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RESEARCH NOTE

Silicon envy: How global innovation clusters hurt or stimulate each other across developed and emerging markets

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Abstract
The authors examine intercluster dynamics among rival global clusters on monthly counts of patents, startups, and new product commercializations between 1999 and 2014 while controlling for numerous exogenous variables. Results show that rival innovation clusters facilitate rather than hinder each other's growth due to resources complementarities. Reverse fertilization occurs from emerging to developed clusters, contrary to the received wisdom. This study is the first to show intercluster dynamics as important drivers of cluster growth. To explain the counterintuitive findings, the authors draw upon the coopetition view which suggests mutually beneficial growth across all rival clusters rather than zero-sum gains.
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INTRODUCTION

The success of Silicon Valley has prompted governments worldwide to try to emulate its success by fostering "silicon" clusters of their own (*The Economist*, February 18, 1999). This phenomenon an important question: How does the success of these new clusters affect the growth of existing clusters? The received wisdom in the scholarly literature and business press holds that the emerging innovation clusters, particularly those located in low-wage Asian economies, steal from Silicon Valley's growth in terms of talent, startups, and capital (Estrin, 2008). The business press documents the rising loss of US jobs to low-wage emerging economies (Lahart, 2010) and the spreading belief that the "Age of America" is nearing its end due to the fierce competition from lower-cost producers in Asia (Arends, 2011). As early as 2008, a *New York Times* article (Miller, 2008) and an empirical paper (Fairlie & Chatterji, 2008) point to deteriorating entrepreneurship and innovation in Silicon Valley due to global competition. In contrast, Bresnahan et al. (2001) and Saxenian (2002) offer case studies concluding that the emerging clusters develop capabilities complementary to the

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market requirements in the developed regions, hinting at clusters stimulating rather than competing with each other. These arguments, however, have been anecdotal.

Most of the clusters literature focuses on indigenous local factors to explain growth in clusters or firms located within clusters (see Table 1 for a review). While this local approach has been useful in gaining an initial understanding of the phenomenon, it ignores the *non-local sources* of the growth of emerging clusters. Chaminade & Vang (2008: 1685) suggest that innovation clusters should instead be viewed as "specialized regional hubs in global value chains, which are constituted through dynamic relations and interactions with local and trans-local organizations and firms." Accordingly, recent studies stress the importance of *external* factors in driving growth in innovation clusters (Adams, 2011). More recently, Cano-Kollmann et al. (2016) call for research that studies the interrelationships among regions, firms, and individuals and their coevolution across the geographical space. Li & Bathelt (2017) call for both conceptual and empirical researches that examine trans-local and global pipelines for knowledge and innovation generation. These studies signal possible (organizational and individual) linkages among global innovation clusters, which may hurt or stimulate each cluster's growth.

The coopetition view of global competition suggests mutually beneficial growth among clusters (Brandenburger and Nalebuff, 1996; Fleming, 2001; Luo, 2007; Singh, 2005). It argues that despite overlapping markets, *resource complementarity* among inventors, firms, and regions foster innovation collaborations, foreign investments and global diffusion of technologies, leading to positive dynamics across clusters. We build on the coopetition view to test the dynamic intercluster relationships, using a vector autoregressive (VAR) model at the monthly level over a 16-year period between 1999 and 2014. We examine ten prominent global digital technologies clusters, located in both developed and emerging markets.

Our research makes theoretical, modeling, and substantive contributions. Our *first* contribution lies in providing the only empirical analysis of the dynamics across global innovation clusters using time-series data. We address the call for work that focuses on the factors that drive geography-based success (cf. Peng, 2004). Indeed, the intercluster research lacks a systematic investigation of cause-and-effect among cluster dynamics. We include important outcome variables of growth in new product commercializations, patents, and startups while accounting for regional, national, and inter-cluster factors. We focus on digital technologies industries as they are the fastest growing, most pervasive, and most wealth-creating (Hamel & Valikangas, 2003). Information and communication technologies and biotechnologies are also the first high-tech industries to fragment and globalize. *Second*, in contrast to the "regional competitive advantage" theory (Porter, 1998) and the focus on indigenous local factors, both of which dominate the literature, our results provide evidence for the existence of intercluster dynamics as important drivers of cluster growth. We provide an empirical test for the coopetition view and show that rival clusters in general facilitate rather than hurt each other's. Our findings are relevant to managers, entrepreneurs, and policymakers in IT innovation clusters worldwide.

LITERATURE ON INTERCLUSTER DYNAMICS: THE COOPETITION VIEW

We refer to an emergent perspective on intercluster dynamics: the *coopetition* view, which suggests mutually stimulative relationships across clusters. While the dominant "regional competition" view argues that the mobility of individual labor and the expansion of multinational organizations results in the loss of human capital, and suggests the growth of one region hurts the growth of the other, the *coopetition* view takes reverse spillovers among clusters into account (Shaver, 1998; Zaheer, Lamin & Subramani 2009). The coopetition view of *clusters* draws upon social network theory (Burt, 1992; Uzzi and Spiro, 2005) and diffusion of innovation theory (Rogers, 1995) and emerges from research on patent networks (Fleming, 2001; Fleming et al., 2007; Singh, 2005), on R&D alliances (Oxley & Sampson, 2004; Parkhe, 1991).

Coopetition combines the positive-sum, efficiency-enhancing effects of competition and cooperation (Luo, 2007) and results in the gain of social capital, which is a collective (as opposed to private) and non-rivalrous resource jointly owned by parties in a relationship (Burt, 1997). The cooperation aspect of coopetition may increase in response to higher *competitive asymmetry* (or strategic non-overlap) and greater *resource complementarity* (or *resource interdependence*; Henderson & Mitchell, 1997). In the absence of resource complementarity (or the presence of strategic overlap), companies are

Table 1 Review of the empirical work on clusters

Authors	Journal	Theory	Focus	Unit of analysis	Dependent variable	Data	Geographic focus
Baptista & Swann (1998)	Research policy	Competition view (Agglomeration)	Indigenous cluster factors	Firm	Number of innovations	Secondary data	UK
Almeida & Kogut (1999)	Management science	Coopetition view (social network theory)	Intercluster spillovers due to labor mobility	Patent citation	Patent citations	Secondary data	USA
Furman, Porter & Stern (2002)	Research policy	Competition view (agglomeration)	Indigenous cluster factors	Country	Number of patents	Secondary data	USA
Hellmann & Puri (2002)	Journal of finance	Competition view (agglomeration)	Indigenous cluster factors	Firm	Firm Human resources policies	Survey and secondary data	USA (Silicon valley)
Bell (2005)	Strategic management journal	Coopetition view (social network theory)	Indigenous cluster factors	Firm	Firm innovativeness based on expert ratings	Survey data	Canada (Toronto)
Gilbert, McDougall & Audretsch (2008)	Journal of business venturing	Coopetition view (social network theory)	Indigenous cluster factors	Firm	Number of commercializations and relative sales growth after IPO	Secondary data	USA
Fairlie & Chatterji (2008)	NET institute working paper	Competition view (Agglomeration)	Indigenous cluster factors	Cluster	Rate of business creation at individual owner level	Survey data	USA (Silicon valley)
Li (2009)	Research policy	Competition view (agglomeration)	Indigenous cluster factors	Cluster	Number of patents	Secondary data	China
Zhang & Li (2010)	Strategic management journal	Coopetition view (social network theory)	Indigenous cluster factors	Firm	Product innovation	Survey data	Guandong (China)
Samila & Sorenson (2010)	Management science	Competition view (agglomeration)	Indigenous cluster factors	Cluster	Number of patents, number of firm starts, and employment	Secondary data	USA
Libaers and Meyer (2011)	Research policy	Competition view (agglomeration)	Indigenous cluster factors	Cluster	Firm international intensity (% of international sales)	Secondary data	USA
Alcácer & Zhao (2012)	Management science	Coopetition (industrial organization)	Intercluster spillovers due to labor mobility	Firm	Cross-cluster teams and patent citations	Secondary data	USA
Delgado, Porter & Stern (2014)	Research policy	Competition view (agglomeration)	Indigenous cluster factors	Industry	Regional economic performance (industry employment growth and patenting growth)	Secondary data	USA
Ozer & Zhang (2015)	Strategic management journal	Coopetition view (social network theory)	Indigenous cluster factors	Firm	Product innovation	Survey data	Shanghai (China)

likely to engage in a competitive rent-seeking behavior, leading them to follow a zero-sum approach toward other rivals. However, in the presence of resource complementarity, firms pursue mutual opportunities for realizing positive-sum benefits through collaboration (Brandenburger & Nalebuff, 1996).

Research suggests that knowledge circulates and innovations diffuse through two types of networks: individual and organizational linkages across regions (Cano-Kollman et al., 2016). The coopetition view argues that individual inventors and organizations collaborate, forming networks at a global scale; and technologies coevolve with global market demand. These notions lead to the generation of social capital and mutually stimulative interactions transcending regional boundaries (Beugelsdijk & Mudambi, 2013; Fleming, 2001; Verbeke, 2003). Accordingly, we propose three mechanisms that foster coopetition across clusters: learning through hiring, innovation collaborations among individual inventors and firms, and global diffusion of technologies.

Learning through hiring increases the firms' ability to access technologically distant knowledge from other firms through the recruitment of their talent (Song, Almeida & Geraldine, 2003). Oettl & Agrawal (2008) show that firms which lose an inventor to another company gain by receiving knowledge from the inventor's new company and country, as these inventors serve as brokers. Second, interfirm and intrafirm boundary spanners create global professional communities of connected immigrants to access knowledge from both local and distant actors (Schilling & Phelps, 2007; Tallman, 2003; Uzzi & Spiro, 2005). Together, these individuals are important drivers for the diffusion of knowledge and innovation in their home countries (Lin et al., 2016). Fleming, King & Juda (2007) refer to this as the concept of small-world networks of locally dense interactions among interactions connected via a few bridging ties. While social proximity certainly increases the ease and likelihood of sharing, tacit innovation knowledge also diffuses at a global scale between inventors, organizations, and technological communities (Fleming, 2001; Singh, 2005). The presence of *a global inventor community* is evident in (1) technical publications and citations and (2) coauthorship and other collaborations among inventors. Moreover, global firms enter innovation collaborations to generate superior value by allowing mutual use of information and synergistic combinations of *complementary* capabilities (Parkhe, 1991). These collaborations provide flexibility because partners share the risks related to innovation development, gain access to expertise unavailable internally (asymmetrically available elsewhere), transfer tacit knowledge, and/or retain their own resources for future deployment (Aulakh & Kotabe, 1997). Once a company internalizes partner know-how or jointly develops new skills with its partner, it can apply them to new geographic markets, products and businesses (Agarwal & Ramaswami, 1992; Ivus et al., 2017).

The third mechanism driving mutual stimulation in intercluster dynamics is the global diffusion of innovations (Rogers, 1995), which leads to the coevolution of new technologies and global market demand. The rise of global coopetition signifies the existence of production networks and market dynamics at a larger geographic scale (Aulakh and Kotabe, 1997; Li and Bathelt, 2017; Rugman and Verbeke, 2003). In efforts for higher returns, global firms in developed cluster seek to eventually sell their products in distant emerging markets (particularly, Asian markets; Birkinshaw and Hood, 2000; Kuemmerle, 1999). For example, Cadence Design Systems invested on an R&D center in 2007 to be close to where their customers are expanding. The know-how and the investments of these developed firms may spur greater inventive activity by the rival emerging cluster firms (Adner, 2002; Sood et al., 2012). As rival firms gradually penetrate the market, the competition face leads the existing firms to invest in new technologies and new regions (Fernhaber et al., 2008; Liu et al., 2009). For example, the entry of IBM into the personal computer market pioneered by Altair and then Apple helped to create and increase local and global demand. Some firms in emerging clusters may create innovations by combining their existing technologies and local advantages (e.g., skilled labor, time zone differences, and low-cost development capabilities) with their insight into unserved demand and technical complementarity (Agarwal and Ramaswami, 1992; Bathelt & Li, 2014; Buckley & Casson, 1998). Being colocated with foreign firms may increase both their consciousness of and drive for competing at an international level (Belderbos et al., 2015; Buckley et al., 2002; Vernon, 1966). This process may lead to reverse globalization, in which firms in the emerging clusters seek new niches across their national borders and enter profitable market niches in developed clusters (Berry, 2017; Hernandez & Guillén, 2018; Immelt et al., 2009). As these developing firms gain competitive power and move up the global value chain, they invest in developed markets to establish a global presence (Li and Bathelt, 2017; Luo and Tung, 2007; Manning, 2013). Arora et al. (2001) provide Greycell Technologies (now Unimobile) as an example for reverse globalization. This company, which develops software for mobile telecommunications, moved its headquarters to the Silicon Valley to have better access to global market, particularly after receiving venture capital investments from "business angels" from California.

DATA

We identified the boundaries of the major global digital technologies clusters by plotting the corresponding metropolitan and surrounding areas indicated by the governmental institutions (e.g., Census Bureau's, ministries, and other government agencies) in each country as well as books and journal articles written by cluster researchers (e.g., Saxenian, 2002; Rowen et al., 2007). We demarcated clusters around contiguous regions having two or more establishments based on their address information (c.f., Almeida and Kogut, 1999). We collected 16 years (1999–2014) of monthly data at the cluster level for top 10 global innovation clusters in our analysis. We formed two cross sections of the clusters referring to Bresnahan et al.'s (2001) distinction and the World Economic Situation and Prospects (WESP) classification prepared by the United Nations (UN) Secretariat: (1) emerging clusters (Silicon Plateau in Bangalore, Zhongguancun in Beijing and Silicon Island in Taipei, Silicon Fen in Cambridgeshire, Silicon Wadi around Tel Aviv), and (2) developed clusters (Shinjuku in Tokyo, Silicon Forest in Seattle (WA), Silicon Hills in Austin (TX), Route 128 surrounding Boston area (MA) and Silicon Valley; please see Table 2 for a detailed list of cities and counties within the clusters). Our selection of clusters consists of top global IT clusters included Saxenian and her colleagues' works and the Startup Genome ranking of reports the leading startup ecosystems across the world (compiled in association with Telefónica Digital and researchers at Stanford University and the University of California, Berkeley).

Three indicators of growth in innovation are the *change* in the number of patents by inventors from each cluster, the number of startups, and the

Table 2 Cities and counties surrounding each cluster

Developed clusters	
Silicon valley counties:	Alameda, Santa Clara, Santa Cruz, San Mateo
Silicon Hills (Austin) counties:	Travis, Hays
Silicon Necklace (Route 128, MA) counties:	Essex, Middlesex, Norfolk, Suffolk
Silicon Forest (Seattle) counties:	Island, Jefferson, King, Kitsap, Mason, Pierce, Skagit, Snohomish, Thurston
Shinjuku (Tokyo) cluster cities:	Shinjuku, Tokyo, Akiruno, Akishima, Chōfu, Chofu, Fuchu, Fuchū, Fussa, Hachiōji, Hachioji, Hamura, Higashikurume, Higashimurayama, Higashiyamato, Hino, Inagi, Kiyose, Kodaira, Koganei, Kokubunji, Komae, Kunitachi, Machida, Mitaka, Musashimurayama, Musashino, Nishitokyo, Ōme, Ome, Tachikawa, Tama
Emerging clusters	
Zhongguancun (Beijing) districts:	Chaoyang, Chongwen, Dongcheng, Fengtai, Haidian, Shijingshan, Xicheng, Xuanwu, Changping, Daxing, Fangshan, Huairou, Mentougou, Pinggu, Shunyi, Tongzhou, Miyun, Yanqing
Silicon Plateau (Bangalore, Karnataka) cities:	Bagalkot, Belagavi, Bellary, Bidar, Chamarajanagar, Chikballapur, Chikkamagaluru, Chitradurga, Dakshina Kannada, Davanagere, Dharwad, Gadag, Hassan, Haveri, Kalaburagi, Kodagu, Kolar, Koppal, Mandya, Mysuru, Raichur, Ramanagara, Shivamogga, Tumakuru, Udupi, Uttara Kannada, Vijayapura, Yadgir
Silicon Wadi (Tel Aviv) cities:	Tel Aviv, Rehovot, Haifa, part of Jerusalem
Silicon Fen (Cambridgeshire) cities:	Burwell, Cambridge, Chatteris, Cottenham, Ely, Godmanchester, Huntingdon, Littleport, March, Peterborough, Ramsey, Sawston, Sawtry, Soham, St Ives, St Neots, Whittlesey, Wisbech, Yaxley
Silicon Island (Taipei) counties:	Hsinchu, Miaoli, Taoyuan, Yilan

Table 3 Operationalization of variables

Endogenous variables		
Patents[a]	The citation weighted counts of patents developed by inventors located in each cluster	Thomson innovation database (using patent classes corresponding to USPTO 345, 364, 395, 438, 435 and 514 for IT and 424, 435, 436, 514, 530, 536, 800, 930 for biotech; c.f. Almeida and Kogut, 1999; Jaffe, Trajtenberg & Henderson, 1993; Rothaermel & Thursby, 2007)
Startups	The number of startups founded each month at the cluster level	Capital IQ database
Commercializations[b]	The monthly number of commercializations by firms located in each cluster	Predicasts' PROMT, Lexis-Nexis and Factiva Press Releases
Exogenous variables		
Country-level factors	The gross domestic product (GDP)	International monetary fund international financial statistics
	The total R&D investments	International monetary fund international financial statistics
	The talent pool (the number of number of science and engineering Ph.D. graduates) in each country	National science foundation science and engineering indicators
Cluster-level factors	The amount of venture capital investments in each cluster	SDC Platinum VentureXpert Database (c.f., Aggarwal & Hsu, 2014)
	The number of and the total value of IPOs	SDC Platinum VentureXpert Database (c.f., Aggarwal & Hsu, 2014)
Intercluster variables	Patent collaborations (the share of authorship of the patent inventors located in other clusters (the ratio of other cluster inventors to the total number of inventors for each patent developed by inventors located in each cluster)	Thomson innovation database
	Talent mobility across clusters	UNESCO institute education statistics
	The number of R&D alliances across clusters	SDC platinum database
	Cross-cluster venture capital investments	SDC platinum VentureXpert database

[a] Referring to Agrawal, Cockburn, Galasson & Oettl's (2014) approach, we assigned a patent to a cluster depending upon the location of the inventor in our counting. If a patent has at least one inventor from a particular cluster, then we increase the count for that cluster by one. Thus, a patent with three inventors located in three different clusters raises the patent count for each of those clusters by one. However, if all three inventors are located in the same cluster, then we enter one added count for the particular cluster.
[b] Consistent with the approaches of Sorescu, Shankar & Kushwaha (2007), we collected data on new product announcements using the keywords "launch," "introduce," "introduction," "commercialize," "commercialization," and "new product".

number of new product commercializations in each cluster (please see Table 3 for a list of measures). We draw upon Yiu and Lau's (2008) conceptualization of entrepreneurship, which encompasses two types of activities: innovation and venturing. Innovation refers to the firm's commitment to developing and introducing new products (i.e., patenting and commercialization; Delgado et al., 2014), while venturing refers to the creation of new business (i.e., startups; Delgado et al., 2010). We concentrated on IT industry [SIC codes for hardware (i.e., 3571–3579, 3661–3679, 3695, 3823–3826), communication (i.e., 4812–4899), and software and service (i.e., 7371–7379)] and biotech industry (2060, 2200, 2221, 2800, 2820–2821, 2834, 2840, 2844, 2870, 2911).

Method: Vector Autoregressive Model Specification

Following the procedures as outlined by Wiesel, Pauwels & Arts (2011) and Horváth & Wieringa (2008), we employed persistence modeling using pooled vector autoregression estimation with exogenous variables (VARX) for our empirical analysis (please see Table 4 for an outline).

Equation 1 presents this model in matrix form:

$$\gamma_t = \sum_{n=1}^{p} \Gamma_n \gamma_{t-n} + \Phi X_t + e_t, \tag{1}$$

where $t = \{T_0, T_1, T_2, \ldots T\}$ is the time period index, Y_t is the six-dimensional vector of the endogenous variables that results from stacking the two cluster

Table 4 Overview of methodological steps

		Methodological step	Relevant literature	Research question	Notes
1	Estimation of the stationarity properties of model indicators	Augmented Dickey–Fuller Test Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test Zivot–Andrews test Cointegration analysis	Enders (2004), Zivot & Andrews (1992), Johansen (1995), Pauwels et al. (2004), Nijs, Dekimpe, Steenkamps & Hanssens (2001)	Are variables stationary (/evolving)? Are unit root results robust to unknown breaks? Are evolving variables in long-run equilibrium?	VAR models are specified in levels or changes depending on integration of the data The unit root tests were both implemented with and without deterministic time trend
2	Determination of the variables to be included in the model as endogenous	Granger causality tests Wald test for Granger causality using the Chi-square test statistic	Granger (1969), Trusov, Bucklin & Pauwels (2009), Lütkepohl (2005)	Which variables are temporally causing which other variables?	The tests are run for lags between 1 and 12 months
3	Pooling of clusters into developed versus emerging groups to increase power and generalizability	Constant coefficient model (CCM) Chow tests Comparison of IRF results of unit-by-unit model to those of CCMs	Horváth & Wieringa (2008)	Is pooling appropriate? Is the CCM better fit than unit-by-unit model?	Pooling is meaningful for our study
4	Model of dynamic interactions	Vector autoregressive model	Dekimpe & Hanssens (1999)	How does the change in one cluster's innovation productivity impact the change in another's productivity, accounting for the unit root and cointegration results?	Indicators of growth in innovation include the change from 1 year to the next in the number of patents, startups and new product commercializations in each cluster
5	Estimation of dynamic cumulative effects of an unexpected shock in an innovation productivity indicator on the other endogenous indicators	Generalized impulse response functions (GIRFs) from VAR model estimates	Dekimpe & Hanssens (1999), Pauwels et al. (2004), Nijs, Dekimpe, Steenkamps & Hanssens (2001)	What are the short- and long-term dynamics among global clusters? E.g., does the change in emerging cluster patents (/startups or/commercializations) impact the change in developed cluster patents (/startups or/commercializations)?	Period 1 effect is short-term "immediate," the next periods' effects (until IRF stabilizes) are "dynamic" effects. Their sum represents long-term "cumulative effects." 1 standard error (68% confidence interval, corresponding to $t = 1$) is used to determine significance of effects
6	Tests for the assumptions of the VAR residuals	Durbin–Watson and Lagrange multiplier tests (for autocorrelation) Jarque–Bera test (multivariate normality) White heteroskedasticity tests	Pauwels et al. (2004), Luo (2009), Tirunillai & Tellis (2012)	Are our results robust to deviations from the assumptions?	We did not find any violations at the 95% confidence level

Table 5 Descriptive statistics on metrics for growth in innovation

	New product commercializations		Number of patents		Number of startups	
	Mean	SD	Mean	SD	Mean	SD
San Jose, CA (Silicon Valley)	5.36	8.25	136.31	56.89	10.07	22.48
Tokyo, Japan (Shinjuku)	1.41	1.65	11.69	5.82	2.39	1.96
Route128, MA (Silicon Necklace)	1.15	1.37	29.14	14.89	9.51	21.42
Seattle, WA (Silicon Forest)	0.86	0.97	17.58	8.83	3.13	7.47
Austin, TX (Silicon Hills)	0.53	0.96	2.98	2.13	4.22	10.02
Bangalore, India (Silicon Plateau)	3.15	7.28	0.33	0.62	2.77	4.67
Beijing, China (Zhongguancun High-Tech Park)	2.55	2.70	1.93	2.45	1.13	2.44
Taipei, Taiwan (Silicon Island)	1.76	1.81	21.01	12.45	0.69	1.38
Tel Aviv, Israel (Silicon Wadi)	1.54	1.60	5.57	3.43	3.04	7.03
Cambridge, UK (Silicon Fen)	0.07	0.28	9.69	7.54	3.45	7.28

Means and standard deviations are based on monthly data from 1999 to 2014.

cross sections with each three productivity indicators. Γ_n are the coefficients matrices of the lags of endogenous variables, X_t is the vector of exogenous variables listed above, and Φ is its coefficients, and e_t is the six-dimensional vector of residuals. We also specified an intercept C, a time trend T and monthly seasonal dummies (using January as the benchmark).

By using VAR analysis, we are able to capture immediate, lagged, carryover and feedback effects. For example, the change in the number of patents in developed clusters (e.g., Silicon Valley) may foster the increase in emerging cluster patents (e.g., Zhongguancun). This may be defined as contemporaneous (immediate) or carryover (lagged) effects. If the increase in developed cluster patents is influenced by the current and past patent levels in emerging clusters, then we would conclude that there exist feedback reversed effects. Finally, VAR models capture and control for carryover effects (i.e., the self-reinforcing effect) such as the effect of the patents increase in developed clusters in the previous periods on the subsequent periods.

The off-diagonal terms of the matrix Γ_n estimate the cross-carryover effects among the endogenous variables, and the diagonal elements estimate the carryover effects. The χ vector contains the p exogenous variables (i.e., each country's GDP per capita, R&D investments, interest rate and size of talent pool, and the amount and the cross-cluster flow of venture capital investments, and the number of and the total value of IPOs in each cluster, the number of R&D alliances, the share of authorship, and the mobility of Ph.D. students).

$$\begin{bmatrix} \Delta DevelopedSTUP_t \\ \Delta EmergingSTUP_t \\ \Delta DevelopedPAT_t \\ \Delta EmergingPAT_t \\ \Delta DevelopedCOMM_t \\ EmergingCOMM_t \end{bmatrix} = \sum_{n=1}^{p} \begin{bmatrix} \gamma_{1,1}^n & \cdots & \gamma_{1,6}^n \\ \vdots & \ddots & \vdots \\ \gamma_{6,1} & \cdots & \gamma_{6,6} \end{bmatrix} \begin{bmatrix} \Delta DevelopedSTUP_{t-n} \\ \Delta EmergingSTUP_{t-n} \\ \Delta DevelopedPAT_{t-n} \\ \Delta EmergingPAT_{t-n} \\ \Delta DevelopedCOMM_{t-n} \\ EmergingCOMM_{t-n} \end{bmatrix} + \begin{bmatrix} \phi_{1,1}^n & \cdots & \phi_{1,p}^n \\ \vdots & \ddots & \vdots \\ \phi_{6,1} & \cdots & \phi_{6,p} \end{bmatrix} \begin{bmatrix} \chi_1 \\ \chi_2 \\ \vdots \\ \chi_p \end{bmatrix} + \begin{bmatrix} e_{DevelopedSTUP,t} \\ e_{EmergingSTUP,t} \\ e_{DevelopedPAT,t} \\ e_{EmergingPAT,t} \\ e_{DevelopedCOMM,t} \\ e_{EmergingCOMM,t} \end{bmatrix}$$

Next, from the VAR model estimates, we derived the generalized impulse response functions, which capture the dynamic cumulative effects of an unexpected shock in an innovation indicator on the other endogenous indicators in the system.

RESULTS

The results on descriptive statistics, stationarity and cointegration tests, and Granger Causality tests are presented in Tables 5, 6a, 6b, and 7. We estimated the VAR model (as depicted in Eq. 1) with three lags (as suggested by all four information criteria: Akaike,

Table 6 Descriptive statistics on exogenous variables

a

	Number of IPOs		Value of IPOs (million $)		Venture capital investments (million $)		Share of developed cluster partners		Share of emerging cluster partners		Investments from emerging clusters (million $)		Investments from developed clusters (million $)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Austin, TX (Silicon Hills)	0.70	1.04	88.27	256.10	2968.30	9675.68	41.82	18.48	6.80	4.61	23.58	122.52	1434.32	4611.98
Beijing, China (Zhongguancun High-Tech Park)	1.02	1.99	123.99	616.34	1376.20	4033.04	0.64	0.83	1.68	2.14	135.73	1298.04	447.17	1024.16
Bangalore, India (Silicon Plateau)	0.32	0.66	16.39	104.40	516.58	6047.05	2.34	2.77	0.32	0.55	106.91	734.30	235.45	1538.15
Cambridge, UK (Silicon Fen)	0.14	0.46	12.12	87.82	428.40	2482.83	38.13	19.09	7.20	5.17	17.82	71.58	327.26	904.27
Route128, MA (Silicon Necklace)	1.92	1.98	177.37	376.10	6282.50	7861.60	62.06	21.72	11.07	6.16	229.63	627.49	3134.31	3794.09
Seattle, WA (Silicon Forest)	0.67	0.91	78.87	267.95	2096.97	5850.11	52.44	29.47	4.97	3.14	26.55	138.17	1085.92	3376.36
San Jose, CA (Silicon Valley)	6.04	4.69	728.98	1412.34	14,906.23	29,077.25	118.47	43.79	13.24	7.66	600.03	1747.40	8628.74	16,137.31
Taipei, Taiwan (Silicon Island)	1.74	2.57	32.87	105.03	53.49	286.23	1.70	1.60	15.76	9.91	8.53	67.22	8.88	53.91
Tel Aviv, Israel (Silicon Wadi)	0.16	0.47	8.61	30.45	452.11	859.13	0.41	0.67	1.77	1.83	19.87	58.53	87.53	212.48
Tokyo, Japan (Shinjuku)	2.14	2.79	95.28	246.77	191.60	907.79	19.32	9.47	2.34	1.76	18.02	178.19	17.66	108.47

b

	R&D Investments (billion in local currency)		GDP per capita (current US$)		Interest rate		Number of Ph.D. graduates (science and engineering)		Number of graduates from developed countries		Number of graduates from emerging countries		R&D alliances btw developed and developed cluster firms		R&D alliances btw developed and emerging cluster firms		R&D alliances btw emerging and emerging cluster firms	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
China	490.61	397.07	3233.81	2228.20	7.34	0.96	23,488.31	11,198.62	185,852.20	73,000.46	46,462.42	24,360.15			2.44	2.10	2.44	3.20
India	280.96	211.07	948.44	406.67	48.53	6.60	4165.26	4028.34	81,324.72	20,613.04	19,630.76	11,303.74			0.44	0.63	0.63	1.09
Israel	30.50	8.12	25,802.07	6530.82	4.04	0.41	522.57	537.44	3043.56	456.21	995.90	457.08			0.06	0.25	0.31	0.48
Japan	16,182.97	1099.76	37,234.46	4700.44	105.10	15.68	7015.74	1825.99	4920.50	1366.19	33,942.68	10,479.62	8.69	15.65			1.06	2.14
UK	23.42	4.18	37,626.50	7114.49	0.61	0.06	9499.16	1123.88	56.36	52.93	8425.06	1649.28			0.56		1.81	1.83
USA	330.77	107.68	45,001.45	6154.18	1.00	0.05	31,239.71	5680.28	1525.92	599.77	14,263.22	1672.08	12.63	10.63			4.56	5.18

Means and standard deviations are based on monthly data from 1999 to 2014.

Table 7 Summary of unit root/stationarity tests of the endogenous variables

	# of new product commercializations			# of patents			# of startups		
	ADF test	KPSS test	Levin, Lin and Chu test	ADF test	KPSS test	Levin, Lin and Chu test	ADF test	KPSS test	Levin, Lin and Chu test
Developed Clusters	− 4.524**	1.986**	− 27.686**	− 2.237(ns)	1.845**	− 15.274**	− 5.325**	1.260**	− 36.176**
Emerging Clusters	− 4.408**	0.133 (ns)	− 16.961**	0.009 (ns)	2.226**	− 15.884**	− 4.514**	1.649**	− 32.057**

	ADF test	KPSS test	ADF test	KPSS test	ADF test	KPSS test
Austin	− 6.525**	1.324**	− 11.163**	0.847**	− 3.963**	1.327**
Beijing	− 1.864 (ns)	1.610**	− 3.387**	1.405**	− 2.734 (ns)	0.176 (ns)
Bangalore	− 4.163**	1.381**	11.662**	1.265**	− 2.783 (ns)	0.293 (ns)
Cambridge	− 10.704**	0.950**	− 3.099*	1.242**	− 3.596**	1.192*
Route128	− 2.547 (ns)	0.958*	− 1.910 (ns)	1.652**	− 1.955 (ns)	1.611**
Seattle	− 5.526**	0.552*	− 3.623**	0.776**	− 1.774 (ns)	1.518**
Silicon Valley	− 13.077**	0.721*	− 3.987**	0.664*	− 1.640 (ns)	1.462**
Taipei	− 1.271 (ns)	1.396**	− 2.953*	1.693**	− 2.796 (ns)	1.414**
Tel Aviv	− 2.148 (ns)	1.437**	− 3.431*	1.563**	− 2.882*	1.097**
Tokyo	− 8.609**	0.390 (ns)	− 2.551 (ns)	1.199**	− 2.244 (ns)	0.152 (ns)

For the pooled data: The critical values for ADF test are − 2.864 at 5% (*) and − 3.437 at.%1 (**) level; and for the KPSS test 0.463 at 5% (*) and 0.739 at 1% (**) level.
For the individual series: The critical values for ADF test are − 2.886 at 5% (*) and − 3.486 at.%1 (**) level; and for the KPSS test 0.463 at 5% (*) and 0.739 at 1% (**) level.

Schwartz, Hannan-Quin, and Final Prediction Error). The models explained 30% of the variation in commercialization growth (33% of the variation in developed and 27% in emerging clusters), 41% in patent growth (31% of the variation in developed and 51% in emerging clusters), and 58% in startups growth (56% of the variation in developed and 61% in emerging clusters), as indicated by the adjusted R^2 results. In order to show the explanatory power of the intercluster dynamics on cluster innovation growth *beyond* the exogenous variables, we compared the adjusted R^2 results of our full model (including the intercluster dynamics) versus an alternative model (including only exogenous variables and excluding the other clusters' growth metrics). The inclusion of the intercluster dynamics resulted in an approximately *four* times increase in the explained variation in cluster growth.

We tested the parameter heterogeneity/homogeneity across the cross sections by conducting a series of Chow tests (Horváth and Wieringa, 2008). For each cross section, we regressed patents and startups on commercializations. Since all *F*-values were nonsignificant ($F_{\text{developed}} = 0.22$, $p = 0.80$; $F_{\text{Emerging}} = 0.07$, $p = 0.93$), indicating that the cross-sectional time-series data could be pooled. Thus, we concluded that pooling is meaningful for our study.

We also find strong support for the key premise of this paper that the clusters affect each other on the innovation metrics. As indicated by the minimum p values (across all lags) of the Wald test (Chi-square) statistic for Granger causality, the change in each innovation metric for each cluster is significantly (at $p < 0.05$) Granger caused by at least the change in three innovation metric of another cluster. The direction of causality is often dual. Hence, we confirmed the existence of temporal causal relationships among the innovation metrics, which requires their inclusion as endogenous variables in a dynamics system model such as a vector autoregressive model.

Estimated Effects Among Clusters

Tables 8 and 9 present the results of the immediate and cumulative effects of growth in innovation across clusters. We focus on and interpret cumulative effects and report the immediate effects only in the tables (since they are consistent).

Figure 1 provides sample IRF results for the response of the growth variable of one cluster to an impulse by the same growth variable of the other clusters. First, our findings indicate that the growth in emerging clusters stimulates the growth in developed clusters. Specifically, the impact of the growth in emerging clusters on the growth in

Table 8 Immediate and cumulative effects among clusters

	Impact of emerging clusters on developed clusters			Impact of developed clusters on emerging clusters			Impact of emerging clusters on emerging clusters		
	Immediate effect	Cumulative net effect	# of periods	Immediate effect	Cumulative net effect	# of periods	Immediate effect	Cumulative net effect	# of periods
# of commercializations	0.000	0.362	12	0.000	0.297	12	0.852	2.125	12
# of Patents	– 0.266	– 0.107	12	– 0.011	0.006	6	0.701	0.415	6
# of Startups	0.509	0.739	3	0.021	0.058	8	0.475	2.157	12

Table 9 Immediate and cumulative effects among clusters based on number of units

	H1: Impact on developed clusters			H2: Impact on emerging clusters			H3: Impact on emerging clusters		
	Immediate effect	Cumulative net effect	# of periods	Immediate effect	Cumulative net effect	# of periods	Immediate effect	Cumulative net effect	# of periods
# of commercializations	0.000	0.085	12	0.000	0.078	12	0.225	0.561	12
# of patents	– 0.012	– 0.005	12	– 0.002	0.001	6	0.144	0.085	6
# of startups	0.008	0.011	3	0.002	0.006	8	0.049	0.222	12

An "impulse" is defined as "one SD innovation"; i.e., an increase in the impulse variable by 1 standard deviation (c.f. Pauwels et al., 2004). To calculate the effect of a unit change in the impulse variable, that standard deviation number of the impulse variable is required to be obtained from the VAR model estimation. For instance, a one-standard deviation increase to the number of commercializations in developing clusters yields a cumulative increase in the number of commercializations in emerging clusters of 0.297. Because the number of commercializations in emerging clusters has a standard deviation of 3.79, this means that a unit increase in the number of commercializations in developed clusters yields an immediate increase of 0.297/3.79 = 0.078 units in the number of startups in developed clusters.

developed clusters depends on the metric for growth: emerging clusters' growth hurts the productivity increase in developed cluster patents (– 0.107), but stimulates the productivity increase in developed cluster commercializations (0.362) and startups (0.739). Thus, we find support on commercializations and startups, but not on patents. Second, the growth in developed clusters both stimulates the growth in emerging clusters in terms of commercializations (0.297), patents (0.006) and startups (0.058). Third, we observe a positive pattern of relationships among the emerging clusters, consistent with our predictions (for commercializations: 2.125; patents: 0.415; startups: 2.157).

Effect of Exogenous Variables

Tests of the influence of exogenous variables on the metrics for growth in innovation across the cluster groups provide three important results (see Table 10 for results). First, general economic conditions such as GDP per capita positively impact cluster startup growth, while interest rates in general exert a negative influence on patents growth (c.f., Meyer et al., 2009). Second, cluster-specific factors such as the value of IPO's and venture capital investments more significantly increase the growth in commercializations and patents (c.f., Aggarwal & Hsu, 2014). Third, inter-cluster variables such as talent mobility and patent collaborations followed cross-cluster investments across clusters are relatively the most influential factors on the growth of developed and emerging clusters (c.f., Almeida & Kogut, 1999; Fleming et al., 2007; Singh, 2005).

DISCUSSION

We fill a major gap in the literature by exhibiting mutually stimulative influences across developed and emerging innovation clusters. Recently, intense controversy in the US has surrounded the issue of job loss due to global competition and became a critical issue in the 2016 Presidential election. Subsequently, the new administration has brought many policy changes geared toward enhancing the innovation productivity in US clusters at the expense of the rival global clusters. In contrast to this prevalent "regional competition" view in the scholarly literature and business press, our results show that individuals and/or firms may not take away innovation know-how and managerial skills when they leave a developed cluster depriving of that knowledge. Rather, they take that

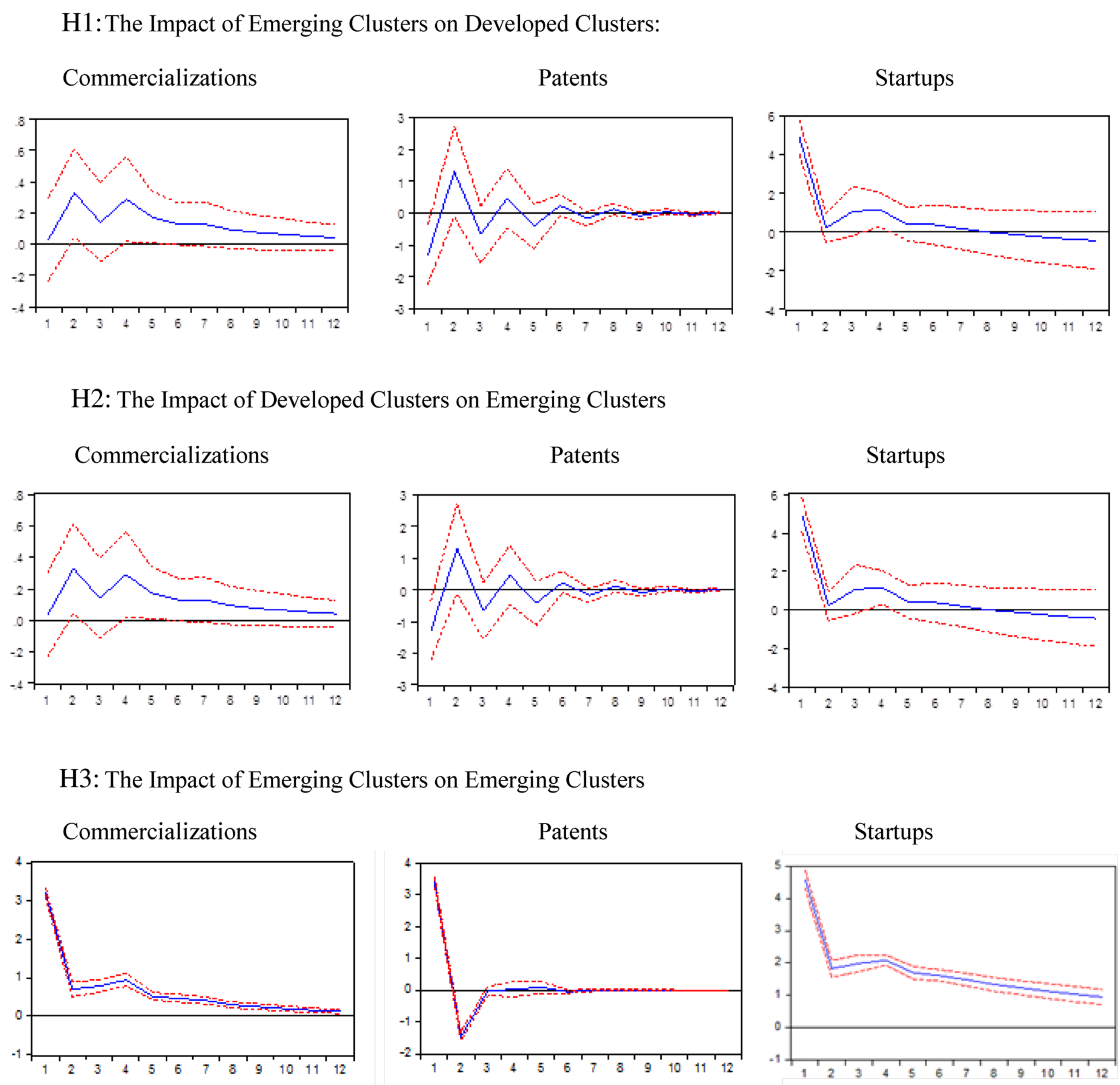

Figure 1 IRF results.

knowledge and embed it in every cluster wherein they locate (including emerging innovation clusters) allowing it to further flourish when combined with the local knowledge. Our research leads to the following four main findings:

First, our results show that innovation growth in developed clusters stimulates growth in the emerging clusters. Patent networks extend from developed regions to those in emerging innovation clusters, leading the latter to benefit from the intellectual capital created and shared. The result on startups is indicative of the global linkages among the startups across different innovation clusters. Scholarly research and anecdotal evidence suggest that the developed cluster entrepreneurs receive support from venture capitalists to establish subsidiaries of their startups in other emerging innovation clusters (Haemmig, 2003), leading them to stimulate the startup growth in these other locations. Hence, these transnational entrepreneurs

Table 10 Influence of exogenous variables on innovation metrics

Variables	Clusters	# of new product commercializations		# of patents		# of startups	
		Developed	Emerging	Developed	Emerging	Developed	Emerging
# of IPOs	Developed	**0.262**	− 0.295	0.092	− 0.056	0.035	0.055
	Emerging	0.045	− 0.313	− 0.008	0.017	− **0.146**	− 0.111
Value of IPOs	Developed	0.000	**0.002**	0.000	0.000	0.000	0.000
	Emerging	0.000	**0.005**	0.000	0.000	0.000	0.000
Venture capital	Developed	**0.000**	**0.000**	**0.000**	0.000	0.000	**0.000**
	Emerging	**0.000**	0.000	0.000	0.000	0.000	0.000
GDP	Developed	0.000	− **0.001**	− **0.001**	0.000	0.000	**0.000**
	Emerging	0.000	0.001	**0.001**	0.000	**0.000**	**0.001**
R&D investments	Developed	0.000	0.000	**0.002**	0.000	0.000	0.000
	Emerging	0.000	0.000	0.001	0.000	0.000	0.000
Interest Rate	Developed	0.051	− 0.528	− 0.250	− **0.179**	− 0.010	− 0.022
	Emerging	− 0.155	**3.096**	− **2.559**	− 0.047	− 0.170	0.069
Ph.D. graduates	Developed	0.000	0.000	**0.000**	0.000	0.000	0.000
	Emerging	0.000	0.000	0.000	0.000	0.000	0.000
Talent mobility to developed clusters		0.000	**0.000**	0.000	0.000	0.000	0.000
Talent mobility to emerging clusters		0.000	− **0.001**	− **0.001**	**0.000**	0.000	0.000
Share of developed cluster inventors		**0.008**	**0.155**	**0.068**	− **0.006**	− 0.001	**0.013**
Share of emerging cluster inventors		− 0.012	**0.533**	− **0.331**	0.007	**0.452**	− **0.094**
R&D alliances with developed cluster firms	Developed	− 0.066	0.466	0.515	− 0.094	0.035	0.032
	Emerging	− 0.159	0.737	**2.946**	− 0.132	0.340	− 0.341
R&D alliances with emerging cluster firms	Developed	0.159	− 0.233	− **6.451**	− 0.158	− 0.040	− 0.273
	Emerging	0.150	− 1.779	0.648	0.415	− 0.515	0.887
Investments from developed clusters	Developed	0.000	0.000	0.000	0.000	0.000	**0.000**
	Emerging	0.000	**0.000**	**0.000**	0.000	0.000	0.000
Investments from emerging clusters	Developed	0.000	**0.000**	**0.000**	0.000	0.000	**0.000**
	Emerging	0.000	0.000	0.000	0.000	0.000	0.000

Significant values are represented in bold.

build their home market by deepening the connections to the developed markets and providing bridging social capital (c.f., Kenney et al., 2013).

The result on commercializations signifies the existence of production networks and market dynamics at a larger geographic scale. In efforts for greater market share, larger firms serving the broader market enter into these emerging markets by developing new product technologies, such as India and China, which offer large talent pools at lower costs and a wide global customer base. A number of studies find positive productivity spillovers from foreign investment to local firms, when larger developed firms gain access to emerging markets (Meyer & Sinani, 2009). Exposure to developed firms' activities can encourage the local firms to adopt new technologies, marketing approaches or other organizational innovations. Mancusi (2008) finds that spillovers increase innovative productivity in weaker emerging countries, with leading countries being a source of knowledge flows. Castellani and Zanfei (2003) also suggest that larger asymmetries indicate greater opportunities for technology transfer, which constitute a mechanism for the productivity growth in developed clusters to impact that in emerging clusters.

Second, we find that emerging innovation clusters in general stimulate each other's growth, likely because these innovation clusters focus on different but complementary sources of regional advantage, in this case hardware versus software. Hence, emerging cluster interactions do not follow from their stated competitive nature, as predicted by the regional competitive advantage theory. Luo (2007) argue that cooperation under "coopetition" will increase when competing players face increasingly competitive threats from other rivals who challenge their position in the areas in which they have common interests. Nascent firms by nature concentrate their technological resources and marketing effort on specific geographic markets to avoid direct competition with other firms. Different technology foci for example in China versus India may also entail *complementarity* regarding product technologies and marketing capabilities. This complementarity may lead these innovation clusters to focus on different markets, avoid competition but collaborate with each other. For example, an increase in market demand for hardware may increase demand for software or telecommunications service. Hence, hardware patents issued in Beijing may stimulate compatible software patents and commercializations in Bangalore.

Third, emerging innovation clusters' growth stimulates the increase in emerging cluster commercializations and startups, but hurts the productivity increase in developed cluster patents. The result on patents, together with two findings on the exogenous variables (see Table 10), indicates that emerging clusters compete with developed clusters for patents. The findings on the dynamics in commercializations and startups, on the other hand, are indicative of "global reverse innovation" (Immelt et al., 2009); i.e., a contemporary phenomenon of producing innovations in developing markets to tap into value segments in other wealthy regions across the globe. The firms located in emerging innovation clusters pursue market demand at a global scale and create product technologies *complementary* to those particularly in these developed markets. Such complementarity may foster collaborations with firms located in other emerging innovation clusters. They combine their local advantages (e.g., skilled labor, time zone differences, and low-cost development capabilities) with their ability to identify the connection-led sources of growth (e.g., unserved demand and technical complementarity). While firms in developed clusters set up research centers in emerging regions, other firms from developing clusters (e.g., Infosys) establish offices in developed clusters (such as Silicon Valley or Shinjuku) to exploit market opportunities there. Through this process, leading specialist firms from emerging innovation clusters contribute to the growth of developed innovation clusters.

Fourth, among the exogenous variables, general economic conditions such as GDP positively impact cluster startup growth, while interest rates in general exert a negative influence on patents. Cluster-specific factors such as the value of IPO's and venture capital investments increase the growth in commercializations and patents. Talent mobility benefits emerging cluster commercializations, while patent collaborations foster cluster growth in patents and commercializations. Our finding also shows that cross-cluster investments benefit emerging cluster startups, developed cluster patents and emerging cluster commercializations, indicating how investments flow across global value chains.

This study has implications for firm strategy and government policy. First, US government and Silicon Valley firms could see emerging innovation clusters not as perennial threats but also as partners in the global growth of high-tech innovations. They should appreciate and embrace "reverse global innovation" as a source of cross-cluster fertilization for growth. The existence of complementary relationships among global innovation clusters suggests different product and marketing strategies than those that were appropriate under full intercluster competition. Second, we find that within cluster and across cluster venture capital are more influential on cluster growth compared to general economic conditions. Hence, the government should encourage the role of private equity and foreign direct investment. Our results also suggest that policymakers should encourage rather than restrict talent migration so that talent can freely migrate to the cluster with the best strategic deployment, employment match, and corporate returns. Policymakers should foster the growth of the talent pool in their countries by investing in the development of advanced degree programs. This may increase the number of inventors taking the boundary-spanning roles in the intercluster networks. Policymakers may organize international events to draw scientists from around the world to disseminate knowledge, build interpersonal networks, and train other scientists.

CONCLUSION

Our research offers both substantive and modeling contributions to the research on innovation, strategy, and public policy. First, the extant clusters research is dominated by qualitative studies and/or short-term focus. This is the first study to provide quantitative evidence for the interrelationships across global innovation clusters using persistence modeling. Results show that rival innovation clusters facilitate rather than hinder each other's growth due to resources complementarities. Reverse fertilization occurs from emerging to developed innovation clusters, contrary to the received wisdom in the scholarly literature and business press. To explain the counterintuitive findings, we draw upon the coopetition view which suggests mutually beneficial growth across all rival clusters rather than zero-sum gains.

Second, as opposed to focusing on one variable, we collected entirely new and rich time-series data on a number of variables on the most prominent innovation clusters, spanning both developed and emerging markets. We examine intercluster dynamics of ten rival global clusters on monthly counts of patents, startups, and new product commercializations between 1999 and 2014 using a vector autoregressive model. Furthermore, we included a number of exogenous variables to test the anecdotal premises in the literature. Third, this research is the first to provide empirical support for the coopetition view at the cluster level. We show that coevolution occurs at the cluster level, making each cluster's growth an important driver of another's growth. This contrasts the widespread focus in the literature on indigenous local factors within the clusters.

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