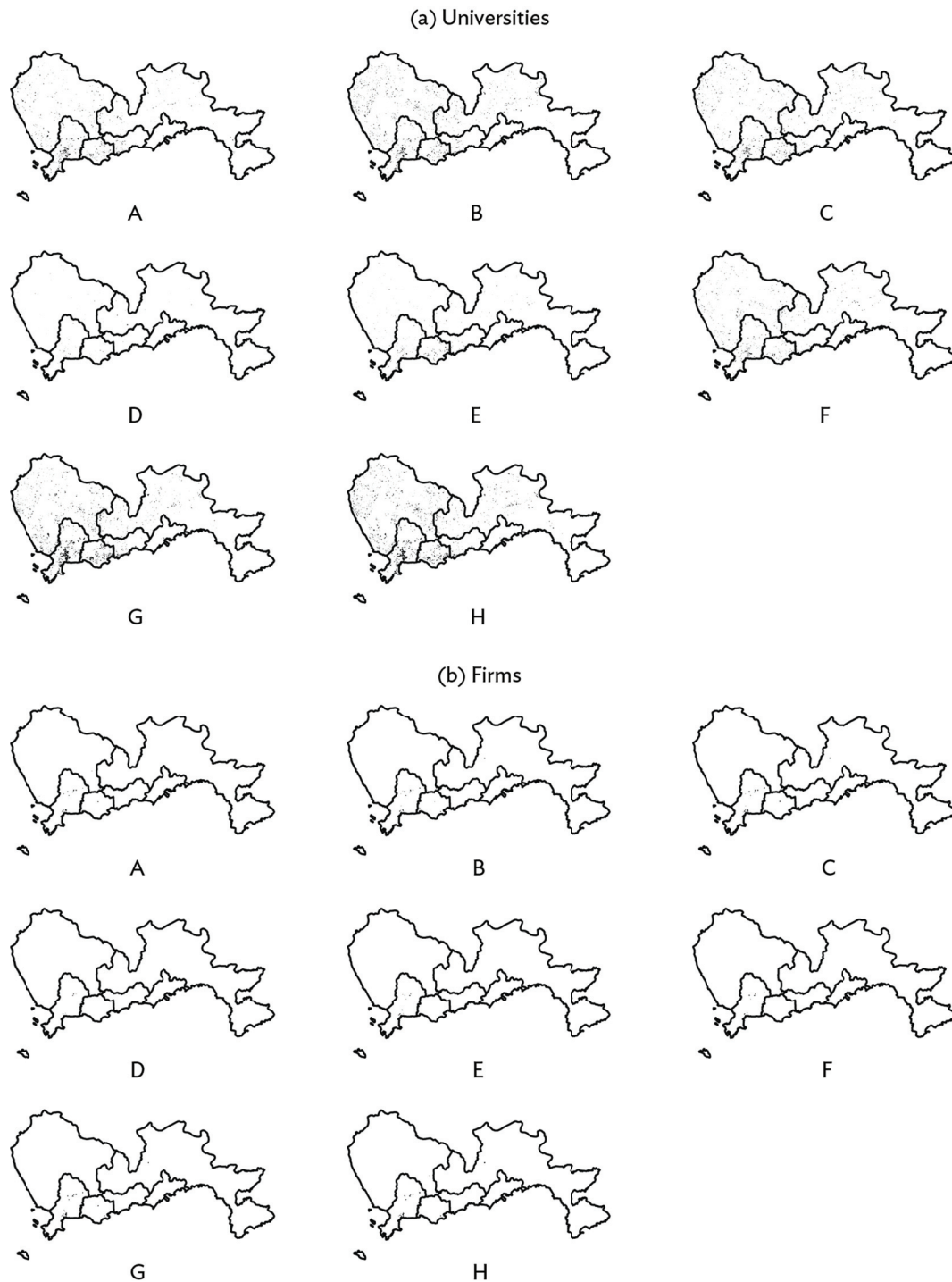
Colocalization is studied at the patent field level, meaning we can construct eight maps for each of the studied applicant types. In each case, the limited number of university locations make spotting patterns harder; larger points make the key agglomerations in Nanshan district clear in the top panel of Figure 4. Firm locations are spread across the map in most of the application types, albeit the lower numbers in textiles and paper (D) and fixed construction (E) mean that the maps are lighter. Although not conclusive, there is a suggestion from the maps that where a university applicant appears to the northeast of the map (types B, C, G, and H) there is also a larger number of firm patent applications in that area. Differences in the spatial distribution can be seen when we plot the eight different fields; human necessities and electrical applications from universities demonstrate the strongest patterns. Links between universities and firms are perhaps best shown by the number of applications from the large areas that do not have any universities. In the northwest of the map, there are no universities, but we do see a lot of applications from firms, particularly in physics, operations and transport, and electrical fields. From the maps, it is not immediately apparent whether patent applications from one type are attracting, or repelling, innovation of the other type. We seek to understand more about the relationships between these locations, following Marcon and Puech (2003) to evaluate the spatial innovation linkages.

Figure 3: Locations of Patent Applicants in Shenzhen, 2011–2015



Notes: Universities and research institutes are plotted using larger points to ensure that they are visible on the small maps. Source: The patent application data is sourced from the National Intellectual Property Administration (2011–2015). The shapefile for Shenzhen is from a commercial source.

Figure 4: Patent Application Locations, 2011–2015



Notes: Patent field types are denoted as in Table 1: human necessities (A), operations and transport (B), chemistry and metallurgy (C), textiles and paper (D), fixed construction (E), mechanical engineering (F), physics (G), electrical (H). University plots use larger point markers for clarity.

Source: The patent application data is sourced from the National Intellectual Property Administration (2011–2015). The shapefile for Shenzhen is from a commercial source.

IV. METHODOLOGY

Possessing detailed data information on patenting sites, we adopt distance-based methods to identify the spatial innovation linkage between firms and universities. The distance-based methods are developed as continuous function of space, providing information about concentration at all scales simultaneously. Critically, they do not rely on zoning. The seminal work by Ripley (1976, 1977) provided a univariate $K(r)$ function which sums g on the range 0 to r to compare the distribution of a set of points with a random distribution, where g is a ratio of the joint probability of finding two points in a particular observed pair of locations and the marginal probabilities of each point being in the observed location and r denotes distance. The K function has been used in the ecology literature to characterize interactions assuming a homogeneous point process for which the probability to find a point is the same everywhere. Its use remained incidental in spatial economics until the works of Marcon and Puech (2003, 2009) and Duranton and Overman (2005). Two key limitations with $K(r)$ are noted by Marcon and Puech (2017). Firstly, the assumption that points could be randomly distributed fails to recognize the physical impediments to certain locations that prevent their development; Shenzhen, as mapped in Figure 2, has clear mountainous and sea regions that are not suitable for location. Secondly, $K(r)$ does not include any options for weighting, though this second limitation does not impact our analysis due to the lack of obvious weighting within the patent dataset.

Addressing the limitations of $K(r)$, Marcon, Puech, and Traissac (2012) propose an M function which compares the number of neighbors of interest to the total number of neighbors for a reference point up to a certain distance r relative to the same ratio in the whole area of analysis, where the reference points are indexed by f , neighbor points by n , all points whatever their type by a ; their numbers are N_f , N_n , and N_a , respectively. The numerator is the average ratio of neighbor points around the reference points and the denominator is the average ratio of neighbor points in the population. With a simple interpretation, $M_{f,n}(r) > 1$ implies that the reference and neighbor points attract each other, while a value of $M_{f,n}(r)$ below 1 suggests repulsion. A further feature of this function is that the value does depend on which point type is chosen as the reference; this is evidenced very clearly in our application.

$$M_{f,n}(r) = \frac{N_a - 1}{N_f N_n} \sum_{f=1}^{N_f} \frac{\sum_{n=1}^{N_n} \mathbf{1}(\|x_f - x_n\| \leq r)}{\sum_{a=1, a \neq f}^{N_a} \mathbf{1}(\|x_f - x_a\| \leq r)}$$

Consider firms located in an area. If proximity to universities is attractive to a firm, we could expect that firm has more neighbors being universities around it than if it were locating randomly. On the contrary, finding fewer neighbors of universities than expected implies that firms locate away from universities. Similarly, consider universities located in an area. In the benchmark case known as complete spatial randomness, universities could locate at any place with constant density and they locate independently of each other. Now suppose that the location choice for university is not random but relies on the location of other universities, research institutes, firms, and other organizations. If proximity to firms is attractive to a university, that university will have more firm neighbors around it than if it were to locate randomly; on the contrary, finding fewer firm neighbors than expected implies that universities locate away from firms.

We follow Marcon and Puech (2017) in viewing the process of colocalization identification as being a five-step operation. First, we calculate the number of neighbors of interests within a certain distance. Second, we compare it with the number of all neighbors within fixed radius circles of each reference point. The M function uses the full circle to identify neighbors rather than only those on the

edge like Ripley (1977). Third, we calculate the average ratio of neighbors around the reference point. Fourth, we compare the average ratio within a certain distance with the average ratio of neighbor points in the whole area. Finally, a null hypothesis of independence is needed to create a significance test for the characteristics of interest as suggested by Marcon, Puech, and Traissac (2012). Practically the implementation of the bivariate M function involves the assumption that any point within either the reference set or the neighbor set may possibly be located at any position where there is a data point in the overall set of patents. This is an important advance because it ensures that the model is only trying to place points in locations where innovation could possibly occur. Independence in this sense is testing whether the points are independently distributed across the set of possible patent locations and not over the land area of Shenzhen. It is seen in Figure 3 that there are obvious blank areas and other areas where patent activity is much denser; the method used here reflects that and does not apportion attraction simply because a university–firm pair exists within one of the denser areas. Thus, random datasets are generated for the bivariate M function by redistributing the actual point set on the actual location set (coordinates). Following Loosmore and Ford (2006)’s goodness-of-fit to obtain a correct p value to reject the null hypothesis, they first compute the average value of $M(r)$ on all simulations, where s is the number of simulations and $M_i(r)$ is the value of $M(r)$ in the i^{th} simulations. The statistic u_i is computed for the i^{th} simulation by summing up all values of r , where Δr is the difference between the next value of r and the present one,

$$\overline{M_r} = \frac{1}{s-1} \sum_{i=1}^s M_i(r)$$

$$u_i = \sum_r [M_i(r) - \overline{M_r}]^2 \Delta r$$

The same statistics for the actual data u is compared to u_i to get the p value,

$$P_u \approx \frac{\sum_{i=1}^s \mathbf{1}(u_i > u)}{s}$$

To avoid $P_u = 0$ or $P_u = 1$ for p values if u is always greater or smaller than u_i , we could assume that another simulation would have given a value of u_i higher or lower than u and express $P_u < 1/s$ or $P_u > 1-1/s$.

Using the R package, dbmss, (Marcon et al. 2015) the M function is estimated for each of the eight different patent fields, with each of the universities and firms as reference type and neighbor type. This results in our studying 128 combinations.⁸ In each case, all other patent applications within the Shenzhen area are used as the possible locations for innovation to be randomized over.

V. COAGGLOMERATION

To fully appreciate coagglomeration between universities and firm patent applications, we must both recognize the bidirectional nature of the relationship and the potential for applications in one field to influence the location of applications in other fields. This latter need was evidenced in the literature in the strong coagglomeration forces discussed by Forman, Goldfarb, and Greenstein (2016) and others. Working systematically through the 128 combinations, we split the presentation by the field of the firm

⁸ University type A as reference to firm type A as neighbor is different from firm type A as reference to university type A as neighbor.

patent; splitting by firm recognizes the interest in how university innovation transfers to firms. A final choice for the modeling is the distance r to use for the search. We perform the analysis over a distance of 50 km but find that almost every spatial pattern has dissipated by around 40 km, and that in order to see the effects closer to the reference points, 30 km is an optimal choice for the plotting.⁹

Figures 5–12 provide the M functions as estimated together with the confidence interval around independence. Plots are labeled according to their reference category and then the neighbor category, the letters corresponding to those of Table 1. Hence Firm A Uni A means that firm patent applications in the human necessities field are the reference category and university patent applications in the same field are the neighbor type. In every case where the M function line sits below the shaded confidence interval, we have repulsion of the two types of application, and where it sits above, we have attraction. In order to test the significance of observed patterns, a goodness-of-fit test is available within dbmss (Marcon et al. 2015), but this returns a p value below 0.001 in every case and so we do not report the figures individually.

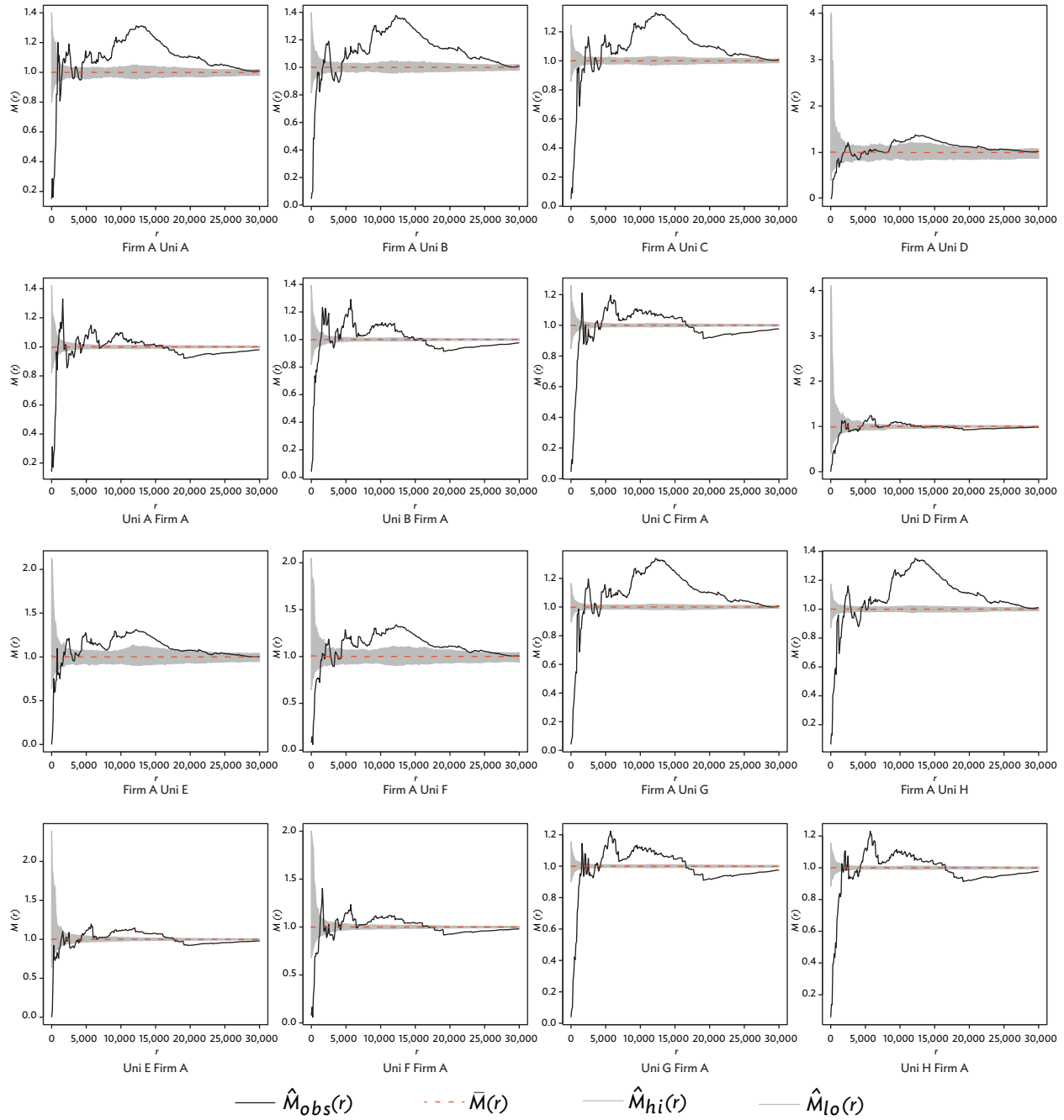
Figure 5 plots the M functions related to applications from firms in the human necessities field. In the first and third rows of the figure, firm patents in field A are taken as the reference category such that the figure label begins with Firm A. In each figure, there is an initial area of repulsion which exists over the first 1 km to 2 km, followed by a large attraction range. In most cases, the attraction range continues past 25 km. Many of the M functions display a small repulsion region after the initial attraction, this appears between 4 km and 5 km. Many of these early patterns may be attributed to the campus nature of university design in the PRC and hence, we should not place too much importance to such short-lived effects. What is clear is that firm innovation in the human necessities category is not only attracted by university innovation in the same field but also by other patent fields. Reversing the order, the effects are notably different, although there is an attraction, it dissipates after around 17 km to be replaced by a repulsion over the next 10 km. Plot Uni D Firm A is perhaps the hardest to observe this pattern within, but even with the low number of university patent applications in textiles and paper (D), there is still an attraction to human necessity patents over the medium distance.

Moving to consider firm patents in operations and transport (B), we see a very different pattern emerging. In every case, there is significant repulsion of innovation almost throughout the entire 30 km range. A small exception is where we also consider Type B applications from universities, as here, a short attraction around 20 km is seen. We can see that type B innovation in firms is weakly attracted by university innovation in physics (A) and electrical (H) over the 20 km to 25 km range. However, the broad message of repulsion is entirely at odds with the attraction picked up above. When reversing the relationship, taking university as the reference category, there is even stronger evidence of repulsion. Aside from a small insignificant region of attraction around 4 km in the case of university patents in mechanical engineering (F), there is nothing but high levels of significance in the results.

Across the two firm patent types A and B, two very distinct patterns emerged, the first is an attraction pattern and the second is a clear repulsion. When considering firm patents in the chemistry and metallurgy (C) field, the pattern is very close to the second type (Figure 7). Taking the firm as the reference category, there are small ranges of attraction around the 20 km mark as there were in Figure 6. Firm innovation in field C is significantly attracted by university innovation in field B, G, and H, but surprisingly not by the same patent field. When reversing the relationship, once again there are no regions of insignificance; university innovation repels firm innovation across the full 30 km.

⁹ We make 50 km plots available on request. Plots are not included as an appendix within the paper as this would take the file size over the 3 megabyte limit.

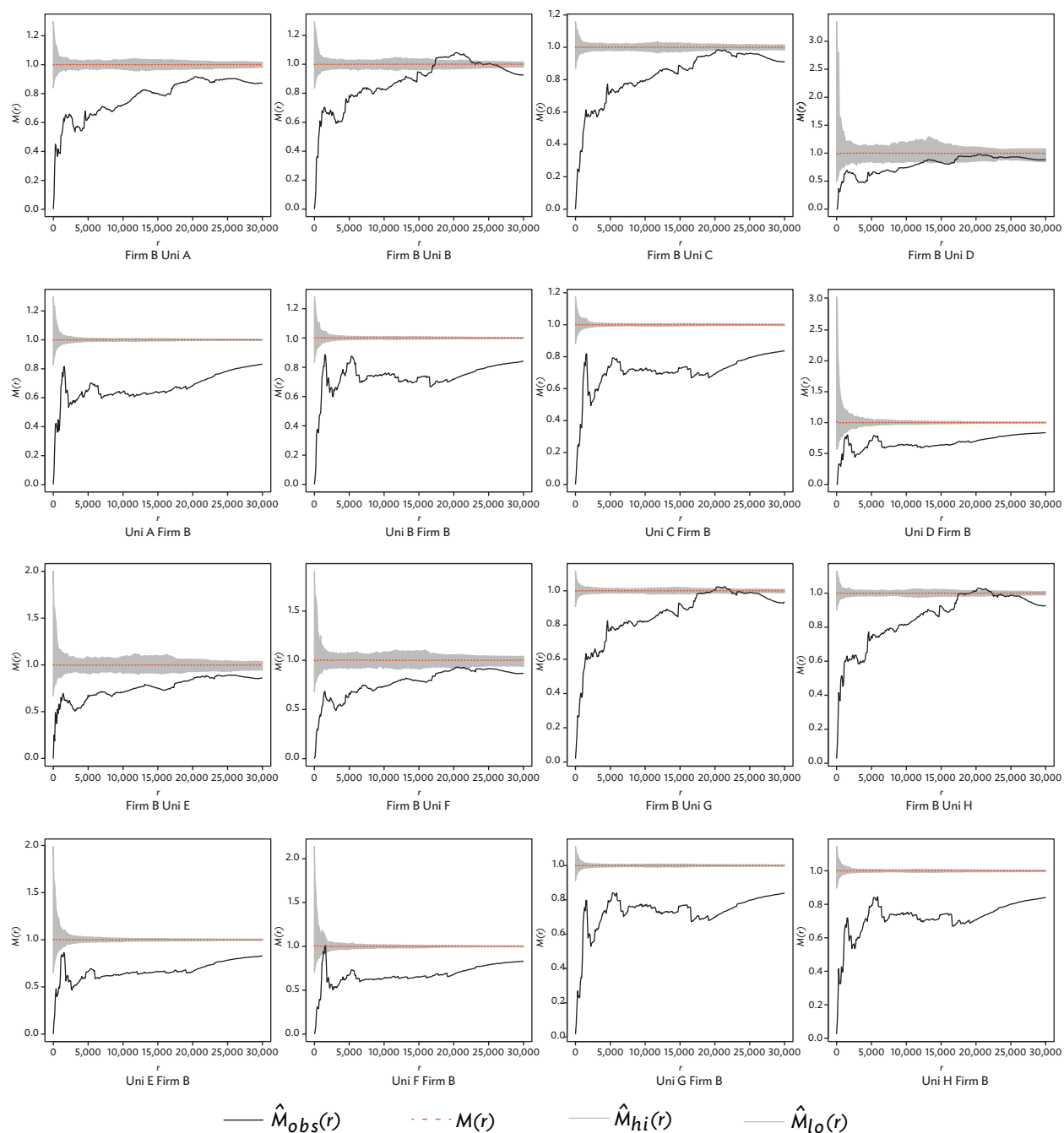
Figure 5: Coagglomeration of Firm Patent A with University Patent A-H



Notes: The figures plot the coagglomeration of firm patent A with university patent A-H. The first and third rows take firm as the reference; the second and fourth rows take university as the reference. Labels are written below the plots and show the reference point type followed by the neighbor category. Shaded areas represent 95% confidence intervals around the null hypothesis of zero relation. Plots are generated over the 30 km radii.

Source: The patent application data is sourced from the National Intellectual Property Administration (2011–2015).

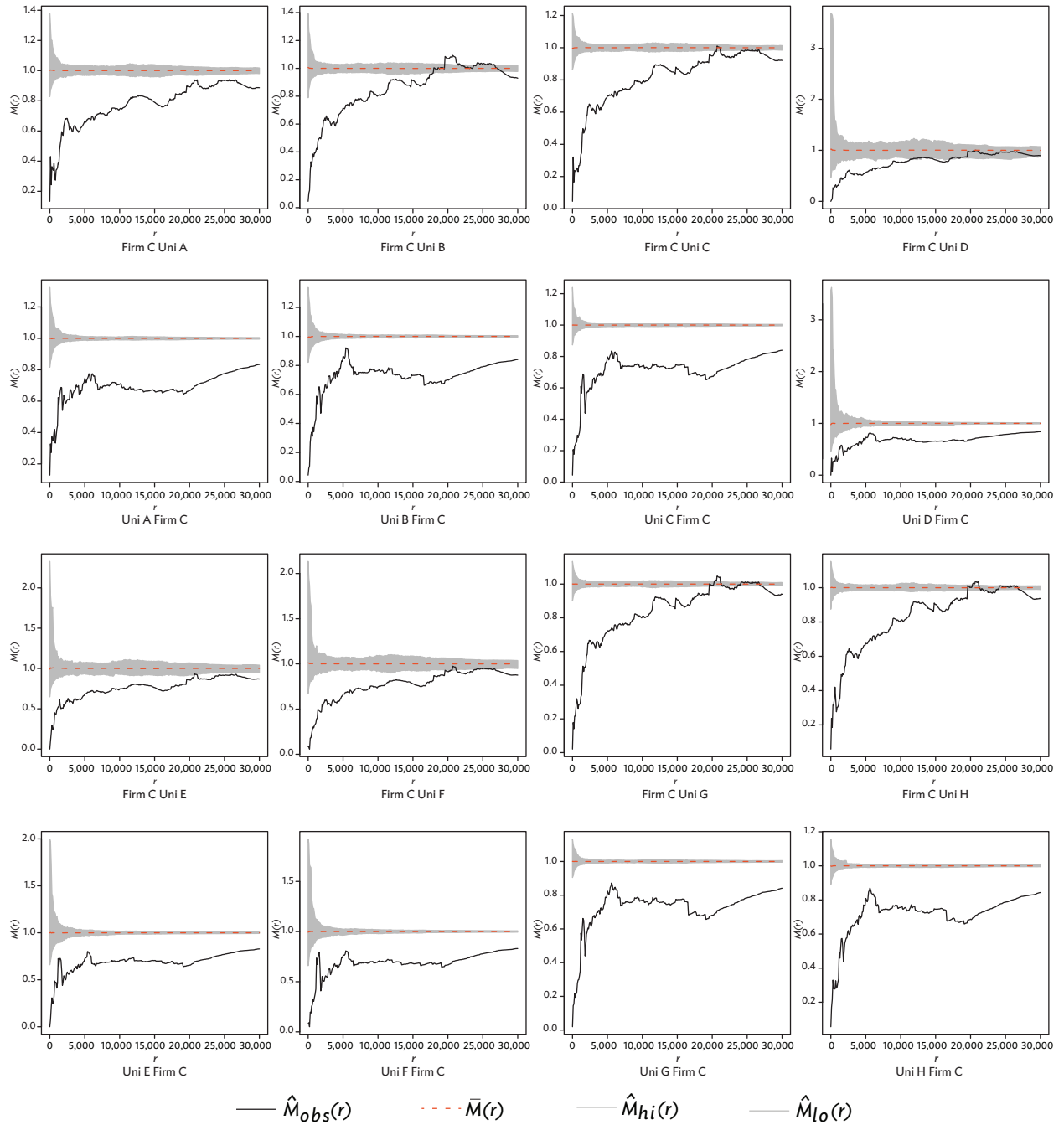
Figure 6: Coagglomeration of Firm Patent B with University Patent A–H



Notes: The figures plot the coagglomeration of firm patent B with university patent A–H. The first and third rows take firm as the reference; the second and fourth rows take university as the reference. Labels are written below the plots and show the reference point type followed by the neighbor category. Shaded areas represent 95% confidence intervals around the null hypothesis of zero relation. Plots are generated over the 30 km radii.

Source: The patent application data is sourced from the National Intellectual Property Administration (2011–2015).

Figure 7: Coagglomeration of Firm Patent C with University Patent A–H



Notes: The figures plot the coagglomeration of firm patent C with university patent A–H. The first and third rows take firm as the reference; the second and fourth rows take university as the reference. Labels are written below the plots and show the reference point type followed by the neighbor category. Shaded areas represent 95% confidence intervals around the null hypothesis of zero relation. Plots are generated over the 30 km radii.

Source: The patent application data is sourced from the National Intellectual Property Administration (2011–2015).

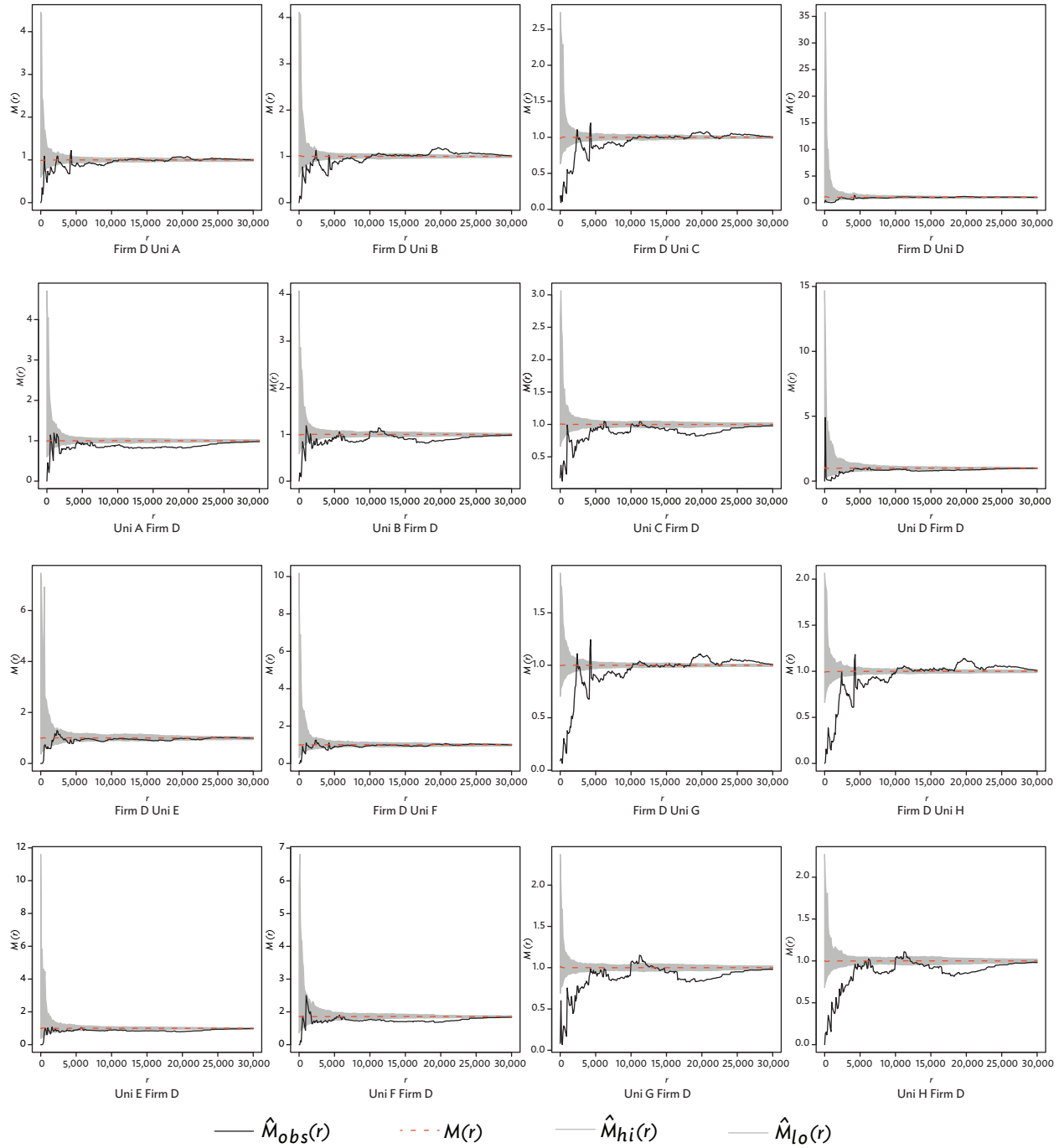
A low number of patent applications within the textiles and paper (D) field mean that the initial confidence intervals over low radii are very large. Graphs become compressed to accommodate the high values of the upper bound of the confidence interval as a consequence, as seen in Figure 8. Across the 30 km, there are regions of attraction and repulsion, typically more than one of each type covering a distance of around 5 km per region. Tests that the overall effect differs from random remain significant in almost all cases with p values ranging from 0 to 0.06. Of those not significant at the 5% level, all have firms as the reference category, the fields being textiles and paper (D), fixed construction (E), and mechanical engineering (F).

Figure 9 displays the coagglomeration pattern for patents in the field of fixed construction (E). There is an attraction played out over a longer distance with the repulsion, for the firm as reference category, that ended around 2 km in Figure 5 persisting until almost 10 km in every case. Attractions are found from 10 km until around 25 km and once again, all of these patterns are highly significant. Taking the university applications as reference, there is again strong repulsion over the first 10 km, with weak attraction around the 15 km mark. Unlike the case with firms as reference, there is then a significant repulsion evidenced between 20 km and 30 km, appearing most clearly in the plots for Uni A Firm E, Uni B Firm E, Uni G Firm E, and Uni H Firm E. Patent applicants from field E, fixed construction, include developers of roads, railways, and bridges demanding and occupying larger space, which drives them further from universities, research institutes, and where innovation in other categories takes place. This may explain why there is a broader initial repulsion region than there was in the cases studied elsewhere in this paper.

Mechanical engineering is another field where we might expect a large amount of innovation to take place in larger factories and construction sites with their associated larger distances from other innovation. In Figure 10, with firms as the reference category, regions of repulsion can be seen extending beyond 15 km in every case; this is even further than for fixed construction (E). After a brief significant attraction, we then see returns to repulsion by the end of the 30 km range. Firm innovation in mechanical engineering is strongly attracted by university innovation in operations and transport (B), chemistry and metallurgy (C), physics (G), and electrical (H) fields. Switching the order such that university innovation is the reference category removes the attraction region significantly, we do not see any evidence of universities surrounding the innovative firms in patent field F. Such a result is entirely intuitive since seldom would we expect universities to locate to serve such traditional sectors of industry.

Figure 11 displays the attraction pattern once more for firm patents in physics (G), albeit with an initial repulsion range that stretches to 5 km, being 7 km for university patents in chemistry and metallurgy (C) and just 3 km when the university patent is in physics (G). Firm innovation in physics is attracted by university innovation within the 30 km radius and are pronounced in almost all cases; $M(r)$ peaks above 1.2 around 15 km for many patent types. It should be noted that a peak this high represents an aggregation at least 20% higher than would be the case under random allocation. Reversing to consider universities as the reference category still displays attraction beyond 5km, but the magnitude is much smaller than in the firm reference case. This implies that the innovation spillover from university to firm is more than that from firm to university. Although the values of $M(r)$ do get closer to 1, the attraction remains significant according to the goodness-of-fit tests.

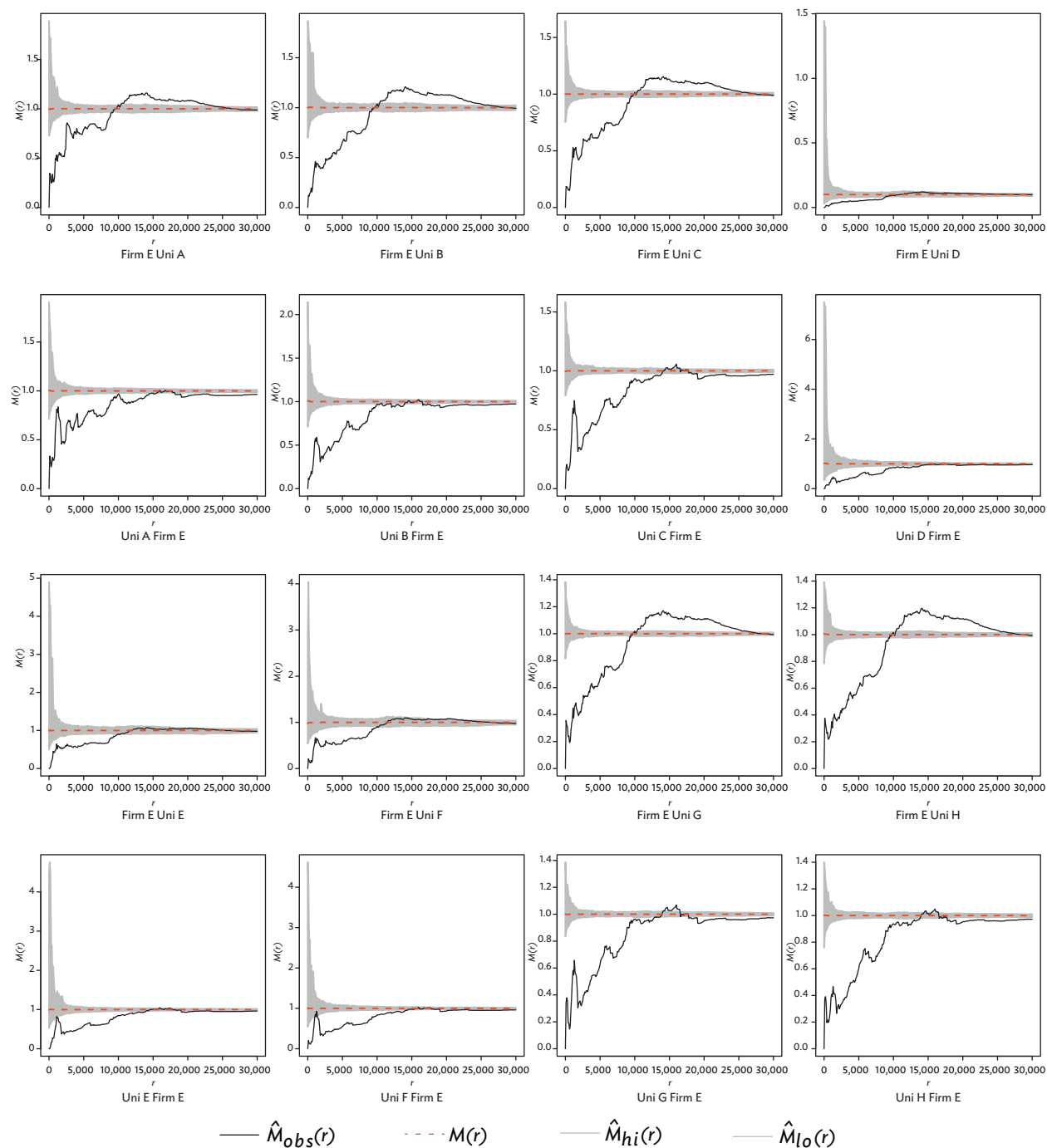
Figure 8: Coagglomeration of Firm Patent D with University Patent A–H



Notes: The figures plot the coagglomeration of firm patent C with university patent A–H. The first and third rows take firm as the reference; the second and fourth rows take university as the reference. Labels are written below the plots and show the reference point type followed by the neighbor category. Shaded areas represent 95% confidence intervals around the null hypothesis of zero relation. Plots are generated over the 30 km radii.

Source: The patent application data is sourced from the National Intellectual Property Administration (2011–2015).

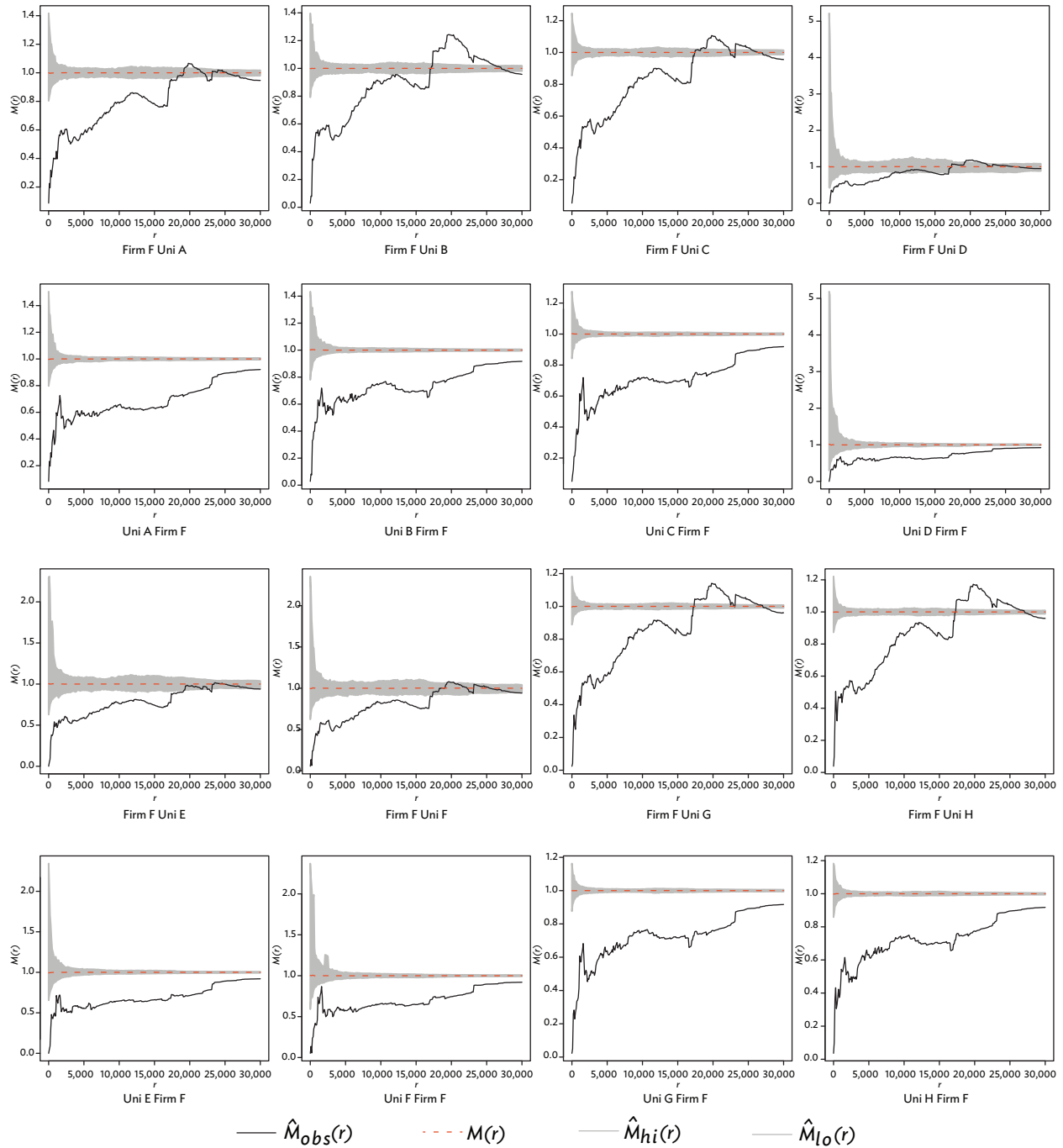
Figure 9: Coagglomeration of Firm Patent E with University Patent A–H



Notes: The figures plot the coagglomeration of firm patent E with university patent A–H. The first and third rows take firm as the reference; the second and fourth rows take university as the reference. Labels are written below the plots and show the reference point type followed by the neighbor category. Shaded areas represent 95% confidence intervals around the null hypothesis of zero relation. Plots are generated over the 30 km radii.

Source: The patent application data is sourced from the National Intellectual Property Administration (2011–2015).

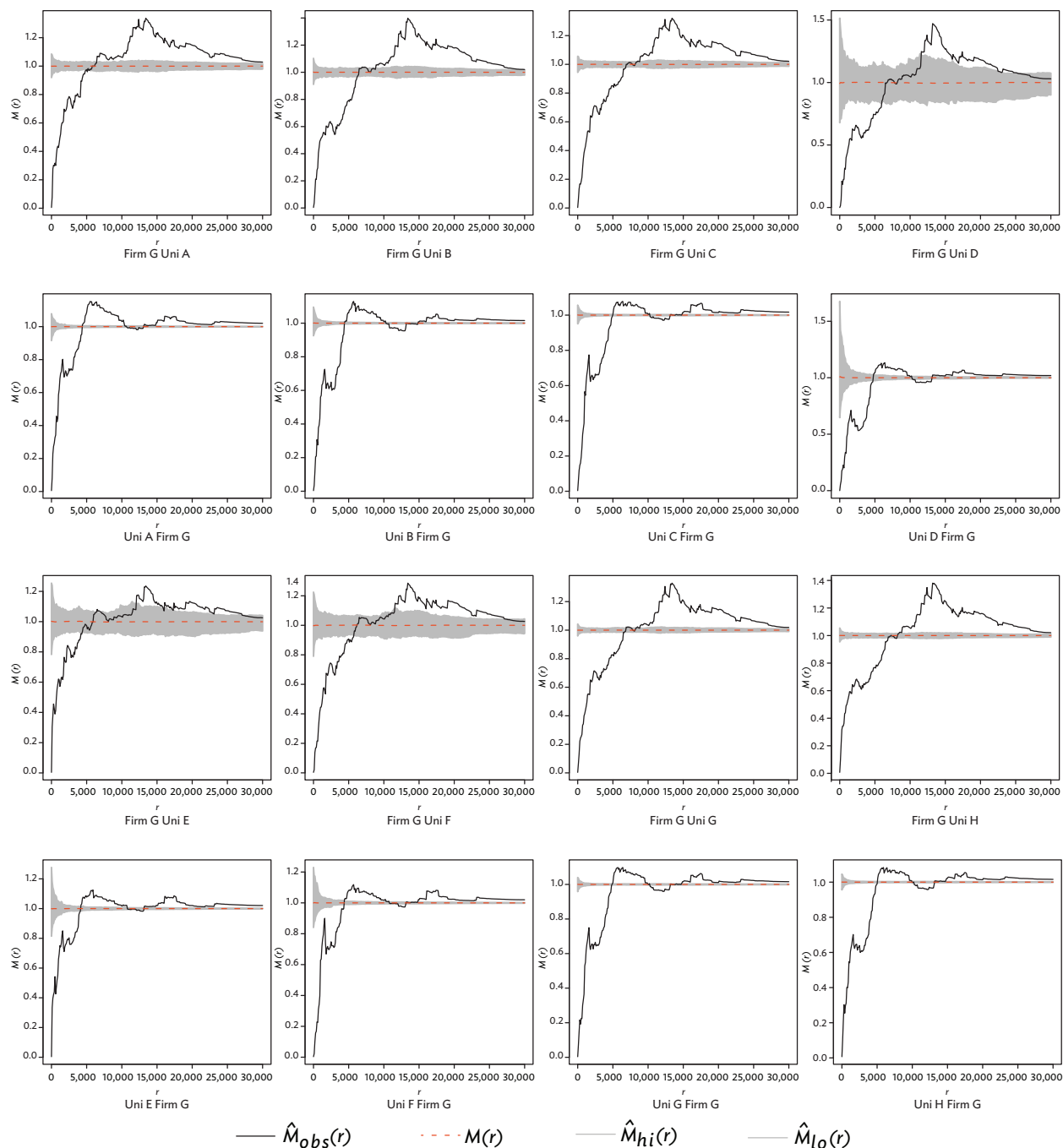
Figure 10: Coagglomeration of Firm Patent F with University Patent A-H



Notes: The figures plot the coagglomeration of firm patent F with university patent A-H. The first and third rows take firm as the reference; the second and fourth rows take university as the reference. Labels are written below the plots and show the reference point type followed by the neighbor category. Shaded areas represent 95% confidence intervals around the null hypothesis of zero relation. Plots are generated over the 30 km radii.

Source: The patent application data is sourced from the National Intellectual Property Administration (2011–2015).

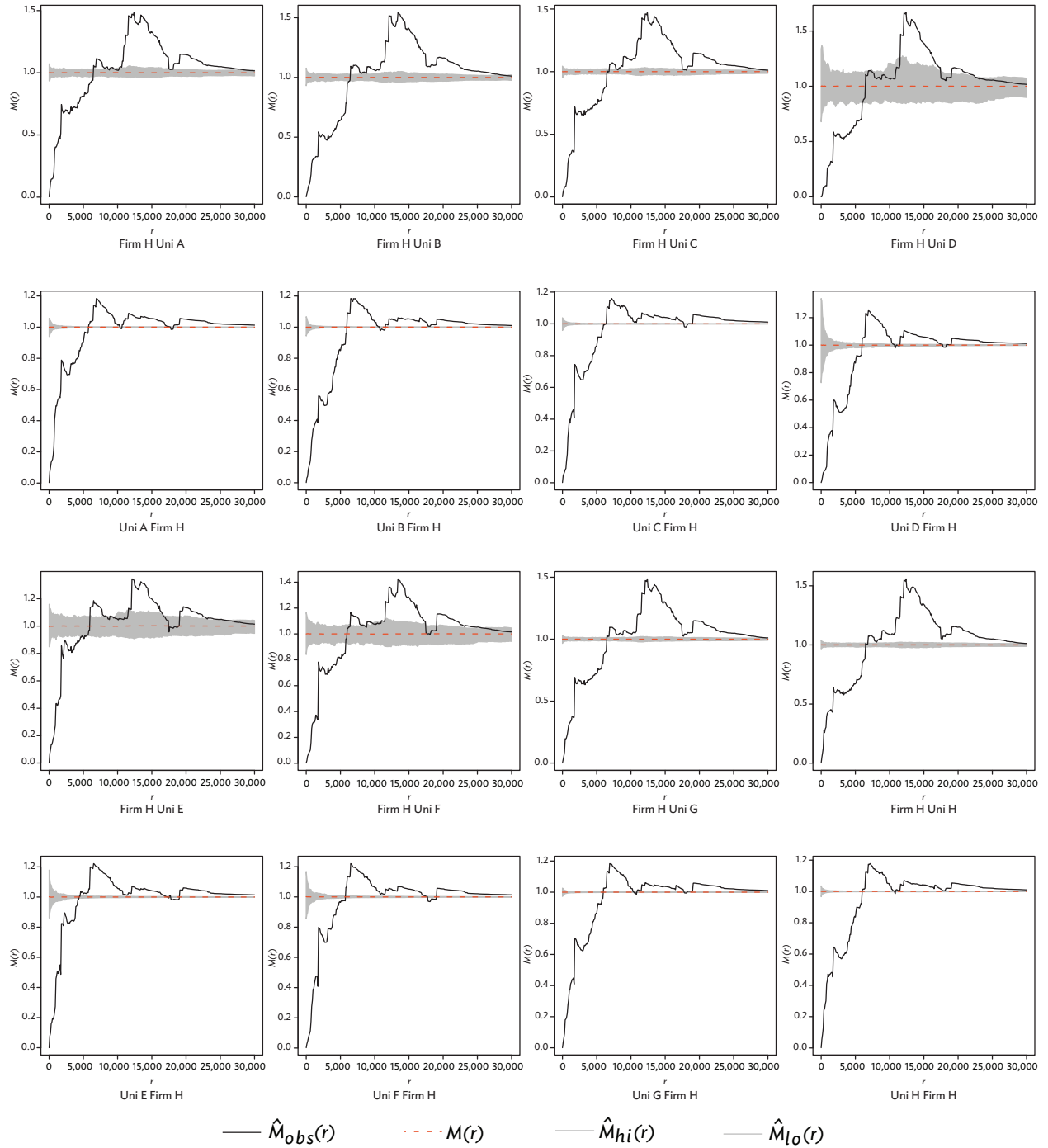
Figure 11: Coagglomeration of Firm Patent G with University Patent A-H



Notes: The figures plot the coagglomeration of firm patent G with university patent A-H. The first and third rows take firm as the reference; the second and fourth rows take university as the reference. Labels are written below the plots and show the reference point type followed by the neighbor category. Shaded areas represent 95% confidence intervals around the null hypothesis of zero relation. Plots are generated over the 30 km radii.

Source: The patent application data is sourced from the National Intellectual Property Administration (2011–2015).

Figure 12: Relative Colocation of Firm Patent with University Patent A-H



Notes: The figures plot the coagglomeration of firm patent H with university patent A-H. The first and third rows take firm as the reference; the second and fourth rows take university as the reference. Labels are written below the plots and show the reference point type followed by the neighbor category. Shaded areas represent 95% confidence intervals around the null hypothesis of zero relation. Plots are generated over the 30 km radii.

Source: The patent application data is sourced from the National Intellectual Property Administration (2011–2015).

Finally, Figure 12 considers firm patents in the electrical field (H); the attraction pattern is shown once again. With the firm as reference category, the attraction begins around the 7 km mark and continues to the end of the 30 km range, albeit that most plots also display a point around 20 km where $M(r)$ goes back close to 1. Compared to the physics (G) patents discussed against Figure 11, the maximum value of the attraction is much higher, pointing to at least 50% more university neighbors being found surrounding firm innovators than if the location pattern was random. The lowest maximum is 30% between fixed construction (E) patents from universities and the electrical (H) patents from firms. Reversing to consider the university patents as the reference category, we can see that the attraction begins at a marginally lower r than for the corresponding plots with firms as reference. Once attraction starts, we do not see any repulsion regions involving type H firm patents; some small points close to 1 are observed on the various combinations but these are very small distance ranges and almost always insignificant.

Across the 128 cases of coagglomeration of university and firm innovation, two clear patterns have emerged. First, there are those characterized by an attraction pattern, one that typically begins around the 5 km to 10 km mark and runs for the remainder of the 30 km window, and those best described as being repulsion patterns with little attraction anywhere in the 30 km. Attraction patterns are seen when firms are patenting in the field of human necessities (A, Figure 5); physics (G, Figure 11); and electrical (H, Figure 12). Repulsion is then seen in operations and transport (B, Figure 6) and chemistry and metallurgy (C, Figure 7). Patents in textiles and paper (D) did not display strong patterns owing to the low numbers of observations, but theirs was closer to the repulsion pattern than the attraction. Finally, the two patent types that involve large plants and construction sites, fixed construction (E, Figure 9) and mechanical engineering (F, Figure 10), show attraction and repulsion, respectively, but the pattern of repulsion is active over a much longer distance than is seen in other cases. A motivation for these two being different may lie in the nature of their operations compared to other technology fields; further research is needed. Table 2 summarizes the results that we obtain.

Table 2: Summary of Patent Colocalization Patterns

Patent Field Type	Pattern	Max p	Attraction Min (km)	Range ^a Max (km)
Human necessities (A)	Attraction	0.015	4	25
Operations and transport (B)	Repulsion	0.000	20	25
Chemistry and metallurgy (C)	Repulsion	0.002	20	25
Textiles and paper (D)	Repulsion	0.060 ^b	na	na
Fixed construction (E)	Attraction*	0.010	12	30
Mechanical engineering (F)	Repulsion*	0.004	18	25
Physics (G)	Attraction	0.000	8	30
Electrical (H)	Attraction	0.000	5	30

na = not available.

Notes: This table presents a summary of the patterns identified from $M(r)$. Max p reports the maximum p value for any of the goodness-of-fit tests that the true pattern exhibits independence. A single * is used to represent the longer distance over which the patterns display in types E and F.

^a In the case of repulsion, we report the range over which small ranges of attraction are seen on some plots within the set. Very little consistency is noted within the overall repulsion pattern in type (D) textiles and paper.

^b Only three of the combinations involving firm patents in textiles and paper (D) show a p value greater than 0.050 with the majority of patterns remaining significantly different from independence at the 1% level.

Source: This table summarizes the patterns of patent colocalization using data sourced from the National Intellectual Property Administration (2011-2015).

Although difficult to capture, it should be noted that there are differences between each of the 128 combinations of patent field pairs and reference institutions. While the broad conclusions have value, it has been evidenced through this section that there remains a need to think more carefully about the specific combination being studied to ensure reactions to the observed patterns have the necessary robustness.

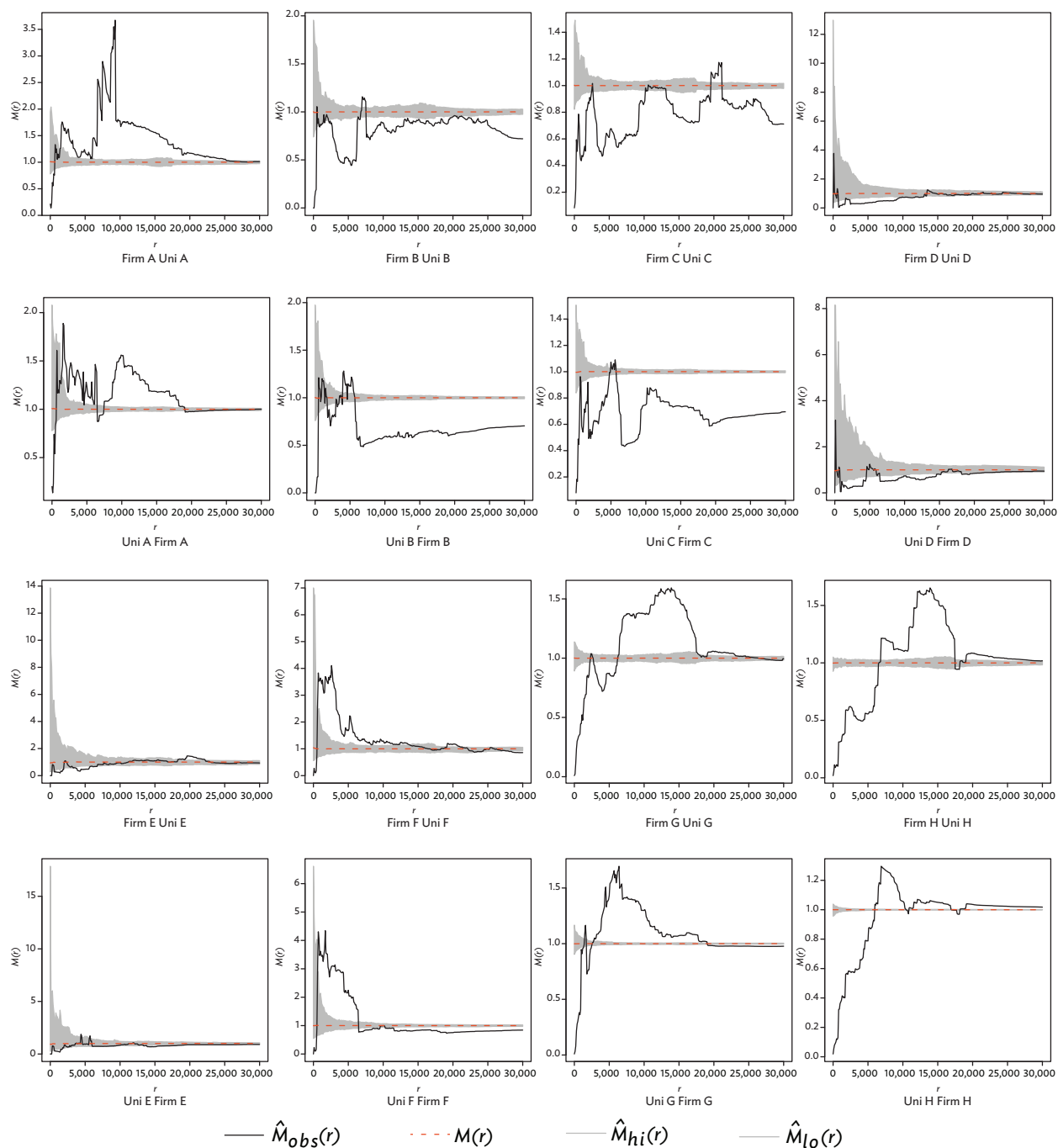
A. The 11th Five-Year Plan, 2006–2010

Comprehensive results are reported above for the 12th Five-Year Plan, in which cooperation between universities and firms was seen as a key cornerstone of policy. To understand whether the results are sensitive to the study period and the initiatives taken in the 12th Five-Year Plan, the analysis from the 2006–2010 period is also considered. It was seen in Figure 1 that prior to 2011, the number of applications was notably lower, there are in fact just under 145,000 compared to the 335,000 in the set covered above. For brevity, the full set of results are not reported here.

A number of different patterns are observed in Figure 13, but broadly, we can still see the attraction pattern in human necessities (A), physics (G), and electrical (H) fields. Repulsion is again seen strongly in operations and transport (B) and chemistry and metallurgy (C). In the case of patents in textiles and paper (D), Figure 8 continues to show repulsion but with limited significance due to the low number of patents. Firm patents in fixed construction (E) show attraction when firms are the reference category and repulsion when universities are the reference; the former is consistent with our results in the 12th Five-Year Plan stage. Mechanical engineering (F) displays attraction over the first 8 km, something which was not seen in any of the other cases; a colocalization of patents would suggest strong spillovers that then dissipated. Understanding more about this may again present a useful dynamic story.

Through this brief look at an earlier period, we have confirmed that the results reported are not unique to the period but are a natural extension of earlier patterns. With the pace of development in Shenzhen, and more broadly in the PRC, it can be of little surprise that the degrees of innovation accelerated so greatly between the two 5-year plan periods. Likewise, it should be unsurprising that the result has seen certain patterns become more pronounced, but that few have changed slightly.

Figure 13: Relative Colocation of Firms and Universities in the Same Field (30 km)



Notes: The figures plot the relative colocation of firm patent C. The first and third rows take firm as the reference; the second and fourth rows take university as the reference. Labels are written below the plots and show the reference point type followed by the neighbor category. Firm A Uni A has firm patents in field A, human necessities, as the reference category and university patents of the same type as the neighbor. Shaded areas represent 95% confidence intervals around the null hypothesis of zero relation. Plots are generated over the 30 km radii.

Source: The patent application data is sourced from the National Intellectual Property Administration (2006-2010).

VI. POLICY IMPLICATIONS

Universities are by design centers for innovation, and this does spill over into the production of patents and intellectual property. Within the agglomeration literature, much is made of the knowledge spillovers that can come to firms who locate with others in similar fields. Combining these to gain benefits from the innovation of universities is a natural extension of the theory that has been given strong consideration in the literature. Results have been very mixed, however. In this paper, we employ spatial point pattern analysis of patent applications in Shenzhen, PRC, to question the extent of colocalization of innovation between firms and universities; our conclusions then inform on the strength of spillovers between the two. We verified that the insights gained are broadly robust to time.

Forman, Goldfarb, and Greenstein (2016) is one of a growing number of studies to suggest that it is important to consider not only technology spillover within the same technology field but also that there will be coagglomeration across fields. Our results demonstrated consistency across all eight of the possible university patent types for each of the firm patent types. Such a robustness is encouraging for innovation policy to promote these areas and to obtain attraction for innovation in other fields. This cross field attraction is also consistent with the results of Abramovsky and Simpson (2011) and their assertion that precise field did not matter in the university–firm innovation relationship. Critically, the attraction of firms to universities is consistently larger than that of universities to firms, albeit that the presence of attraction was found to be similar in all cases. Consequently, the results presented here suggest that encouraging innovation in any one of the four attraction fields (human necessities [A], fixed construction [E], physics [G], and electrical [H]) could create development in the other four fields and bring benefit to the Shenzhen region.

Jaffe (1989); Audretsch, Lehmann, and Warning (2005); and Abramovsky, Harrison, and Simpson (2007) are among many to identify the importance of geographic proximity to universities in promoting innovation; within the four attraction fields, our results agree with this. Given that science parks are often designed with universities as active collaborators, our evidence demonstrates the wisdom of this strategy for firms active in the electrical high-technology area. Li and Zhu (2017) suggested weak association with universities, something that we identify in a number of the other patent fields where repulsion is the dominant pattern. In the cases where repulsion was dominant, there was some evidence of longer distance attractions of the type found by Abramovsky and Simpson (2011); such longer distance attraction is present as part of the overall attraction in the attraction cases too. Shorter distance repulsion between universities and firms may be the result of zonal planning precluding certain types of innovation activity within the main industrial parks; that there is consistency across all eight university fields suggests this is not true, however. An alternative interpretation is that, over a short distance, attraction pattern is shown between universities since the knowledge distance between similar types of organizations is shorter than that between university and firm. Our evidence does support the use of universities to enable firm innovation but cannot provide a causality to the relationship.

Within the PRC's context, much of the development of innovation is managed through the creation of science parks, technology zones, and university towns that are all designed on blank canvases to align with the best available theory of the time. Shenzhen was the first innovation-led city, obtaining the designation in 2008, and is home to some of the PRC's largest high-technology firms. Compared to major neighbors, Guangzhou and Hong Kong, China, Shenzhen is a new city and is highly planned in its expansion. Our work on attraction therefore represents a genuine environment in which firm locations can be considered to be less hindered than might be the case in an established urban ecosystem. Li and Wang (2019) observed that high-tech firms were often within 5 km of universities in

Nanjing's science parks; our low distance attractions are consistent with this, but over a much larger area. The suggestion of our work is that such possibilities for attraction can yield significant spillovers and that embedding universities should remain a cornerstone of policy irrespective of the insignificance found elsewhere. Our contribution is to direct the fields of study that the universities would be best focused on.

Some further questions are raised by our work that will require more exploration. Patents in fixed construction are necessarily linked to firms that operate far from existing developments, while those in mechanical engineering are also born of firms requiring bigger land takes. These fields need more analysis, but do display consistent patterns across the eight university patent types. Looking at the previous 5-year plan, insignificance was found and a curious attraction across short distances was detected in mechanical engineering. The evolution from close attraction to overall repulsion is the area where more analysis is needed to determine the true pattern.

Overall attraction between university patenting activity and firm innovation is shown to be strong; use of universities as catalysts for development has clear promise. However, there are also channels which we are unable to evidence within this dataset. First, universities are increasingly opening graduate research centers, or research hubs and these have very different functionality to the traditional research institutes. Second, universities are also educational establishments producing graduates for roles in the very firms whose innovation performance is being considered. To what extent this creates spillover that is not spatial or is a secondary motivation for proximity is open to discussion; firms will certainly benefit from a skilled workforce on the doorstep. These two elements speak to the broader importance of knowledge spillovers and labor productivity in agglomeration, respectively. Our valuable insights thus have links to the long-standing colocation arguments (Ellison and Glaeser 1997; Ellison, Glaeser, and Kerr 2010; Kerr and Kominsers 2015) and labor productivity in particular (He, Chen, and Schramm 2018; Melo et al. 2017).

VII. CONCLUSIONS

University innovation is a strong attractor of firms, particularly in the higher technology sectors where the line between theoretical research and commercializable intellectual property are closest together. Employing the spatial point pattern analysis of Marcon and Puech (2009), we find distances over which the promotion of innovation in the higher education sector will attract an increase in patenting by firms. Increased patenting is then part of a chain that leads to new markets, cementing of market power, and the ability to fund further innovation and hence, further future strength. The virtuous circle of innovation begetting profits repeats not only within particular industrial fields, but also across other areas. Diverse coagglomerations have been identified as most beneficial to the wider urban area giving planners further motivation to recognize these conclusions in designing science parks and spatial master plans. There are significant distance horizons over which university and firm innovation attracts each other, while firms (universities) attract firms (universities) over shorter distances. Further, we showed that these attraction distances are different for firms attracting universities compared to the stronger pull of university innovation on firms. Being able to discern this differential within the spatial point pattern is a selling point of the Marcon and Puech (2009) methodology to the economics literature and allows us to provide new evidence of universities also locating proximate to innovative firms especially in human necessities, physics, and electrical fields.

Our work is set within the city of Shenzhen owing to the leading innovation status that the city has in the PRC's development. Shenzhen's flexible planning and regulation environment is hardly found, and nor could it be replicated in other cities. Fine graining the categories, the definitions of

university, and extending the period can represent potentially fruitful directions for further work. Notwithstanding these future research directions, this study has evidenced a number of important phenomenon in innovation coagglomeration along both directions, representing a significant advance over existing studies. Policy has therefore been justified in promoting universities as an integral part of new science park planning, and our results now allow that recommendation to be fine-tuned around the fields in which the universities will be innovating. Coagglomeration of university and firm innovation commands greater inclusion in development strategies. Harnessing these attraction forces, and developing new industrial organizations, becomes a critical task for industry, academics, and policy makers alike.

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Attraction or Repulsion?

Testing Coagglomeration of Innovation between Firm and University

Agglomeration theory suggests the geographical proximity of firms in production activities. The authors add to the literature by identifying whether universities are attracted by firms in patents production and the size of such attraction. Using a large patent dataset from Shenzhen, the first innovation-led city in the People's Republic of China, and employing a spatial point process analysis technique, the authors found varying attraction and repulsion distances between the same type of innovative units and across university-firm innovation pairs. Attractions are shown within identical technology fields and across different technology fields. Weak support is offered to the integration of firms into the university-led innovation clusters in science parks. Firm innovations in the technological fields like Human Necessities, Physics, and Electrical should deserve more policy attention.

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