The Impacts of Externally Hired Senior Technology Executives on Startup Complementor Innovation in Software Platform Ecosystems

ONLINE APPENDIX

Appendix A. Sample and Measures

Table A1. Distribution of Sample Firms' Number of Employees

	(1)	(2)	(3)	(4)	(5)	(6)
Number of Employees Range	**Number (Percentage) of Firms in the Sample**	**Number (Percentage) of Firm-Quarter Observations**	**Number of External Senior Technology Executive Hires**	**Percentage of Firms with External Senior Technology Executives**	**Percentage of Observations with Founder CEO**	**Percentage of Observations with Senior Technology Executives in Founding Team**
1-50	29 (47.54%)	281 (40.55%)	3	10.34%	91.46%	58.36%
51-100	10 (16.39%)	100 (14.43%)	3	30.00%	88.00%	50.00%
101-250	10 (16.39%)	145 (20.92%)	12	50.00%	57.93%	35.17%
251-500	7 (11.48%)	97 (14.00%)	4	14.29%	41.24%	73.20%
501-1000	2 (3.28%)	40 (5.77%)	11	100.00%	72.50%	100.00%
1000-5000	3 (4.92%)	30 (4.33%)	0	0%	76.67%	0.00%
Total	61 (100%)	693 (100%)	33			

Table A2. Keywords to Identify Senior Technology Executives

"cio" **OR** "cto" **OR** "ciso" **OR** "cdo" **OR** [("vp" OR "vice president" OR "chief") **AND** ("software" OR "engineer*" OR "developer" OR "solution*" OR "architect" OR "data" OR "technical" OR "analyst" OR "system" OR "network" OR "designer" OR "programmer" OR "swe" OR "tech*" OR "security" OR "testing" OR "algorithm" OR "digital" OR "information" OR "Apache" OR "Hadoop" OR "product" OR "project" OR "scientist" OR "science" OR "it" OR "eng" OR "cloud")]

Table A3. Keywords to Identify Senior Technical Employees

("technical lead" OR "senior" OR "lead" OR "manager" OR "director" OR "sr." OR "principal") **AND** ("software engineer" OR "software developer" OR "solutions" OR "architect" OR "technical support engineer" OR "solution architect" OR "systems architect" OR "data engineer" OR "systems analyst" OR "technical staff" OR "system designer" OR "network engineer" OR "big data" OR "developer" OR "engineer" OR "programmer" OR "swe" OR "architect" OR "analyst")

Appendix B. Correlations

Variable	1	2	3	4	5	6	7
1. *LayerExpansion*							
2. *WithinLayer*	**-0.1833**						
3. *TechExecIn*	0.0341	**0.1183**					
4. *TechExecOut*	-0.0004	**0.1419**	**0.3551**				
5. *FirmAge*	-0.0475	**-0.1191**	**-0.161**	0.0651			
6. *LayerScope*	**0.1904**	**0.1915**	0.0732	**0.2109**	-0.0268		
7. *LayerSimilarity*	**0.1403**	**0.1486**	**0.1399**	0.0698	**-0.1619**	**0.5528**	
8. *Alliances*	0.0469	**0.295**	**0.2328**	**0.1915**	**-0.0855**	**0.5336**	**0.2909**
9. *Patents*	-0.0528	**0.1041**	-0.0336	**0.163**	**0.1094**	**0.221**	-0.0094
10. *Trademarks*	-0.0177	**0.1031**	**0.2328**	**0.2139**	0.0655	**0.3235**	**0.2377**
11. *Funding*	0.0223	**0.1672**	**0.2323**	**0.1917**	0.0326	**0.4854**	**0.3144**
12. *Acquisitions*	-0.0304	0.0379	0.0217	0.0714	0.0562	**0.2921**	**0.1384**
13. *EcosystemSize*	-0.0698	**-0.1054**	**-0.2276**	0.0024	**0.3227**	-0.0483	**-0.3335**
14. *SeniorTechMob*	0.0392	**0.1605**	**0.4195**	**0.3997**	0.0239	**0.3411**	**0.3105**
15. *NonTechExecMob*	-0.0047	0.052	**0.4402**	**0.3874**	0.0737	**0.2538**	**0.1836**

Variable	8	9	10	11	12	13	14
9. *Patents*	**0.1362**						
10. *Trademarks*	**0.2601**	**0.3922**					
11. *Funding*	**0.3777**	**0.2921**	**0.388**				
12. *Acquisitions*	**0.2319**	**0.3494**	**0.6235**	**0.2589**			
13. *EcosystemSize*	**-0.1097**	**0.2012**	**0.0927**	0.0434	**0.1597**		
14. *SeniorTechMob*	**0.256**	**0.0892**	**0.404**	**0.4886**	**0.1705**	**-0.1325**	
15. *NonTechExecMob*	**0.1988**	**0.093**	**0.3127**	**0.4618**	**0.0799**	0.0098	**0.6771**

Note: Number of observations: 693; Correlations in bold are statistically significant at $p < 0.05$ level; We also computed the variance inflation factors (VIFs) to examine multicollinearity. The average VIF is 1.69, and the maximum VIF is 2.38. All VIFs are well below the commonly used threshold of 10 or 5, thus mitigating the concern of multicollinearity in our empirical analysis.

Appendix C. PVAR Model Specifications

Table C1. Model Selection Criteria

Lag	CD	Hansen J	J *p*-value	MBIC	MAIC	MQIC
1	0.8762	115.2187	0.5030	-469.0678	-116.7813	-259.8792
2	0.8715	99.7942	0.5711	-419.0119	-106.2058	-233.2669
3	0.8778	91.6392	0.4320	-361.6865	-88.3608	-199.3850
4	0.8954	68.6359	0.6845	-309.1356	-81.3641	-173.8843
5	0.8699	53.6534	0.7053	-248.5637	-66.3466	-140.3627
6	0.9463	47.5190	0.3704	-179.1438	-42.4810	-97.9931

Note: This table shows the results for estimated models with one to five lags and compared their criteria values. The results suggest that none of the Hansen's (1982) *J* statistics is statistically significant at $p < 0.1$, indicating the validity of our specified number of lags as instruments. Additionally, the one lag model has the smallest values of MBIC, MAIC, and MQIC, outperforming other lag order specifications.

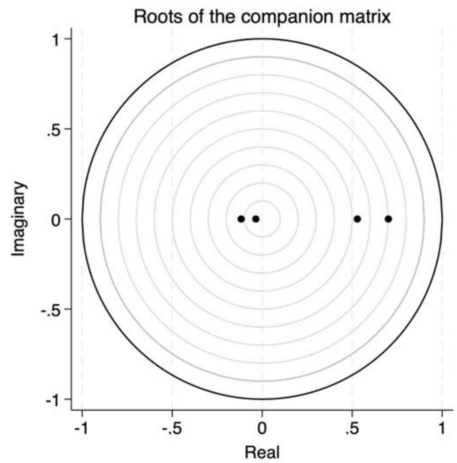

Figure C1. Results of the Unit Root Test

Table C2. Results of the Granger Causality Wald Test

Excluded Variable	Equation			
	LayerExpansion	*WithinLayer*	*TechExecIn*	*TechExecOut*
LayerExpansion	--	1.374	4.574*	0.931
WithinLayer	0.007	--	0.000	0.295
TechExecIn	12.824**	15.463**	--	3.996*
TechExecOut	7.693**	25.884**	6.147*	--
All	17.604**	35.938**	10.441*	5.585

Note: *$p < 0.05$, **$p < 0.01$.

Appendix D. Robustness Checks

Table D1. Results of IRFs for Robustness Checks

Step	(1)	(2)
	TechExecIn → LayerExpansion	***TechExecIn → WithinLayer***
Panel A. Using Three-Year Moving Window to Measure Mobility		
1	**0.0546 (0.0075)**	**-0.064 (0.0119)**
2	**0.0382 (0.0054)**	**-0.0453 (0.007)**
3	**0.0268 (0.0043)**	**-0.0318 (0.0057)**
4	**0.0187 (0.0036)**	**-0.0223 (0.0047)**
5	**0.0131 (0.0031)**	**-0.0156 (0.004)**
6	**0.0092 (0.0026)**	**-0.0109 (0.0033)**
7	**0.0064 (0.0021)**	**-0.0076 (0.0027)**
8	**0.0045 (0.0017)**	**-0.0053 (0.0022)**
Panel B. Using Unweighted Measures of Mobility		
1	**0.0351 (0.0069)**	**-0.0663 (0.0107)**
2	**0.0201 (0.0043)**	**-0.0283 (0.0066)**
3	**0.0117 (0.0029)**	**-0.0164 (0.005)**
4	**0.0069 (0.002)**	**-0.009 (0.0035)**
5	**0.0041 (0.0014)**	**-0.0051 (0.0024)**
6	**0.0025 (0.001)**	-0.0029 (0.0016)
7	**0.0015 (0.0007)**	-0.0017 (0.0011)
8	0.0009 (0.0005)	-0.001 (0.0007)

Panel C. Using 20 Lags as Instruments		
1	**0.0235 (0.0083)**	**-0.0389 (0.0114)**
2	**0.0145 (0.0051)**	**-0.018 (0.0072)**
3	**0.0091 (0.0036)**	-0.0104 (0.0058)
4	**0.0059 (0.0027)**	-0.0057 (0.0044)
5	0.0038 (0.002)	-0.0032 (0.0034)
6	0.0026 (0.0015)	-0.0018 (0.0025)
7	0.0017 (0.0012)	-0.001 (0.0019)
8	0.0012 (0.0009)	-0.0006 (0.0015)
Panel D. Using 15 Lags as Instruments		
1	**0.0218 (0.0077)**	**-0.0242 (0.0104)**
2	**0.0122 (0.0049)**	-0.0107 (0.0066)
3	**0.0076 (0.0035)**	-0.0053 (0.0053)
4	0.0048 (0.0026)	-0.0024 (0.0042)
5	0.0031 (0.002)	-0.001 (0.0033)
6	0.002 (0.0015)	-0.0003 (0.0025)
7	0.0013 (0.0012)	0 (0.002)
8	0.0009 (0.0009)	0.0001 (0.0015)
Panel E. Using Mobility Measures Weighted by Layer Similarity		
1	**0.0297 (0.0059)**	**-0.0547 (0.0139)**
2	**0.0249 (0.0043)**	**-0.0443 (0.0088)**
3	**0.0208 (0.0037)**	**-0.0363 (0.0076)**
4	**0.0172 (0.0034)**	**-0.0292 (0.0064)**
5	**0.0139 (0.0032)**	**-0.0232 (0.0056)**
6	**0.0112 (0.0029)**	**-0.0181 (0.0049)**
7	**0.0088 (0.0026)**	**-0.014 (0.0042)**
8	**0.0069 (0.0023)**	**-0.0107 (0.0036)**
Panel F. Using Outward Mobility as an Exogenous Variable		
1	**0.0324 (0.0077)**	**-0.0348 (0.0125)**
2	**0.0202 (0.0054)**	**-0.0191 (0.0072)**
3	**0.0131 (0.0042)**	**-0.0127 (0.0056)**
4	**0.0085 (0.0034)**	-0.0082 (0.0044)
5	**0.0055 (0.0028)**	-0.0053 (0.0034)
6	0.0035 (0.0022)	-0.0034 (0.0027)
7	0.0023 (0.0018)	-0.0022 (0.0022)
8	0.0015 (0.0014)	-0.0014 (0.0017)
Panel G. Startups with Fewer Than 1,000 Employees		
1	**0.0263 (0.0063)**	**-0.0401 (0.0102)**
2	**0.0168 (0.0041)**	**-0.0241 (0.0059)**
3	**0.0109 (0.003)**	**-0.0158 (0.0043)**
4	**0.007 (0.0023)**	**-0.0102 (0.0033)**
5	**0.0046 (0.0018)**	**-0.0067 (0.0025)**
6	**0.003 (0.0014)**	**-0.0043 (0.0019)**
7	0.0019 (0.001)	-0.0028 (0.0014)
8	0.0013 (0.0008)	-0.0018 (0.0011)
Panel H. Startups with Fewer Than 500 Employees		
1	**0.0361 (0.0133)**	**-0.0392 (0.0132)**
2	**0.0265 (0.0095)**	**-0.0258 (0.0082)**
3	**0.019 (0.007)**	**-0.0189 (0.0062)**
4	**0.0132 (0.0052)**	**-0.0131 (0.0047)**
5	**0.0089 (0.0038)**	**-0.0089 (0.0035)**
6	**0.0059 (0.0027)**	**-0.0058 (0.0026)**
7	0.0037 (0.002)	-0.0037 (0.0019)

8	0.0023 (0.0015)	-0.0023 (0.0014)

Note: The table presents values of IRFs; Standard errors in parentheses; Values in bold indicate significance at $p < 0.05$ level. In Panels A, B, and E using alternative measures of *TechExecIn*, we have used consistent approaches to measure other relevant control variables such as *TechExecOut, SeniorTechMob,* and *NonTechExecMob*.

Difference-in-Differences (DID) Estimations. We first create a binary variable $TechExecEntry_{it}$ to demonstrate the staggered treatment event, which equals one if the startup complementor *i* has an externally hired senior technology executive started in quarter *t* and zero otherwise. To fit the relative time model, we create a set of dichotomous variables indicating the chronological distance to the treatment event. We include nine quarters before (i.e., Pre_j) and nine quarters after (i.e., $Post_j$) the treatment event. We use one quarter before the treatment event (i.e., *Pre1*) as the baseline in our estimation. We cluster the standard errors at the firm level, which is consistent with the unit of our treatment events. We specify the equations for the relative time models as follows:

$$\begin{bmatrix} LayerExpansion_{it} \\ WithinLayer_{it_{it}} \end{bmatrix} = \sum_{j=2}^{9} \beta_j Pre_j + \sum_{j=0}^{9} \alpha_j Post_j + \boldsymbol{\theta X_{it}} + \vartheta_i + \lambda_t + \eta_i \times t + \varepsilon_{it}$$

where Pre_j equals one if the quarter *t*'s chronological distance to the treatment of externally hired senior technology executive in startup *i* is *j* quarters. $Post_j$ equals one if the chronological distance between the treatment in startup *i* at quarter *t* is *j* quarters. $\boldsymbol{X_{it}}$ is the vector of all time-variant control variables as specified in Table 1 of the main paper. ϑ_i indicates the complementor fixed effects. λ_t denotes the quarter fixed effects. $\eta_i \times t$ controls for the startup-specific linear time trend. ε_{it} refers to the error term.

Given that startup complementors strategically decide between the two types of innovation (i.e., layer-expansion innovation versus within-layer innovation) and accordingly allocate resources between them, the two equations are related because of the potential correlations between the errors associated with the two dependent variables. Thus, we employed a seemingly unrelated regression (SUR) specification to simultaneously estimate the two equations (Zellner 1963). We used the small sample adjustment for computing the covariance matrix of the equation residuals. The correlation of residuals in the two equations is -0.2924. The Breusch-Pagan test of independence ($\chi^2 = 59.270$, $p = 0.000$) indicates that we can reject the null hypothesis that this correlation is zero, demonstrating that SUR is preferred.

Table D2 summarizes the estimation results of the relative time model. The coefficients on all pre-treatment dummies are not statistically significant, validating the absence of significant pre-trends. Column (1) in Table D2 shows a significant and positive coefficient on *Post5* ($\alpha = 0.1509$, $p < 0.05$), indicating that an externally hired senior technology executive is positively associated with the startup complementor's layer-expansion innovation; and the effect takes about one year to manifest. Hence, the relative time model estimation supports H1.

Column (2) in Table D2 shows significant and negative coefficients on *Post0* ($\alpha = -0.2025$, $p < 0.05$), *Post1* ($\alpha = -0.2015$, $p < 0.01$), and *Post2* ($\alpha = -0.1637$, $p < 0.05$), demonstrating that an externally hired senior technology executive has an immediate negative effect on the startup complementor's within-layer innovation. Hence, H2 is supported by the relative time model estimation.

Table D2. Results of Relative Time Model Estimations

	(1)	(2)
	LayerExpansion	***WithinLayer***
Pre9	0.0035 (0.0631)	-0.2054 (0.1766)
Pre8	0.1037 (0.0775)	-0.0610 (0.1996)
Pre7	-0.0994 (0.0626)	-0.1212 (0.1235)
Pre6	-0.0159 (0.0455)	-0.0975 (0.1214)
Pre5	0.0024 (0.0859)	-0.2114 (0.1289)
Pre4	0.0368 (0.0954)	-0.0070 (0.1802)
Pre3	-0.0321 (0.0585)	-0.2843 (0.1543)
Pre2	0.0524 (0.0544)	-0.0162 (0.1201)
Pre1	Baseline	Baseline
Post0	0.0129 (0.0439)	**-0.2024* (0.0947)**
Post1	0.0074 (0.0488)	**-0.2015** (0.0756)**
Post2	0.0064 (0.0736)	**-0.1637* (0.0810)**
Post3	0.0249 (0.0802)	0.0163 (0.1013)
Post4	-0.0232 (0.0458)	-0.1296 (0.1000)
Post5	**0.1509* (0.0715)**	-0.0708 (0.1136)
Post6	0.0206 (0.0950)	-0.1000 (0.1158)
Post7	-0.0751 (0.0682)	-0.0654 (0.1689)
Post8	-0.0621 (0.0361)	-0.0085 (0.1051)
Post9	-0.0307 (0.0910)	-0.0067 (0.1447)
FirmAge	-0.1966 (0.1171)	0.3024 (0.2399)
LayerScope	0.2958*** (0.0568)	-0.0867 (0.0679)
LayerSimilarity	1.5846** (0.5839)	-0.0646 (0.7964)
Alliances	-0.0488* (0.0239)	0.0987* (0.0386)
Patents	0.1738* (0.0726)	-0.0026 (0.1363)
Trademarks	-0.0812 (0.0641)	0.1951 (0.1290)
Funding	-0.0539 (0.0420)	-0.0019 (0.0488)
Acquisitions	0.0886 (0.0868)	-0.3605* (0.1785)
EcosystemSize	0.0304 (0.0987)	-0.5677* (0.2235)
SeniorTechMob	-0.1013* (0.0445)	0.1992** (0.0648)
NonTechExecMob	0.0161 (0.0438)	-0.1665** (0.0612)
TechExecOut	-0.0582 (0.0971)	0.1338 (0.0970)
Startup FE	Yes	Yes
Quarter FE	Yes	Yes
Startup-Specific Linear Time Trend	Yes	Yes
R^2	0.4080	0.3809

Note: Number of observations: 693; Significance level: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

Appendix E. Qualitative Analyses

E-1. Content Analysis of Self-Disclosed Job Descriptions by Senior Technology Executives in Sample Hadoop Startups. To better understand the roles of senior technology executives in startup complementors within the Hadoop platform ecosystem, we collected self-disclosed job descriptions and responsibility statements from LinkedIn profiles of senior technology executives in our sample firms during the study period. After removing those without such disclosures, we retained 61 unique job descriptions and responsibility statements for 55 senior technology executives across 24 startups. Typical job titles include Chief Technology Officer (CTO), Chief Product Officer, VP of Products, VP of Product Management, VP of Engineering, VP of Technology, Chief Architect, Chief Scientist, VP of Solutions Engineering, and corresponding Senior VP roles, etc.

We conducted a content analysis of these descriptions to identify recurring areas of responsibility. Following an iterative coding process, we reviewed the descriptions, grouped similar responsibilities into common areas, and refined the areas through repeated comparison and discussion. Table E1 shows representative excerpts for the identified responsibility areas.

The coding results indicate that senior technology executives in Hadoop startups occupy roles involving both strategic technology decision making as well as direct participation in product development and implementation. The first area consists of responsibilities related to setting technology direction, shaping product strategy, and defining product roadmaps. The second category reflects direct involvement in technical architecture, software development, platform design, and implementation activities.

Table E1. Evidence on Senior Technology Executives' Roles in Startup Innovation

Responsibility Area	**Representative Excerpts**
Technology Strategy and Product Direction	"… I was brought in by the lead investor to **set product direction** …" "I am responsible for developing and communicating **a long-term technology vision**…**shape the roadmap**… I am also instrumental in **identifying emerging technologies and market trends**..." "… responsible for the **strategic vision** and concerted delivery across all the products within Emerging Products …" "… create **strategic roadmap and capabilities** within [the firm's] platform. … Overall responsible to … **drive product strategy** and development **...**" "… have **full responsibilities for the product line**. This includes ... **spearheading the product differentiation strategy and design**…" "… Responsible for overall Product Marketing and Product Management for [the firm's] products and solutions- including **product strategy**, go to market, **positioning**, pricing and **roadmap**. …" "… Led [the firm's] **product vision and strategy** based upon Blue Ocean strategy model. …"
Technical Development and	"… Architecture, design, coding, operations, pre-sales. All the things one would expect at a startup. **Production Python coding** of cloud-based control plane for data integration. **Set up DevOps infrastructure** (on AWS), including developer and integration automated

Implementation	testing. …” “… I was **personally responsible for** the design, development and maintenance of **a large subset of them**; while working with my team's Tech Leads on **the overall design and implementation**. …” “… **Design and hands-on implementation** of the [firm's] Data Platform … **helped design and implement the Pylon data analysis platform** to enrich, filter, classify and aggregate ...” “… I was responsible for **all software development** … **Lead** the technical team … **Led product management for the core platform**…” “… Responsible for **all aspects of software design and development** of [the firm's] innovative data protection products. …” “… Architected and directed the development of [the firm's] next generation data platform …” “… Acted as **a resource for general Hadoop and ecosystem knowledge** to the entire company… wrote the majority of ODPi first ever runtime technical specification. ...” “… I was **actively involved in advancing container technologies** and contributing to the growth of node.js …”

E-2. Case Narratives from Sample Hadoop Startups. We constructed detailed case narratives from representative sample firms that had hired external senior technology executives to qualitatively examine whether the executives' prior technical expertise aligns with the platform layers the firm subsequently expands into. For each case, we first coded the executives' prior technical experience, identifying the specific technical layers in which they had expertise (see Columns (1) and (2) of Table E2). In parallel, we documented each firm's product innovation history, highlighting the technical layers of products launched before and after the executive's arrival in Columns (3) and (4) of Table E2. Next, we compare the layers of the executive's prior technical expertise with the firm's covered technical layers in products released before the executive joined. Based on this comparison, we categorized the executive's prior technical expertise into “new” and “overlapping” layers, indicating whether it differs from or overlaps with the firm's prior technical layers, respectively (see Column (1) of Table E2). Finally, we assess whether the executive's new technical expertise aligns with the firm's subsequent expansion into the new platform layers (i.e., marked as bold in Columns (1) and (3) of Table E2).

The case narratives, as shown in Table E2, reveal patterns consistent with our proposed knowledge-based explanation. Specifically, when executives' prior knowledge in a specific layer that was not previously covered by the firm, that knowledge frequently translated into the firm launching products in that same layer after the executive's arrival, providing qualitative evidence that the executive's new knowledge directly drives layer-expansion innovation. Detailed discussions are presented in Section 4.4.2 of the main paper.

Table E2. Case Narratives Showing How Externally Hired Senior Technology Executives Drive the

Firm's Layer-Expansion Innovation				
	(1)	(2)	(3)	(4)
Case	**Executives' Prior Expertise in Layers**	**Details of Executives' Prior Expertise in Layers**	**Subsequent Firm Layer Expansion**	**Representative Narrative**
Firm A	<u>*New:*</u> **Data Access**, Cloud <u>*Overlapping:*</u> Data Storage	Executive A has experience as Director of Product Strategy and VP of Products at a firm focused on commercializing PostgreSQL for enterprise use with a focused database platform plus enterprise add-ons, tools, and subscriptions layered around PostgreSQL. The executive has led the product strategy and product roadmaps for several new products including an Enterprise Manager, a Cloud Server, and data warehouse engine.	**Data Access**	The executive joined the firm as Vice President Products. Prior to the executive's arrival, the firm has a main product focusing on enterprise use of Cassandra database in the Hadoop environment. Its products focus on the "Data Storage" layer. In about 9 months after the executive's arrival, the firm launches a new product, which is an integrated big data platform that unifies real-time data management with Cassandra, batch analytics with Apache Hadoop, and enterprise search with Apache Solr in a single, scalable cluster. By combining these technologies, it delivers Google-like search capabilities, real-time and cross-datacenter performance, automatic sharding, and simplified data management—without the need for complex data movement—while enabling search access through Cassandra Query Language (CQL). This new product release expands to the "Data Access" layer.
Firm B	<u>*New:*</u> **Data Management**, Development Tool <u>*Overlapping:*</u> Data Processing, Data Storage, Data Access	Executive B was the main contributor of Hadoop at Yahoo!, with extensive technical knowledge of Hadoop in various layers such as "Data Processing", "Data Storage", "Data Access", "Data Management", and "Development Tool".	**Data Management**	The executive took the role of Chief Architect of the firm. Prior to the executive's arrival, the firm released the first product focusing on commercializing Hadoop with an enterprise distribution platform. It packages Hadoop resources from "Data Storage", "Data Processing", and "Data Access" layers. During the period of 1-9 months after the executive's arrival, the firm has further incorporated several packages from the "Data Management" layer in two consecutive product releases.
Firm C	<u>*New:*</u> **Cloud** <u>*Overlapping:*</u> Security	Executive C was Vice President of Global Operations and Corporate IT in a firm positioned as a cloud-based security and compliance software provider. The executive was responsible for all aspects of the technical side of the firm's products.	**Cloud**	The executive joined the firm as Vice President of Information Technology, CIO, and Security Officer. The firm has already been a matured complementor in the Hadoop ecosystem, with products covering many layers, including "Data Storage", "Data Processing", "Data Access", "Data Management", "Development Tool", and "Security". In about 8 months after the executive's arrival, the firm has announced a series of cloud deployment, operations, security, data governance and user experience

				advancements, thus officially expanding its product offering to the "Cloud" layer.
Firm D	*New:* **Development Tool** *Overlapping:* Data Storage	Executive D was Senior Director of Software Engineering in a digital music firm. The executive was responsible for the digital distribution infrastructure that involved in "Data Storage" of digital music copies and drove new tech initiatives focusing on providing APIs and developer tools (i.e., the "Development Tool" layer).	**Development Tool**	Executive D joined Firm D as Chief Architect. The firm offers its core products featuring Hadoop-based analytics solutions, which covers "Data Storage" and "Data Access" layers. The firm's two subsequent product releases in 1-2 years after the executive's arrival strengthened the core analytics functionalities and added the "Development Tool".
Firm E	*New:* **Cloud** *Overlapping:* Data Access, Development Tool	Executive E was Director of Product Management and responsible for managing the firm's flagship products. The flagship products include business intelligence server products, Eclipse tools, and early SaaS initiatives.	**Cloud**	The executive joined the firm as VP of Products. The firm had two product releases prior to the executive's arrival, featuring the "Development Tool" and a professional edition with extensive analytics functions (i.e., "Data Access"). In about 3 months after the executive's arrival, the firm released a new product integrating all previous functions and expanding it to the "Cloud" layer.
Firm F	*New:* **Security**, **Cloud**	Executive F was Chief evangelist/architect for security services platforms and has extensive experience in security applications. Executive F2 was Senior Engineering Manager at Google responsible for its cloud-native services.	**Security**, **Cloud**	Executive F1 joined the firm as CTO and labeled his/her job role as "aka The Cloud Guy". Executive F2 joined the firm as VP Engineering in about 3 months after Executive F1 joined. Prior to both executives' arrivals, the firm has released its first Hadoop-related product covering "Data Storage", "Data Processing", "Data Access" layers. After their arrivals, the firm released its second product focusing on big data-as-a-service solutions, thus expanding the position to the "Cloud" layer. Soon after this new product, the firm has further extended to the "Security" layer with the third new product in its portfolio.
Firm G	*New:* Data Storage, **Data Processing**, **Data Access**	Executive G was Grid Computing Architect focusing on the core Hadoop-based infrastructure and perform analysis of the entire stack. The executive was also actively involving in Apache Software	**Data Access**, **Data Processing**, Security, Data Management	The executive joined the firm as Chief Hadoop Evangelist to provide technical knowledge about Hadoop. The firm launched its first product focusing on the "Cloud" layer prior to the executive's arrival. Soon after the executive's arrival, the firm starts to release a series of expansions to its core cloud-based solution to cover "Data

		Foundation by submitting patches and write documentation with an operational focus for Hadoop. The executive has technical knowledge of Hadoop, covering layers such as "Data Storage", "Data Processing", and "Data Access".		Access", "Data Processing", "Security", and "Data Management" in a subsequent manner.
Firm H	*<u>New:</u>* **Development Tool** *<u>Overlapping:</u>* Data Access, Cloud, Security	Executive H was Director, Business Development involving in the firm's core products that feature collecting, indexing, and analyzing large volumes of data, their extension to security applications, a service running in the public cloud, and two software development kits (SDKs) for Python and JavaScript. The executive has knowledge in "Data Access", "Cloud", "Security", and "Development Tool" layers.	**Development Tool**	The executive joined the firm as Chief Product Officer. Prior to the executive arrival, the firm has already offered a wide range of functionalities, including "Data Access", "Cloud", "Data Storage", and "Security", which are largely overlapped with the executive's prior experiences. In about a year after the executive's arrival, the firm has released a new product providing developers opportunities to extend the core functions, thus expanding to the "Development Tool" layer.
Note: "*<u>New</u>*" indicates the executive's expertise that is different from the hiring firm's prior product layers; "*<u>Overlapping</u>*" means the executive's expertise that is overlapped with the hiring firm's prior product layers.				

E-3. Interviews with Senior Executives in Technology Startups. We collected interview data through Qualtrics using a computer-assisted telephone interviewing (CATI) process. Qualtrics recruited qualified respondents based on the screening criteria specified in our interview protocol. During each interview, a moderator presented one question at a time and recorded respondents' verbal answers, which were subsequently transcribed for analysis. In total, we conducted 34 interviews with participants who (1) have worked or are currently working as a senior technology executive in tech startups (N = 23), or (2) have not worked as a senior technology executive in a tech startup but have closely interacted with senior technology executives in a tech startup (N = 11; e.g., Chief Financial Officer, Director of Operations, Director of Growth Marketing, Head of Innovation, Head of Design, and Senior Developer). The interviews lasted 38 minutes on average, with durations ranging from 22 to 83 minutes.

The interviews cover a broader set of technology startups rather than Hadoop complementors alone for generalizability and practical considerations. Most technology startups develop products on top of existing software platforms and technology stacks such as iOS, Android, Java, SAP, Hadoop, Linux, Python, AWS, and Azure. As a result, technology startups provide an appropriate setting for understanding how senior technology executives draw on prior experience when making product and technology decisions. During the interviews, respondents frequently referred to platform ecosystems, cloud technologies, software architectures, artificial intelligence, deep learning, blockchain, and related technologies when discussing innovation decisions. In addition, given the relatively small number of Hadoop startups in our sample, recruiting senior technology executives from these firms was challenging.

We analyzed the interview data using a qualitative content-analysis approach. Two authors independently coded all interview transcripts. Specifically, we began with open coding to identify recurring concepts and themes that emerged from each interview question. We then grouped quotes into common categories. The two coders compared their coding results and resolved discrepancies through discussion. A third author subsequently reviewed the coding structure and the correspondence between the identified themes and representative quotes. Table E3 summarizes the interview evidence related to the knowledge-based mechanisms examined in this study, including the cognitive and technical dimensions of tacit knowledge and their implications for senior technology executives' innovation prioritization and resource allocation.

Table E3. Interview Evidence on Knowledge-Based Mechanism

Theme	Representative Quotes
Cognitive Tacit Knowledge	"… the new member obviously **comes with a new mindset and idea**, which could influence the development of a product as it may lead to **a shift in new ways of developing or prioritizing and delivering a product**…" "Obviously, when a tech executive enters the game, they assist in **expanding the scope of the product by amalgamating technology and the idea behind it**. They might even **bring in a new idea that amends the primary vision behind the original product**. …" "… [new senior technology executives] are always **bringing in fresh perspectives to the table to make things better**, which not only **challenges the way things are usually done** but also **helps companies find new business opportunities… adding completely new features or looking into new technological avenues**…" "I have seen this happen many times in different companies **when people from different mindsets and backgrounds come in**... someone with **a different perspective** might suggest changing the approach to make it more viable in the market, **based on their experience**..." "...they do tend to explore more of how the product will or will not perform in the market, **which often brings new ideas**."
Technical Tacit Knowledge	"In the past, … **a [new] senior manager with a lot of experience in machine learning brought in new ideas that changed the way products were made in a significant manner**. Before he joined the company, simple algorithms were used to make predictions. He did, however, see a way to improve the product by **adding new deep learning techniques**." "One example is **a highly skilled and experienced IT executive** who knows a lot about AI. In order to make the product more appealing to a more advanced and data-driven market, this executive would tell the product development team to **add AI features to it**." "… a senior in my previous company who was new to our team and had **immense knowledge about deep learning AI and many other things**... He taught the whole team regarding **newer technologies, took our idea into consideration, guided us how we can improve them**..." "...from **past positions** at more established tech companies, that executive brought plenty of experience ... [and] **introduced the scrum methodology.**.."
Prioritization and	"Their primary task also revolves around **reassessing the product initiatives that already**

Resource Allocation	**are in the pipeline** while considering factors like market demand, user feedback, resource availability, and technical feasibility.” “...**resource management is something that is usually in most cases heavily changed or impacted whenever a new senior arrives** as they bring in fresh perspectives...” “Resource management is very important here because **they need to make sure that the engineering team understands these new priorities** and works on all of their other projects at the same time.” “Startups typically have **limited budgets and smaller teams** ... senior executives need to **prioritize projects** that offer the highest potential for rapid growth...” “...to ensure the alignment of the product roadmap to the realities of the current technology stack... [they] brought **a deep understanding of resource management, which allowed them to set a more realistic timeline** for product development.” “...**evaluating** the programming languages, frameworks, databases, and infrastructure currently in use ... **identifying gaps and shortcomings** ... **looking for opportunities to enhance the stack**...”

Appendix F. Additional Analysis on Boundary Conditions

Table F1. Effect Heterogeneity by Startup Development Stage

Step	(1)	(2)	(3)	(4)
	Early-Stage Ventures (1-50 Employees)		**Growth-Stage Ventures (51-500 Employees)**	
	TechExecIn → *LayerExpansion*	*TechExecIn* → *WithinLayer*	*TechExecIn* → *LayerExpansion*	*TechExecIn* → *WithinLayer*
1	**-0.0244 (0.0089)**	**0.0809 (0.0114)**	**0.049 (0.0064)**	**-0.048 (0.0121)**
2	**-0.0104 (0.0035)**	**0.0255 (0.0083)**	**0.0353 (0.0047)**	**-0.0394 (0.008)**
3	**-0.0046 (0.0021)**	**0.0137 (0.0052)**	**0.0281 (0.004)**	**-0.032 (0.0066)**
4	-0.0021 (0.0012)	0.0063 (0.0034)	**0.0214 (0.0036)**	**-0.025 (0.0056)**
5	-0.001 (0.0008)	0.0034 (0.0022)	**0.0162 (0.0034)**	**-0.019 (0.0049)**
6	-0.0005 (0.0005)	0.002 (0.0015)	**0.0121 (0.0032)**	**-0.0143 (0.0043)**
7	-0.0003 (0.0003)	0.0013 (0.0012)	**0.009 (0.003)**	**-0.0107 (0.0039)**
8	-0.0002 (0.0002)	0.0009 (0.001)	**0.0067 (0.0027)**	**-0.008 (0.0035)**

Note: The table presents values of IRFs; Standard errors in parentheses; Values in bold indicate significance at $p < 0.05$ level.

Founding-Team Technical Leadership. We first collected the list of founding members, their job titles, and descriptions of responsibilities for each startup from Crunchbase, LinkedIn profiles, and Google search. Next, we manually coded whether each founding member was a senior technology executive when the startup was founded using the same criteria as our identification of senior technology executives (as explained in Section 3.2.2 of the main paper). For those without a functional title (e.g., listed as “founder” or “cofounder”), if their responsibilities included management of products and innovations, we categorized them as senior technology executives on the founding team. Empirically, we split the sample into startups with a senior technology executive on the founding team and those without and separately estimated the main PVAR specifications for each subsample. Table F2 presents the IRFs from the split-sample analysis.

Table F2. Effect Heterogeneity by Founding-Team Technical Leadership

Step	(1)	(2)	(3)	(4)
	With Senior Technology Executives on the Founding Team		Without Senior Technology Executives on the Founding Team	
	TechExecIn → *LayerExpansion*	*TechExecIn* → *WithinLayer*	*TechExecIn* → *LayerExpansion*	*TechExecIn* → *WithinLayer*
1	0.0023 (0.0085)	0.0062 (0.0115)	**0.0200 (0.0088)**	**-0.0905 (0.0146)**
2	0.0026 (0.0066)	0.0041 (0.0074)	**0.0135 (0.0052)**	**-0.0653 (0.0113)**
3	0.0025 (0.0050)	0.0034 (0.0058)	**0.0103 (0.0034)**	**-0.0483 (0.0103)**
4	0.0022 (0.0038)	0.0026 (0.0043)	**0.0074 (0.0025)**	**-0.0338 (0.0092)**
5	0.0018 (0.0030)	0.0020 (0.0033)	**0.0050 (0.0020)**	**-0.0228 (0.0079)**
6	0.0014 (0.0023)	0.0015 (0.0025)	**0.0033 (0.0016)**	**-0.0148 (0.0065)**
7	0.0011 (0.0018)	0.0011 (0.0019)	0.0021 (0.0012)	-0.0094 (0.0052)
8	0.0008 (0.0014)	0.0008 (0.0015)	0.0013 (0.0009)	-0.0057 (0.004)

Note: The table presents values of IRFs; Standard errors in parentheses; values in bold indicate significance at $p < 0.05$ level.

Appendix G. Empirical Analysis of the Android Platform Ecosystem

Data Collection. Given our focus on startup complementors in a software platform ecosystem, we start our data collection with the list of startups included in the "Android Startups" hub page from Crunchbase ($N = 525$).[1] Crunchbase compiles a comprehensive list of technology startups and has been increasingly used in research related to technology entrepreneurship and startups (e.g., Butler et al. 2020). Next, we collect each startup's official business website and its business descriptions. Four coders have independently performed manual coding of each startup's main business. We then organize a follow-up discussion session to resolve inconsistencies in our independent coding. Based on our final coding, we only keep the startups whose main business model is based on their mobile apps. In other words, we remove startups that (1) use mobile apps as supplements to main business activities, (2) only provide software development kits (SDKs), (3) only provide app development platforms (e.g., no-code development platforms for Android developers), (4) only offer devices (e.g., hardware, wearable devices) compatible with the Android platform, and (5) only provide software development services or consulting services for clients. This exclusion has resulted in 142 startups that primarily provide mobile apps in the Android platform ecosystem.

Next, we collect the mobile app data for these Android startups from data.ai (formerly known as App Annie), which has been used in prior studies about mobile apps (e.g., Foerderer et al. 2021; Kummer & Schulte 2019; Liang et al. 2019). We identify 1777 unique mobile apps released on the Android platform by our sample firms. We then collect detailed data about each of these apps including (1) the initial release date and the primary category, (2) the installation of a specific SDK at a given date, (3) the version release history, and (4) the longitudinal data of the number of user reviews and the average app ratings.

Finally, we collect all LinkedIn profiles of individuals who have ever worked at each Android startup in our sample using the "LinkedIn Company Employees Export" API. We obtain 647 LinkedIn profiles for 61 unique Android startups. After merging data from different sources, we aggregate it to the firm-quarter level to form an unbalanced panel data. The first observed quarter for each Android startup is

[1] Crunchbase's hub page lists popular startups in the same market space based on the highest 30-day trend score. The hub page often updates monthly. The link to the "Android Startups" hub can be accessed at https://www.crunchbase.com/hub/android-startups. We compiled our initial list of Android startups from the hub page in July 2024.

the quarter when its first mobile app was released on the Android platform. Our final sample includes 1042 firm-quarter observations of 61 startups in the Android platform ecosystem during 2011-2018.

Measures. We use each mobile app's initial release date, version release history, and SDK installations to construct the measure of the startup's layer-expansion and within-layer innovation. In line with prior research (e.g., Foerderer 2020; Foerderer et al. 2018), we identify each firm's releases of new apps and version updates of existing apps as its innovation. Given that mobile apps extensively use the Android platform's boundary resources in the form of SDKs (Chung et al. 2023; Karhu et al. 2018), we use whether the firm installed a new SDK in its new apps or app updates to distinguish between layer-expansion innovation and within-layer innovation. This is because, directly tied to Android's layered modular architecture, both Android and third-party SDKs abstract the complexity of the Android platform's underlying technical stack[2] by packaging subsets of system functionality such as networking, location, and graphics into reusable and developer-friendly components (Chung et al. 2023). In other words, SDKs bundle pre-built tools, APIs, and libraries that developers can use to simplify feature implementation and expand the functionalities of their apps. For example, adopting Android biometric SDK allows apps to integrate fingerprint and facial recognition authentication while standardizing security implementation across devices. Similarly, adopting location mapping SDKs such as Google Maps allow apps to incorporate real-time navigation and precise geospatial representation. In summary, SDK adoption allows app developers to add app functionalities efficiently. Hence, adoption of new SDKs in the context of Android is similar to layer-expansion innovation in the Hadoop context in that both allow complementors to incorporate more functionalities into their products.

Accordingly, we code the variable $LayerExpansion_{it}$ as one if the startup i released product innovations (i.e., either launching a new app or an existing app's version updates) that use new SDKs in quarter t and zero otherwise. The variable $WithinLayer_{it}$ equals one if the startup i released product innovations (i.e., either launching a new app or an existing app's version updates) but did not use any new SDKs in quarter t and zero otherwise. In our final sample of 1042 firm-quarter observations, 123 have layer-expansion innovations (i.e., $LayerExpansion_{it} = 1$), and 652 have within-layer innovations (i.e., $WithinLayer_{it} = 1$). Among the 123 firm-quarter observations with layer-expansion innovations, the average number of new SDKs installed by the startup is 30, indicating that Android startups often install a larger set of SDKs when expanding their SDK usage. In addition, we observe 66 firm-quarter observations with uninstallation of SDKs; however, most of them ($N = 59$) have concurrent new SDK installations.

We use senior technology executives' LinkedIn profiles to identify their job transitions and aggregate them to construct measures for the external hiring and turnover of senior technology executives at the firm-quarter level. First, four coders have independently coded all collected LinkedIn profiles' (N = 647) job titles to label senior technology executives. We take several iterations to resolve inconsistencies. In total, we identified 84 inter-firm job transitions of senior technology executives in the 61 Android startups in our sample. Consistent with our main analysis using the Hadoop platform ecosystem, we use a two-year moving window and weight each job transition using the number of years the senior technology executive was in the same level of position when constructing the mobility measures. Specifically, the variable $TechExecIn_{it}$ refers to logarithm of one plus the total weighted number of technology executives that moved from another firm to the focal startup i in the two years prior to quarter t. The variable $TechExecOut_{it}$ measures logarithm of one plus the total weighted number of technology executives that moved from the focal startup i to another firm during the two years prior to quarter t.

[2] Android platform's technical stack includes Linux Kernel, Hardware Abstraction Layer, Native Libraries and Android Runtime, Java API Framework, and System Apps. Refer to https://developer.android.com/guide/platform for more details.

We also control for a set of time-variant factors that may influence the Android startup's product innovation and senior technology executives' mobility. Table G1 summarizes the measurements and descriptive statistics of all variables for the Android startup sample. Table G2 shows the pairwise correlations among all variables.

Table G1. Variable Definition and Descriptive Statistics

Variable	Definition	Mean	S.D.	Min	Max
LayerExpansion	1 if the firm has released an existing app's version updates or a new app that uses new software development toolkits (SDKs), and 0 otherwise	0.12	0.32	0	1
WithinLayer	1 if the firm has released an existing app's version update or a new app that uses the same set of SDKs, and 0 otherwise	0.63	0.48	0	1
TechExecIn	Log (1 + number of new technology executives coming from another firm, weighted by the executive's number of years in his/her prior job at the same level within the past two years)	0.10	0.41	0	3.08
TechExecOut	Log (1 + number of technology executives moving to another firm, weighted by the executive's number of years in his/her prior job at the same level within the past two years)	0.05	0.27	0	1.87
Diversification	Log (number of unique primary categories among the firm's all apps)	0.67	0.82	0	2.71
TotalApps	Log (number of active apps the firm has released)	1.38	1.44	0	4.81
HighRatingApps	Percentage of apps with average rating above 4 out of the firm's total number of active apps	0.25	0.38	0	1
LowRatingApps	Percentage of apps with average rating below 3 out of the firm's total number of active apps	0.69	0.41	0	1
AppAge	Log (1 + average age [i.e., measured as the number of quarters since the app's release date] of the firm's all active apps)	2.06	0.75	0	3.56
AppReviews	Log (1 + total number of reviews in each quarter for the firm's all active apps)	4.33	5.24	0	17.25

Note: Number of observations: 1042

Table G2. Correlations

Variable	1	2	3	4	5	6	7	8	9
1. *LayerExpansion*									
2. *WithinLayer*	-0.47*								
3. *TechExecIn*	-0.01	0.01							
4. *TechExecOut*	-0.01	0.03	0.15*						
5. *Diversification*	0.23*	-0.06*	-0.07*	0.08*					
6. *TotalApps*	0.20*	-0.02	-0.07*	0.09*	0.77*				
7. *HighRatingApps*	0.22*	-0.02	0.03	-0.07*	-0.11*	-0.14*			
8. *LowRatingApps*	-0.29*	0.09*	-0.01	0.08*	0.11*	0.12*	-0.75*		
9. *AppAge*	0.25*	-0.17*	-0.01	0.02	0.23*	0.27*	0.33*	-0.41*	
10. *AppReviews*	0.37*	-0.15*	0.00	0.01	0.18*	0.17*	0.66*	-0.71*	0.56*

Note: Number of observations: 1042; *$p < 0.05$

PVAR Model Specification. We follow a similar approach as described in Section 3.3 of the main paper and Online Appendix C to specify the PVAR model. Specifically, our reduced form PVAR model identifies the external hiring and turnover of senior technology executives, as well as the complementor's product innovation as endogenous variables. All time-variant control variables and the linear quarter fixed effects are specified as exogenous covariates. We take the following steps to identify the PVAR model. First, we transformed variables using the forward orthogonal transformation (FOD) to control firm fixed effects and enable the usage of lagged values as instruments. Second, we use all lags of endogenous variables prior to FOD transformation as the transformed variables' instruments. Third, we rely on MBIC, MAIC, and MQIC to choose the lag order. As shown in Table G3, none of the Hansen's *J* statistics is statistically significant at $p < 0.1$, indicating the validity of our specified instruments. The results also show that the one lag model has the smallest values of MBIC, MAIC, and MQIC. Fourth, we ran the unit root test to ensure the model satisfies the stationary assumption. Figure G1 shows that all eigenvalues stay inside the unit circle, demonstrating the fulfillment of the stationary assumption.

Table G3. Model Selection Criteria

Lag	CD	Hansen J	J *p*-value	MBIC	MAIC	MQIC
1	0.8252	83.0303	0.3862	-440.0209	-76.9697	-217.3941
2	0.8680	55.1125	0.7780	-363.3285	-72.8875	-185.2271
3	0.8710	48.0073	0.4726	-265.8234	-47.9927	-132.2473
4	0.8810	27.5997	0.6890	-181.6208	-36.4003	-92.5701
5	0.9113	14.7908	0.5400	-89.8195	-17.2092	-45.2941

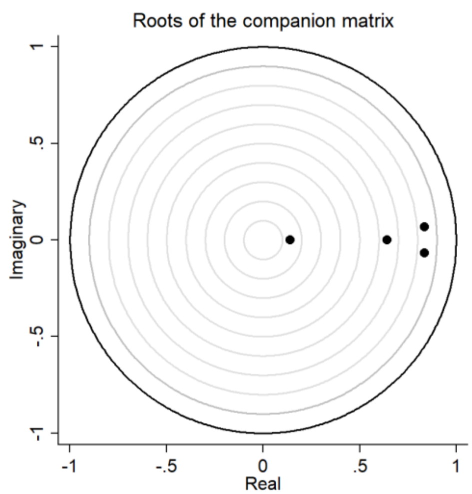

Figure G1. Results of the Unit Root Test

Hence, our reduced form PVAR model is specified as follows.

$$\begin{bmatrix} LayerExpansion_{it} \\ WithinLayer_{it} \\ TechExecIn_{it} \\ TechExecOut_{it} \end{bmatrix} = \boldsymbol{\Phi} \begin{bmatrix} LayerExpansion_{i,t-1} \\ WithinLayer_{i,t-1} \\ TechExecIn_{i,t-1} \\ TechExecOut_{i,t-1} \end{bmatrix} + \boldsymbol{\delta Controls_{i,t-1}} + \boldsymbol{\lambda_i} + \boldsymbol{\psi_t} + \boldsymbol{\nu}_{it}$$

where $\boldsymbol{\Phi}$ is the vector of coefficients for endogenous variables; ***Controls*** indicates the matrices of all control variables; $\boldsymbol{\lambda}$ refers to the firm fixed effects; $\boldsymbol{\psi}$ denotes the linear quarter fixed effects; and $\boldsymbol{\nu}$ refers to the vector of error terms.

Finally, we derive the orthogonal IRFs using the PVAR estimates and the reduced-form residual's variance-covariance matrix. We imposed a recursive structure using Cholesky decomposition by specifying the endogenous variables' ordering using the results of the Granger causality Wald test, as shown in Table G4. Finally, we leverage the Monte Carlo simulation with 200 runs to identify the 95% confidence intervals of IRFs.

Table G4. Results of the Granger Causality Wald Test

Excluded Variable	**Equation**			
	LayerExpansion	*WithinLayer*	*TechExecIn*	*TechExecOut*
LayerExpansion	--	589.477**	64.366**	38.637**
WithinLayer	1.313	--	37.969**	4.419*
TechExecIn	164.767**	286.162**	--	13.464**
TechExecOut	192.035**	46.195**	115.195**	--
All	311.958**	993.190**	442.346**	89.319**

Note: *$p < 0.05$, **$p < 0.01$.

Results of Hypothesis Testing Based on IRFs. Table G5 presents the orthogonalized IRFs, along with robust standard errors, for our hypothesized relationships. Column (1) indicates positive IRFs on the effect of *TechExecIn* on *LayerExpansion*, which is statistically significant at $p < 0.05$ level in all ten forecast quarters. In other words, Android startups with a higher level of externally hired senior technology executives are more likely to release layer-expansion innovations in the subsequent quarter. Hence, H1 is supported. In addition, as shown in Column (2), the IRFs on the effect of *TechExecIn* on *WithinLayer* are negative and significant at $p < 0.05$ level in all ten forecast quarters. Consistent with H2, the result indicates that Android startups with a higher level of externally hired senior technology executives are less likely to release within-layer innovation.

Table G5. Results of IRFs for Hypothesis Testing

Step	(1) ***TechExecIn* → *LayerExpansion***	(2) ***TechExecIn* → *WithinLayer***
1	**0.0263 (0.0022)**	**-0.0406 (0.003)**
2	**0.0421 (0.0035)**	**-0.0581 (0.0039)**
3	**0.0506 (0.0043)**	**-0.0678 (0.0048)**
4	**0.0542 (0.0046)**	**-0.0715 (0.0052)**
5	**0.0545 (0.0046)**	**-0.0711 (0.0054)**
6	**0.0526 (0.0045)**	**-0.0682 (0.0053)**
7	**0.0495 (0.0043)**	**-0.0637 (0.0052)**
8	**0.0455 (0.0041)**	**-0.0583 (0.0051)**
9	**0.0412 (0.0040)**	**-0.0526 (0.0050)**
10	**0.0369 (0.0038)**	**-0.0469 (0.0050)**

Note: The table presents values of IRFs; Standard errors in parentheses; Values in bold indicate significance at $p < 0.05$ level.

Robustness Checks. We run robustness checks similar to our main analysis using the Hadoop platform ecosystem (see Table G6 for the results). First, we use a three-year moving window to construct alternative measures of externally hired and turnover among senior technology executives in Panel A. Second, we run a robustness check using unweighted measures of senior technology executives' external hire and turnover and present the results in Panel B. Third, Panel C and Panel D present the results of IRFs using 20 lags and 15 lags as instruments in the PVAR model specification, respectively. Fourth, we further label Android startups that expand their primary category of apps as an additional form of layer-expansion innovation. In other words, we develop an alternative measure of layer-expansion innovation as Android startups that have released product innovations (i.e., either launching a new app or an existing app's version updates) that use new SDKs or expand into a new primary app category. Panel E shows the IRFs using the alternative measure of layer-expansion innovation. Overall, the results are consistent.

Table G6. Results of IRFs for Robustness Checks

Step	(1) *TechExecIn* → *LayerExpansion*	(2) *TechExecIn* → *WithinLayer*
Panel A. Using Three-Year Moving Window		
1	**0.0396 (0.0028)**	**-0.0438 (0.0032)**
2	**0.0683 (0.0047)**	**-0.0768 (0.0049)**
3	**0.0875 (0.0061)**	**-0.0989 (0.0064)**
4	**0.0986 (0.0072)**	**-0.1116 (0.0077)**
5	**0.1029 (0.0080)**	**-0.1165 (0.0086)**
6	**0.1016 (0.0084)**	**-0.1152 (0.0092)**
7	**0.0960 (0.0086)**	**-0.1088 (0.0094)**
8	**0.0873 (0.0084)**	**-0.0989 (0.0093)**
Panel B. Using Unweighted Measures of Technology Executive Mobility		
1	**0.0297 (0.0026)**	**-0.0346 (0.0037)**
2	**0.0403 (0.0039)**	**-0.0443 (0.0046)**
3	**0.0402 (0.0045)**	**-0.0454 (0.0053)**
4	**0.0351 (0.0046)**	**-0.0404 (0.0053)**
5	**0.0280 (0.0044)**	**-0.0328 (0.0050)**
6	**0.0209 (0.0039)**	**-0.0248 (0.0045)**
7	**0.0146 (0.0033)**	**-0.0176 (0.0038)**
8	**0.0094 (0.0028)**	**-0.0115 (0.0031)**
Panel C. Using 20 Lags as Instruments		
1	**0.0389 (0.0073)**	**-0.0619 (0.0095)**
2	**0.0449 (0.0078)**	**-0.0640 (0.0095)**
3	**0.0475 (0.0089)**	**-0.0656 (0.0105)**
4	**0.0481 (0.0100)**	**-0.0652 (0.0115)**
5	**0.0473 (0.0108)**	**-0.0633 (0.0124)**
6	**0.0456 (0.0113)**	**-0.0605 (0.0132)**
7	**0.0434 (0.0117)**	**-0.0573 (0.0138)**
8	**0.0409 (0.0120)**	**-0.0537 (0.0142)**
Panel D. Using 15 Lags as Instruments		
1	**0.0257 (0.0024)**	**-0.0402 (0.0038)**
2	**0.0416 (0.0039)**	**-0.0583 (0.0056)**
3	**0.0508 (0.0049)**	**-0.0684 (0.0069)**
4	**0.0552 (0.0055)**	**-0.0729 (0.0077)**
5	**0.0563 (0.0059)**	**-0.0735 (0.0081)**
6	**0.0553 (0.0060)**	**-0.0714 (0.0083)**
7	**0.0528 (0.0061)**	**-0.0677 (0.0084)**
8	**0.0494 (0.0061)**	**-0.0630 (0.0083)**
Panel E. Alternative Measure of Layer-Expansion Innovation		
1	**0.0478 (0.0057)**	**-0.0693 (0.0069)**
2	**0.0187 (0.0044)**	**-0.0335 (0.0047)**
3	**0.0085 (0.0038)**	**-0.0208 (0.0038)**
4	0.0045 (0.0035)	**-0.0156 (0.0033)**
5	0.0026 (0.0033)	**-0.0131 (0.0030)**
6	0.0016 (0.0032)	**-0.0116 (0.0029)**
7	0.0010 (0.0030)	**-0.0106 (0.0027)**
8	0.0006 (0.0030)	**-0.0098 (0.0026)**

Note: The table presents values of IRFs; Standard errors in parentheses; Values in bold indicate significance at $p < 0.05$ level.

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