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Startup multihoming in enterprise software ecosystems: The role of skill breadth and organizational learning

Vijayaraghavan Venkataraman [1] | Marco Ceccagnoli [2] | Chris Forman [3]

[1]Indian Institute of Management Bangalore, Bengaluru, Karnataka, India

[2]Scheller College of Business, Georgia Institute of Technology, Atlanta, Georgia, USA

[3]Charles H. Dyson School of Applied Economics and Management, Cornell SC Johnson College of Business, Cornell University, Ithaca, New York, USA

Correspondence
Vijayaraghavan Venkataraman, Indian Institute of Management Bangalore, Bannerghatta Road, Bengaluru, Karnataka, India.
Email: vijay.venkat@iimb.ac.in

Abstract

Research Summary: We investigate startup decisions to multihome to another platform. We develop a theory that shows startup engagement with the initial platform leads first to exploratory learning and later a shift toward exploitation, leading to an inverted U-shape relationship between duration of platform partnership and the likelihood of multihoming. This tradeoff is shaped by the breadth of the startup's skill base. Startups with a broader set of skills initially face slower learning, but over time skill breadth provides greater adaptability that better positions them for multihoming. We test our theory using a novel dataset on SAP partners' multihoming decisions, examining the implications of Oracle acquisitions that increased the expected benefits of multihoming. Our empirical findings are consistent with our hypotheses.

Managerial Summary: The growth phase forms an important part of any startup's evolution, particularly when engaging with digital platform ecosystems, where expansion often

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depends on the ability to multihome. Startups' accumulated experience with a platform shapes how they respond when opportunities to expand to another platform arise. Startups with moderate levels of prior platform experience are most likely to expand, while longer relationships can create dependencies that reduce flexibility. Importantly, the breadth of a startup's skill base changes this trajectory. Startups with diverse skills are better able to avoid lock-in and remain flexible, even after long partnerships. Evidence from the enterprise software ecosystem shows managers should see platform partnerships as both opportunity and risk, investing in broad skill sets to balance deep collaboration with the ability to grow across platforms.

KEYWORDS
enterprise software, learning, multihoming, platform ecosystems, skill breadth, startup

1 | INTRODUCTION

Firms increasingly innovate and grow by participating in platform ecosystems—environments where platform owners provide technological foundations for third-party startups to develop complementary innovations (Gawer & Cusumano, 2008). These ecosystems create opportunities for startups to access large customer bases and scale more quickly but also confront them with dynamic platform contexts that require ongoing adaptation to evolving governance rules and technical standards (Chen et al., 2022a). Yet how startups navigate these ecosystems—and what shapes their ability to do so successfully—remains poorly understood (Nambisan et al., 2018).

A central question for startups working with platform ecosystems is whether to affiliate with multiple platforms—a choice known as multihoming (Cennamo & Santalo, 2013; Chen et al., 2022b; Corts & Lederman, 2009). For startups, multihoming offers benefits such as reduced platform dependency and expanded market access but also introduces new integration costs and operational challenges (Cennamo et al., 2018; Cennamo & Santalo, 2013; Corts & Lederman, 2009). These tradeoffs are shaped not only by market opportunities but also by platform governance arrangements, such as certification and partner management practices and access to boundary resources, that influence how complementors learn and accumulate platform-specific investments over time (Chen et al., 2022a, 2022b).

Recent work has made important progress in understanding how these tradeoffs shape the behavior of startups in platform ecosystems, exploring how platform governance, organizational learning, and co-specialized investments by startups shape multihoming decisions and outcomes (Cennamo et al., 2018; Chen et al., 2022b; Chung et al., 2024; Polidoro Jr. & Yang, 2024). This recent research has been in settings such as ridesharing, gaming, and mobile applications where the user is often an individual consumer. However, in many platform settings, the user is part of a broader organization. In such settings, developers need to cross between technical and commercial spheres of knowledge to create commercial value (Bresnahan, 2019). This creates demand for complementor skills that will shape organizational learning (Levinthal & March, 1993; Pisano et al., 2001) and responses to platform governance decisions (Foerderer et al., 2019a), issues that have not been a focus of earlier work.

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We seek to understand how skill breadth shapes startups' multihoming behavior and their ability to respond to changing opportunities within platform ecosystems. In particular, we focus on the following questions: How does the learning that arises from the duration of startup involvement in a platform ecosystem shape multihoming behavior? And how does the composition of startup capabilities influence this relationship?

To do this, we examine the implications of skill breadth on multihoming within the context of enterprise software, in particular enterprise resource planning (ERP). Skill breadth plays an important role in enterprise software because complementors serving customers across industries must acquire industry-specific knowledge of firm processes, work structures, and customer relationships (Bresnahan, 2019). Because this knowledge must be acquired separately for each customer industry, the breadth of a complementor's skill base becomes a key determinant of multihoming costs and benefits—a mechanism absent from prior work set in the context of consumer platforms.

We develop a theory that proposes that startups' engagement with a platform ecosystem follows an inverted-U learning trajectory. In the early stages, startups primarily engage in exploratory learning (Levinthal & March, 1993; March, 1991), acquiring transferable knowledge through interactions with platform owners, customers, and other complementors (Iansiti & Lakhani, 2009; Ko et al., 2005). During these earlier phases, complementors co-create value through knowledge-sharing routines that not only enable collaboration within a single ecosystem (Dyer & Singh, 1998) but can also be redeployed when engaging with other platforms, thereby facilitating multihoming. However, as engagement deepens, startups shift toward exploitation, embedding themselves through platform-specific investments and co-specialized integration (Agarwal & Kapoor, 2023; Madsen & Cruickshank, 2021; Rietveld & Schilling, 2021). This reduces strategic flexibility and increases path dependency.

Crucially, we argue that this trade-off is shaped by the diversity of the startup's skill base. We extend recent work on worker skills in startups (Grillitsch & Schubert, 2021; Symeonidou & Nicolaou, 2018) by demonstrating that in platform ecosystems, skill composition across domains shapes startups' multihoming capabilities and growth prospects. Startups with limited diversity in their skill base may rely more heavily on platform owners, system integrators, or customers to fill gaps in expertise. This dependence can accelerate early learning and facilitate quick multihoming, but over time it fosters path-dependent routines that reduce flexibility (Levinthal & March, 1993). In contrast, startups with broader skill portfolios initially face higher coordination costs and slower learning (Ethiraj et al., 2005), but over time, this skill breadth provides greater adaptability and better positions them for multihoming (Levinthal & March, 1993).

Our empirical setting focuses on startups affiliated with the SAP platform between 2001 and 2006. A sudden wave of acquisitions by Oracle during this period significantly expanded Oracle's installed base. It reshaped the value of multihoming, creating a change in multihoming incentives that allows us to observe how startups with different profiles responded. Importantly, these acquisitions altered the expected benefits of multihoming without immediately changing the technical architecture or governance rules of the acquired platforms, allowing us to observe how startups respond to shifting incentives under largely stable governance conditions.

We construct a panel dataset from multiple sources that tracks SAP partners' decisions to multihome with Oracle over time. These data allow us to measure how a startup's skill base, SAP partnership duration, and their interaction shape decisions to multihome to Oracle. Our empirical tests provide evidence that is consistent with our hypotheses.

Our study makes several contributions. First, we contribute to research on multihoming in platform ecosystems by showing that the relationship between platform partnership duration and multihoming is not linear. Experience with a home platform initially supports multihoming by generating transferable learning, but over time it can create platform-specific dependence that reduces flexibility. Second, we contribute to the platform governance literature by showing that prolonged exposure to a governance regime can generate learning and platform-specific dependence that shape complementors' responses to changing market opportunities, even when governance rules themselves remain stable. Finally, we contribute to the literature at the intersection of entrepreneurship and platforms (Nambisan et al., 2018) by showing how capabilities developed through platform participation shape startups'

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strategic responses to new ecosystem opportunities. In particular, we provide evidence that skill breadth helps startups preserve strategic flexibility while developing the specialized capabilities required for platform-based growth.

2 | LITERATURE REVIEW

The platform strategy literature has devoted substantial attention to multihoming.[1] One line of work has explored the implications of multihoming for market outcomes using economic theory models. For example, while prior work on digital platforms argues that multi-sided platforms should subsidize one side of the market to maximize profits (Armstrong, 2006; Rochet & Tirole, 2003), Bakos and Halaburda (2020) challenge this result when participants on both sides of the platform can multihome. Athey et al. (2016) demonstrate how consumer multihoming reshapes competition in advertising-supported media markets. It depresses prices, changes how advertisers allocate spending, and pushes publishers toward quality differentiation to reach more consumers.

Empirical research has sought to document how the propensity to multihome influences equilibrium outcomes in competition between platforms and within markets between complementors that are facilitated by these platforms. Corts and Lederman (2009) provide evidence that multihoming across platforms of the same generation by video game publishers makes it less likely that the market will tip toward one platform, that is, that we are less likely to see a winner-take-all market. This paper emphasizes the role that network effects within and across platforms influence equilibrium outcomes.

More recent work has gone beyond a focus on network effects to emphasize how multihoming interacts with other market features to influence equilibrium outcomes. Cennamo and Santaló (2019) examine how generativity creates tension in platform ecosystems and show that multihoming behavior can fundamentally alter platform equilibrium by reducing complementors' incentives to make platform-specific investments. Ozalp et al. (2018) demonstrate how multihoming influences platform competition across console generations, showing that complementors systematically defect from technically advanced platforms to easier alternatives. Multihoming can also have effects on platform owner behavior, such as decisions to enable complements (Toh & Agarwal, 2023).

Given multihoming's influence on platform outcomes, several studies examine platforms' decisions to limit multihoming and enable complements, emphasizing factors beyond network effects. Efforts to reduce multihoming can influence the likelihood of winner-take-all outcomes and industry-wide deal variety (Cennamo & Santalo, 2013; Li & Zhu, 2021), and efforts to reduce multihoming in one platform can have implications for others (Chung et al., 2024).

A key issue that has been explored in recent work has been how learning arising from working within a platform or ecosystem can shape the causes and consequences of multihoming for the complementor. These papers have emphasized the implications of learning for complementors' subsequent platform affiliations (Cennamo et al., 2018; Chen et al., 2022b). They also examine how knowledge gained from one platform transfers across platforms (Chung et al., 2024; Polidoro & Yang, 2024) and business lines within platforms (Chung et al., 2024).

These papers further demonstrate that the rate of learning obtained when affiliating with a platform can be influenced by the technical complexity of the platform or the ecosystem of partners that work with it. While software platforms are often modular, firms must still invest to interoperate with them, and these investments increase with platform or ecosystem complexity (Cennamo et al., 2018; Chen et al., 2022b; Polidoro & Yang, 2024), though greater complexity may also enhance learning benefits (Kapoor & Agarwal, 2017). Since these investments are often platform-specific (Cennamo et al., 2018; Chen et al., 2022b), they reduce transferable learning across platforms, with the relative importance of these factors varying across different institutional contexts.

We study similar themes by examining how learning influences multihoming decisions, but focus on enterprise software platforms rather than the mobile smartphones, open source, video games, and ridesharing contexts of prior work (Cennamo et al., 2018; Chen et al., 2022b; Chung et al., 2024; Polidoro & Yang, 2024; Toh & Agarwal, 2023). Our setting features significant platform-specific investments that shape both affiliation decisions and resulting

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payoffs. While prior research emphasizes technical skills for multihoming, enterprise solutions require complementors to master technical, functional, and industry skills. When complementors lack these complete skill sets, they may rely on platform or ecosystem partners to serve customers effectively. Our key contribution is showing how this breadth of required skills, combined with learning dynamics, co-determines multihoming costs and benefits.

Our research also contributes to the broader literature on platform governance, particularly work examining governance decisions related to resource sharing, provision of information to complementors, and platform modularity.[2] Prior research shows that governance choices concerning platform complexity and modularity shape the technological and market uncertainty faced by complementors (Chen et al., 2022a). In particular, we add to recent work that has sought to understand the implications for learning and platform-specific investments that arise with prolonged exposure to a given governance regime (Cennamo et al., 2018; Chen et al., 2022b; Chung et al., 2024; Kapoor & Agarwal, 2017; Polidoro & Yang, 2024). A key insight of our article is that these dynamics are shaped by complementor capabilities, in particular breadth of skills. In this way, we complement recent work by Zhang et al. (2022) who show that the implications of platform governance decisions for complementors' knowledge sharing are influenced by the latter's knowledge complexity and routineness.

3 | INSTITUTIONAL SETTING

The implications of learning, platform complexity, and platform-specific investments depend on particular features of the platform and its customers. These issues will be particularly pertinent in what the Department of Justice has termed high-function enterprise software—applications that support complex, multi-module processes for large organizations and require integration across functional and industry-specific domains (McAfee et al., 2009). Platforms for such software are widespread and diverse, including customer relationship management (CRM), human capital management (HCM), and financial management systems, though we focus specifically on enterprise resource planning (ERP) platforms as one prominent example within this broader category.

Delivering value from ERP software requires knowledge and skills across three critical areas: technology, business processes, and industry context. We describe these issues in detail in Supplementary Material C but provide an overview here. First, industry-specific knowledge is essential because functional requirements vary significantly across sectors—retail operations require different capabilities than manufacturing processes. Second, business process knowledge enables solution providers to understand core functionalities and translate them into customer-specific implementations. Third, technical implementation capabilities allow developers to navigate enterprise software complexity and create seamless platform integration. While third-party solution providers exhibit varying expertise across these domains, successful implementation requires all three skill sets. Our theoretical framework examines how differences in the breadth of skills influence multihoming behavior.

Unlike mobile app or video game ecosystems, where third-party software requires platform affiliation to function, enterprise software can operate independently of platforms while still serving the same customer base. However, enterprise software firms pursue platform affiliation, requiring certification from the platform, for two primary strategic benefits. First, certification provides market credibility: official platform validation of product quality, technical compatibility, and successful integration significantly enhances customer appeal, driving increased sales and growth (Ceccagnoli et al., 2012; Huang et al., 2013). Second, expanded sales channels: in select cases, platform vendors directly sell partner solutions through their own sales forces, providing additional marketing reach and customer access opportunities for third-party developers (Wilcox & Yemen, 2017).

Overall, ERP ecosystems provide an ideal setting to study capability-driven multihoming. The breadth of technical, functional, and industry skills required for successful integration creates both transferable learning and platform-specific dependencies. These features set the stage for our theoretical framework.

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4 | THEORY AND HYPOTHESES

Our theoretical framework draws on insights from the platform strategy and organizational learning literatures to explain how startups grow and adapt their behavior within platform ecosystems, where internal capabilities and emerging opportunities shape their development over time as alternative platforms become viable. While entrepreneurship research has long emphasized the role of early-stage discovery, resource constraints, and alliance formation, it has paid comparatively less attention to how startups learn and evolve through sustained engagement with a platform over time. In contrast, platform strategy research has highlighted how complementors deepen their integration and face architectural or relational lock-in. Still, it often treats firms as homogeneous actors without examining their underlying learning processes or differences in capabilities. By integrating these perspectives, we aim to develop a theory of startup multihoming rooted in learning shaped by ecosystem participation and the co-evolution of firm capabilities and platform relationships.

4.1 | The role of learning

Complementors in platform ecosystems enhance platform value by offering specialized products and services, yet their ability to engage with multiple competing platforms evolves over time. As partnerships deepen, they face offsetting forces of exploration, which expand adaptability, and exploitation, which constrains flexibility, as explained below.

Early-stage exploratory learning. Early in partnerships, complementors engage in exploratory learning through frequent interactions with platform owners, customers, and other ecosystem participants. This phase involves acquiring transferable knowledge, market insights, technical integration practices, and differentiation strategies that enable complementors to develop unique interfaces, extend underutilized platform features, or create novel functionality combinations (Foerderer et al., 2019; Iansiti & Lakhani, 2009; Wilcox & Yemen, 2017). Consistent with March's (1991) definition of exploration, this learning is characterized by experimentation, innovation, and opportunity-seeking behavior essential for adapting to technical requirements, market dynamics, and evolving standards. Such exploration enables organizations to expand their knowledge base and develop the flexibility needed to respond to uncertainty (Levinthal & March, 1993). These learning processes occur within the constraints and incentives of platform governance, including certification requirements, interface standards, and partner management practices, which shape what knowledge is transferable versus platform specific (Chen et al., 2022a).

A key source of early learning is the platform owner, who helps complementors understand integration requirements, navigate ecosystem complexity, and optimize offerings for the platform's user base. For example, SAP provided Kore.ai with partner and customer insights, technical knowledge of the ERP landscape, and access to the HANA database system to develop enterprise bots. Similarly, complementor Nakisa required close collaboration with SAP to achieve the deep integration necessary for their ERP visualization solutions (Madsen & Cruickshank, 2021). Further details are available in Supplementary Material C.

Beyond platform owners, customer interactions provide crucial learning that enhances complementor adaptability. In enterprise software, successful implementation often requires complementary user innovations, enabling complementors to gain feedback and refine their solutions (Bresnahan et al., 1996). Through boundary-spanning interactions, complementors integrate customer knowledge into their capabilities, incorporating real-world use cases and domain expertise that facilitate broader market adoption (Ko et al., 2005). Platform owners often facilitate these learning opportunities by promoting third-party solutions and providing case studies (Wilcox & Yemen, 2017).

Complementors may also learn from one another. Those who connect with and incorporate technologies from other complementors may experience greater commercialization success (Agarwal & Kapoor, 2023). When these technologies are ecosystem-specific, they similarly require investments to connect their products with the

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technological architecture of the ecosystem (Kapoor, 2018). Thus, uses of complementor technology require further learning from other complementors as well as the platform owner.

All of these interactions between the complementor and members of the platform ecosystem require crossing significant knowledge boundaries (Carlile, 2004). Knowledge-sharing and associated supporting routines between platform owners and their partners will critically determine the extent of value cocreated in the context of business software ecosystems (Grover & Kohli, 2012; Sarker et al., 2012). These activities can involve semi-formalized interactions that enable brokering between the platform owner and complementor, as well as individualized knowledge boundary resources that facilitate frequent exchange of information between the platform and complementors (Foerderer et al., 2019). However, because platform rules are often "black boxed," users can find changes to rules ambiguous (Reineke et al., 2025). Over time, complementors develop routines for brokering and translating knowledge across organizational boundaries (Dyer & Singh, 1998). Crucially, these routines can also be redeployed when multihoming, enabling complementors to adapt previously acquired knowledge and thereby facilitating multihoming.

Later-Stage Dependency and Platform-Specific Investments. In sum, by leveraging both platform owner interactions and customer-driven insights, complementors develop broad competencies that increase their multihoming potential in the early stages of a partnership. However, as the partnership matures, learning shifts from exploration to exploitation, and complementors move from acquiring generalizable knowledge to making deeper platform-specific investments. These investments include aligning with platform standards, achieving certifications, and integrating more tightly with the platform's architecture (Agarwal & Kapoor, 2023; Madsen & Cruickshank, 2021; Rietveld & Schilling, 2021). Such investments are encouraged and reinforced by platform governance mechanisms, which reward deeper alignment while increasing switching costs and dependence (Chen et al., 2022a).

Prior multihoming literature highlights how platform-specific investments shape multihoming decisions and outcomes, particularly when programming languages and interfaces are specialized (Cennamo et al., 2018; Chen et al., 2022b; Chung et al., 2024; Tiwana, 2014, 2015).[3] The extent of these investments typically increases with platform-complementor integration, as deeper integration requires specialized interfaces to optimize platform alignment (Cennamo et al., 2018; Tiwana, 2015).

Nakisa's evolving relationship with SAP illustrates this dynamic. As SAP transitioned from its proprietary ADAP programming language to the NetWeaver technology stack, Nakisa positioned itself as an early adopter.[4] Over time, offerings like Nakisa's Lease Administration software became tightly embedded within SAP's ERP environment (Nakisa, 2020), demonstrating how increasing platform alignment enables greater value co-creation but reduces multi-platform flexibility.

Such deepening integration may be particularly characteristic of enterprise software platforms, where start-ups often begin with standalone packages before partnering with platforms (Ceccagnoli et al., 2012). Unlike mobile or gaming complementors, whose products cannot function independently, enterprise software partners can start as independent entities offering "add-ons" that require minimal integration or user adaptation (Goodhue et al., 2009).

Integration requires start-up complementors to develop processes for adapting to platform changes. Complementors learn through interactions with platform owners, refining their development processes to synchronize with the core platform (Foerderer et al., 2019; Kapoor & Agarwal, 2017). This learning becomes essential as ecosystem complexity increases over time, requiring complementors to respond to interface changes and evolving functionality within enterprise platforms.

Complementors deepen platform relationships by making significant platform-specific investments, such as aligning with technical standards and adapting to evolving requirements (Madsen & Cruickshank, 2021). Certification programs exemplify this dynamic, encouraging ongoing investments in platform alignment rather than one-time compliance. Certified complementors must continuously update their offerings to meet new standards, including API updates, security protocols, and functionality changes (Rietveld & Schilling, 2021).

Further, knowledge mobility from platform owners to complementors may also paradoxically embed complementors within the present platform relationship over time. Platform owners can mitigate appropriability concerns arising among complementors through organizational commitments (Arora et al., 2021; Gawer & Cusumano, 2002).

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This is often crucial to creating a sense of trust between platform owners and complementors (Gawer & Cusumano, 2002). The greater sense of trust will induce complementors to make greater platform-specific investments over time that will not be easily redeployable in other platforms (Jacobides et al., 2018). These may be associated with platform-specific adjustments due to solution configurations (e.g., Kapoor & Agarwal, 2017) or adjustments to the evolving institutional and technological features of the ecosystem.[5]

This need for adaptation, pronounced in later partnership stages, connects to indirect network effects central to innovation platforms. As platforms like SAP's ERP system attract more high-quality complements, they become increasingly attractive to users, reinforcing growth and ecosystem complexity (Cusumano et al., 2020). In enterprise software, where significant innovation stems from user co-invention and vendor learning from implementations (Bresnahan, 2019; Bresnahan et al., 1996), vendors' familiarity with their home platform's accumulated co-invention may reduce the benefits of multihoming.[6] This dynamic pressures complementors to invest in deeper integration as new complements and evolving standards require compatibility with increasingly interdependent components.

Thus, while adaptation and integration occur throughout partnerships, they increase more steeply in later stages as platforms become more robust and interconnected. Ecosystem growth amplifies the importance of relationship-specific investments with both platform owners and other participants, requiring complementors to align with evolving standards and integrate with complementary products. These investments generate platform-specific knowledge that strengthens their position within the home platform but act as sunk costs that increase dependency and reduce multihoming incentives (Iansiti & Lakhani, 2009; Kapoor & Agarwal, 2017).

This combination of early transferable learning and later platform-specific dependency explains an inverted U-shaped relationship between partnership duration and multihoming likelihood. Initially, the benefits of transferable knowledge outweigh the costs of platform-specific investments, increasing the probability of multihoming. Over time, however, the rising costs of dependency and the declining utility of transferable knowledge diminish multihoming feasibility. These dynamics lead to the following hypothesis:

> **Hypothesis 1.** The probability of multihoming follows an inverted U-shaped relationship with the duration of the partnership with the home platform.

4.2 | The moderating role of skill breadth

Complementors vary in the breadth and composition of their capabilities. This variation shapes how they learn from the platform ecosystem and respond to increasing complexity over time. We argue that this variation in skill breadth moderates the inverted U-shaped relationship identified in Hypothesis 1 by influencing both early-stage learning and later-stage dependency.

Skill breadth shapes complementors' initial response to new opportunities. The coordination costs associated with broad skill portfolios slow learning and integration within the home platform. However, when partnership duration is short, high-breadth firms have not yet accumulated substantial platform-specific routines, certifications, and implementation practices. Their capabilities therefore remain less specialized to the home platform and more redeployable across alternative opportunities. As a result, when new opportunities such as the Oracle acquisitions increase the expected returns to multihoming, high-breadth startups with shorter SAP partnership duration may be more flexible and better positioned to respond, even if their early learning within SAP progresses more slowly.

However, while complementors with skill breadth may be more flexible initially, those with a narrow skill base, focused on specific domains, are better-positioned for rapid early-stage learning. Their narrow scope enables specialization, targeted knowledge absorption from the platform ecosystem, and quick alignment with platform standards. This focused learning facilitates knowledge acquisition that can be leveraged for multihoming. However, as Levinthal and March (1993) emphasize, such localized exploitation creates path dependencies that, over time, constrain these complementors with non-transferable routines, limiting adaptability and multihoming capacity.

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For example, in early partnership phases, Nakisa focused on visualizing existing SAP data, such as creating organizational charts for leadership decisions. This narrow capability focus enabled the firm to master specific SAP integration requirements and absorb knowledge efficiently, moving quickly through the initial learning curve (Iansiti & Lakhani, 2009).

Supply chain optimization firm SmartOps followed a similar pattern, initially differentiating from SAP's Advanced Planning and Optimization (APO) module by providing advanced inventory optimization and integration consulting. With narrow but well-aligned capabilities, SmartOps rapidly developed integration routines and became deeply embedded in the SAP ecosystem through close sales team collaboration (Wilcox & Yemen, 2017). However, this narrow scope that enabled early traction also limited later adaptability, as SmartOps became increasingly reliant on SAP's infrastructure and sales support, reducing flexibility to partner with alternative platforms.

Complementors with high skill breadth spanning technical, functional, and domain-specific capabilities face slower early-stage learning due to the complexity of aligning these competencies internally (Carlile, 2004; Grant, 1996). Ethiraj et al. (2005) show that developing capabilities requires substantial coordination and integration effort when multiple interdependent elements must be aligned. However, this initial slowdown has potential benefits for multihoming: over time, broader skillsets improve a firm's adaptive capability in complex and changing environments (Levinthal & March, 1993). Specifically, broader skills foster cognitive flexibility, enabling the recombination of ideas and insights across domains, thus supporting the integration of new technologies or platform updates with lower marginal coordination costs in later stages.

Supporting these arguments, Pisano et al. (2001) find that the value of heterogeneity in experience depends heavily on how gradually broad capabilities are introduced and mastered. When managed over time, this breadth enhances organizational learning and performance. For complementors, this implies that although broader capabilities initially delay multihoming due to complexity, gradual and deliberate integration supports long-term adaptability and reduces the lock-in effects of platform-specific investments. These firms develop routines for cross-domain knowledge translation, enabling them to manage interface updates effectively, changing standards, and growing ecosystem interdependencies.

Thus, greater skill breadth mitigates dependency costs that accumulate in later partnership stages. Firms with diverse capabilities are better positioned to generalize routines and apply coordination capabilities across platforms, enhancing multihoming probability. By contrast, firms with limited breadth struggle to adapt once their focal domains become over-optimized or misaligned with the evolution of the ecosystem.

Importantly, when skill breadth is very high, this moderating effect can do more than flatten the inverted U-shaped curve: the interaction of long partnership duration and broad capabilities may actually reverse the pattern. In such cases, firms may initially struggle to coordinate and realize learning benefits. Still, over time, their diverse skill base enables them to reconfigure routines and exploit new opportunities across platforms, producing a U-shaped trajectory in multihoming likelihood. These dynamics lead to the following hypothesis:

> **Hypothesis 2.** Skill breadth moderates the inverted U-shaped relationship between partnership duration and multihoming probability. Complementors with greater skill breadth exhibit a flatter curve—showing slower initial growth but a more gradual decline in multihoming likelihood over time. At the extreme, high skill breadth can reverse the dynamics, producing a U-shaped pattern of multihoming over time.

5 | DATA AND METHODOLOGY

5.1 | Empirical setting[7]

During our 2001–2006 sample period, SAP was the established ERP market leader while Oracle was emerging as a viable alternative. Oracle's platform-level acquisitions, most notably its acquisition of PeopleSoft in 2004,

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significantly expanded its ecosystem and reshaped competitive dynamics in a way that increased the benefits to SAP complementors for partnering with Oracle. Most prominently, the merger—along with a subsequent merger with Siebel Systems—had a potential demand expansion effect.[8]

We summarize the core arguments here. Analysis of documents from the Department of Justice (DoJ) antitrust case, which sought to block Oracle's acquisition of PeopleSoft, highlights why these acquisitions altered market conditions (McAfee et al., 2009). The DoJ argued that there were only three suppliers in the 'high-function enterprise software' market, a term used to denote large-scale, integrated ERP systems such as SAP, Oracle, and PeopleSoft, and that the merger would reduce this number from three to two.[9] Moreover, the DoJ argued that Oracle and PeopleSoft were each other's closest competitors. In short, if the combined entity Oracle-PeopleSoft became a stronger competitor to SAP (then the clear market leader), this would increase the value to complementors of supporting alternative platforms alongside SAP.

Shortly after the PeopleSoft merger announcement, Oracle CEO Larry Ellison announced "Project Fusion," that would seek to integrate products from PeopleSoft with Oracle's applications, middleware, and database technologies.[10] However, these changes did not come to fruition quickly. This may have been influenced in part by Oracle's decision to support products by PeopleSoft, JD Edwards, and Siebel (the constituent companies that merged with Oracle) until at least 2035 (Clark, 2025),[11] increasing the likelihood that the existing installed base of customers would stay with legacy products. In fact, Oracle Fusion, a set of cloud-based apps that were redesigned from the ground up, was not launched until 2010 (Clark, 2025). As a result, while the merger led to a demand expansion effect, there were few changes to platform governance or technical architecture during our sample.

We use this consolidation as a change in multihoming incentives for SAP complementors, driven by Oracle's expanded market rather than changes in platform governance. The short-run stability of governance and architecture at Oracle allows us to examine how complementor characteristics, specifically the breadth of a startup's skill base and its accumulated experience with the home platform, shape heterogeneous responses to these shifting incentives, as reflected in the likelihood of Oracle multihoming after 2004 (the acquisition time window, ATW) through the end of our sample period in 2006.

5.2 | Sample

We built a comprehensive ERP ecosystem dataset from several secondary sources. We obtained SAP partner lists to identify complementors and their multihoming decisions, augmenting the current partner website with exhibitors from past SAP Sapphire and SAP Insider meetings to avoid survivorship bias. We selected only US-based complementors to ensure comparability and data availability for control variables.

We used Factiva press release data to identify partnership formation years with SAP through keyword-based searches.[12] For each SAP complementor, we identified the earliest press release mentioning both the firm and SAP, assuming this indicates partnership formation by that date. We applied the same approach to identify Oracle multihoming dates.

We then obtained firm sales and size data from the National Establishment Time Series (NETS) database. It is a time series of the archival Dun and Bradstreet (D&B) database; the version we obtained contains information on close to 50 million unique establishments between 1990 and 2013. The dataset covers private and public establishments and includes information on the establishment tree, enabling us to aggregate sales and employee data to the firm level. We matched the list of SAP partners with the NETS database and ended up with 1012 DUNS numbers for headquarters corresponding to 45,339 target establishments. We used the tree structure to aggregate the establishment data to the firm level.

To focus on startups, we selected firms with fewer than 1000 employees when they joined the SAP platform. After the size cutoff, the average age of a complementor at the time of SAP affiliation is 3.4 years, suggesting that our focal firms are both small and young at the time of SAP partnership. Finally, we obtained detailed skill data by

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downloading CVs of partner firms' employees from LinkedIn. We gathered all employee CVs for smaller firms but restricted analysis to a random set of 200 employees for larger startups due to commercial use limits. All employee data was anonymized. The final dataset comprises an unbalanced panel of 222 startups with 999 firm-year observations between 2001 and 2006.

5.3 | Measures

Dependent Variable. The dependent variable is multihoming, which takes a value of zero or one. Multihoming is zero for all firms at the beginning of the sample. It changes to one if and when the focal firm partners with the Oracle platform within the study period. If the focal firm never multihomes, the variable remains at zero until the end of the sample.

Independent variables. *Acquisition time window* (*ATW*): To capture the effects of Oracle's platform acquisitions, we use a dichotomous variable equal to one from 2004 (the year of the first acquisition) through 2006, and zero otherwise.

Partnership duration. To gauge the nonlinear impact of the prior partnership at the time of the Oracle acquisition, we construct two related variables, namely, *Partnership Duration* and its square term, *Partnership Duration Squared*, based upon the number of years spent with the SAP platform as of the start of the ATW.

Skill Breadth. To obtain a measure of the breadth of the startup skill base, we create a measure of whether the startup has previously made critical investments in each of the three dimensions of skills highlighted earlier: technical, functional, and industry. To do this, we construct a novel measure based on the CVs of the employees in the firm. Here, we provide an overview of our approach; more details are available in Supplementary Material B. Supplementary Material B1 discusses the detailed procedure involved in the computation, Supplementary Material B2 provides an illustrative example, and Figure B1 depicts the coordination among skill types.

First, we identify a set of keywords associated with a specific skill type from resources publicly available on SAP's support website. For example, SAP architecture-related terms such as ABAP and NetWeaver, and coding languages such as Java and C++ correspond to technical knowledge; language related to Automotive, Utilities, and Banking provides evidence of industry-specific knowledge; and Materials Management (MM) and Plant Maintenance (PM) are some of the functional modules within the ERP product.

Second, we search within the employee CV for keywords identified above and count all relevant instances of their appearance. We normalize the number of keyword appearances by the length of the CV, computing a measure of intensity of keyword appearances in each of the three areas for the employee. We use only the skills appearing in the past five years at any given moment to account for the obsolescence of skills. We repeat this procedure for everyone identified as a valid startup employee in a given year and for the sample of available CVs for the larger startups. We aggregate our skills measure to the firm-year level by adding them across available employees and dividing them by the number of employees in the sample.

Next, we compute pre-shock values by averaging across 2001–2003 to account for year-specific investment changes that may bias results. To capture breadth of skills, we implement a minimum skill threshold at the 25th percentile within each skill area's sample distribution, ensuring that only non-trivial skill levels across domains support integrated routine development and meaningful breadth.

To further elaborate, for the *Functional 25th percentile* skill measure, we have:

$$Functional\,25th\,percentile_{i,Pre-Shock} = 1$$

$$\text{if } \left[Functional\,Skill_{i,Pre-Shock} > Functional\,Skill^{25th}_{Pre-Shock}\right], 0 \text{ otherwise.}$$

and similar for *Technical 25th percentile* and *Industry 25th* percentile.

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Skill Breadth is obtained as the sum of the three, that is:

$$\begin{aligned} \textit{Skill Breadth}_{i,\ \textit{Pre-Shock}} = {} & \textit{Functional 25th percentile}_{i,\textit{Pre-Shock}} + \textit{Technical 25th percentile}_{i,\textit{Pre-Shock}} \\ & + \textit{Industry 25th percentile}_{i,\textit{Pre-Shock}} \end{aligned}$$

Higher values of *Skill Breadth* indicate higher diversity across skill dimensions in the focal startup within our sample. In the robustness section, we examine two alternative operationalizations of Skill Breadth: a more stringent binary measure identifying startups with capabilities above the threshold in all three skill dimensions and a Blau-type index that captures the distribution of skills across dimensions.

Control Variables. We first control for the *depth* of a startup's skill base. Greater depth may enhance a firm's ability to develop high-quality software and multihome; however, it may reflect platform-specific human capital investments, making multihoming more difficult.

We measure depth by adding our skills measure across all three dimensions:

$$\textit{Skill Depth}_{i,\ \textit{Pre-Shock}} = \textit{Functional Skill}_{i,\ \textit{Pre-Shock}} + \textit{Technical Skill}_{i,\ \textit{Pre-Shock}} + \textit{Industry Skill}_{i,\ \textit{Pre-Shock}}$$

Using data from NETS, we control for a startup's size using yearly sales. Larger firms are more likely to possess complementary assets required for technology commercialization (Teece, 1986). In our setting, it is also plausible that firm sales partly control for the quality of the complementor product (Cennamo et al., 2018).

In addition to the above, we also control for the number of LinkedIn CVs used in the analysis, which varies across firms and over time. Both our skill depth and breadth measures are positively correlated with the number of CVs used. Finally, we include a time-varying control for firm age. This allows us to better disentangle internal organizational learning from learning that arises through deeper engagement with the home platform, which we measure through partnership duration.

5.4 | Identification

A potential challenge for our analysis is omitted variable bias: unobserved factors correlated with firms' accumulated skill investments may also influence the benefits of affiliating with an alternative platform. Our empirical approach relies on the assumption that pre-shock differences in firms' skill bases are slow-moving and largely predetermined over the short horizon we study. Hiring, reallocation, and the development of effective collaboration routines take time, making it difficult for firms to rapidly alter the composition of their skill base in response to anticipated changes in market conditions.

Specifically, controlling for time-invariant firm-level factors, we examine how pre-existing skill breadth and partnership duration with SAP shape firms' multihoming behavior following the Oracle acquisitions described above. The Oracle acquisitions, beginning with PeopleSoft in 2004, represent a salient shift in market structure that enhanced the market opportunities available to complementors choosing to multihome.[13] Not only were these developments pivotal to Oracle's inorganic growth strategy, but they also represented a strong signal for complementors thinking about partnering with Oracle. This meant that Oracle partners had access to significantly greater demand than they had previously experienced. As discussed in Section 5.1, these acquisitions did not entail immediate changes in platform governance or technical architecture during our sample period. This setting allows us to examine how firms with different pre-shock characteristics respond to a common change in multihoming incentives, rather than to changes in governance or technology at the destination platform.

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5.5 | Model specification and estimation methodology

We estimate a linear probability model (LPM) where the dependent variable is $Multihome_{it}$, a binary indicator equal to 1 if firm i in year t engages in multihoming (i.e., whether an SAP partner subsequently establishes a partnership with Oracle) and zero otherwise. The model is estimated on a firm-year panel dataset, with firm fixed effects that control for time-invariant firm-level unobservables and time dummies that control for common events across firms in any given year. Robust standard errors are clustered at the firm level. Our baseline model, used to test Hypothesis 1, is

$$\begin{aligned} Multihome_{it} = {} & \beta_0 + \beta_1 ATW_t \times Duration_{,\ Pre-Shock} + \beta_2 ATW_t \times Duration^2_{,\ Pre-Shock} + \beta_3 ATW_t \\ & \times SkillBreadth_{i,\ Pre-Shock} + \beta_4 ATW_t \times SkillDepth_{i,\ Pre-Shock} + Controls_{it} + \mu_i + \tau_t + \varepsilon_{it}. \end{aligned} \quad (1)$$

This model captures the main effects of duration, its square, and skills after and during the Oracle acquisition without interactions between skills and duration.

Our full model, used to test Hypothesis 2, incorporates duration of partnership with SAP at the start of the acquisition time window ($Duration_{i,pre-shock}$), its interaction with pre-shock skill breadth ($SkillBreadth_{i,pre-shock}$), and their joint interaction with the acquisition time window (ATW_t). This specification examines whether the association between partnership duration and multihoming differs by pre-shock skill breadth following the change in multihoming incentives created by the Oracle acquisitions. That is, our fully specified model is:

$$\begin{aligned} Multihome_{it} = {} & \beta_0 + \beta_1 ATW_t \times Duration_{,\ Pre-Shock} + \beta_2 ATW_t \times Duration^2_{,\ Pre-Shock} + \beta_3 ATW_t \\ & \times SkillBreadth_{i,\ Pre-Shock} + \beta_4 ATW_t \times SkillDepth_{i,\ Pre-Shock} + \beta_5 ATW_t \times Duration_{i,\ Pre-Shock} \\ & \times SkillBreadth_{i,\ Pre-Shock} + \beta_6 ATW_t \times Duration^2_{i,\ Pre-Shock} \times SkillBreadth_{i,\ Pre-Shock} \\ & + Controls_{it} + \mu_i + \tau_t + \varepsilon_{it}. \end{aligned} \quad (2)$$

Our use of the LPM rather than a nonlinear model reflects several considerations. First, the LPM delivers consistent estimates of the parameter of interest (Angrist & Pischke, 2009). A major drawback will be heteroskedastic standard errors, which we address using robust standard errors. However, the LPM allows us to control for unobserved firm-level heterogeneity without loss of observations (as would be the case with a probit or logit, for example). Further, the linear model allows for more straightforward interpretations of implied marginal effects from our parameter estimates (Ai & Norton, 2003; Hoetker, 2007; Wiersema & Bowen, 2009; Zelner, 2009). Last, nonlinear models may be inconsistent when there are many zeroes in the dependent variable, as in our sample (King & Zeng, 2001). Comparable nonlinear models in Supplementary Material A yield qualitatively similar results.

We treat multihoming as a final absorbing state, assuming partners do not subsequently leave Oracle's ecosystem—confirmed by their continued presence on Oracle's partner site. We delete post-multihoming observations and structure the data as an unbalanced panel, dropping firms that partnered with SAP after the ATW to focus on how ex ante skill heterogeneity shapes multihoming responses to new opportunities.

6 | RESULTS

6.1 | Descriptive statistics

Table 1 shows the basic summary statistics, while Table 2 reports the correlations.[14] The dependent variable, multihoming, occurs in only 3% of firm-year panel observations, but 8.1% of firms multihomed at least once over the study window. This shows that while multihoming is not the norm, it is strategically relevant.

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TABLE 1 Descriptive statistics.

Variable	Description	Mean	Std. dev.	Min	Max
Multihoming_{it}	Dichotomous variable (equals 1 when the firm multihomes, 0 otherwise)	0.030	0.171	0	1
$\text{Partnership Duration}_{\text{,pre-shock}}$	Duration of partnership with SAP (difference between the year 2004 and the start of partnership)	4.574	2.394	0	10
$\text{Skill Breadth}_{\text{i,pre-shock}}$	Breadth of skills	2.215	1.107	0	3
$\text{Skill Depth}_{\text{i,pre-shock}}$	Depth of skills	0.131	0.082	0	0.417
Sales_{it}	Sales revenues (in $ billions)	0.384	3.051	0	33.34
No. of CVs_{it}	No. of on LinkedIn CVs	22.61	25.40	0	145
Firm Age_{it}	Age of startup in years	7.799	4.626	1	17

Note: Number of firms: 222; Number of observations: 999.

TABLE 2 Correlations.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	Multihoming_{it}	1						
(2)	$\text{Partnership Duration}_{\text{i,pre-shock}}$	0.122	1					
(3)	$\text{Skill Breadth}_{\text{i,pre-shock}}$	−0.135	−0.133	1				
(4)	$\text{Skill Depth}_{\text{i,pre-shock}}$	−0.053	−0.172	0.689	1			
(5)	Sales_{it}	−0.022	0.131	0.041	−0.003	1		
(6)	No. of CVs_{it}	−0.128	−0.040	0.430	0.200	0.016	1	
(7)	Firm Age_{it}	0.080	0.239	−0.133	−0.121	−0.017	−0.156	1

Despite the initial size threshold for inclusion in the sample, firm-year sales are highly skewed: the mean is $384 million, but the median is much lower, and the maximum exceeds $33 billion. This skew reflects the growth trajectory of some startups over our sample period (2001–2006). Startups often experienced rapid post-partnership scaling—consistent with prior research showing SAP affiliation drives firm growth (e.g., Ceccagnoli et al., 2012). Hence, while firms are small and young at entry (the average age at the time of the SAP partnership, unreported, is 3.4 years), the sample also captures later-stage startup behavior, which is precisely when strategic decisions, such as multihoming, become more salient. On average, firms are 7.8 years old during the observation window, underscoring that the panel covers a critical growth phase rather than only the period of startup infancy.

Average partnership duration with SAP at the time of Oracle's first acquisition-related announcement (in 2004) is 4.6 years (min = 0 and max = 10), providing sufficient across-firm variation to examine how prior home-ecosystem experience is associated with the decision to multihome following the Oracle acquisitions. Average *Skill Breadth* is 2.2 (maximum 3), suggesting that most firms possess capabilities across multiple ERP-relevant areas. The average value of *Skill Depth* is 0.13, suggesting that ERP-specific expertise constitutes a meaningful component of employee skill profiles. The correlation between *Skill Breadth* and *Depth* is 0.689, suggesting that while the two variables are positively correlated, they capture separate aspects of a startup's skill base.

6.2 | Main results

We next present our main regression results in Table 3. Columns 1 and 2 of Table 3 show the estimates of models using only a linear term for partnership duration.[15] These results show that once controls for firm size (Sales and

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TABLE 3 Multihoming: Role of partnership duration and skill breadth.

Variables	(1) Partnership duration w/o controls	(2) Partnership duration	(3) Partnership duration and square	(4) Partnership duration skill breadth interaction
ATW × Duration	0.0259***	−0.0026	0.0777***	0.4797***
	(0.0068)	(0.0049)	(0.0287)	(0.1202)
ATW × Sq. Duration			−0.0075**	−0.0458***
			(0.0029)	(0.0119)
ATW × Skill Breadth	−0.0482***	−0.0732***	−0.0698***	0.3211***
	(0.0157)	(0.0204)	(0.0196)	(0.0845)
ATW × Skill Depth	0.0550	−0.1807	−0.2051	−0.2053
	(0.1898)	(0.1955)	(0.1955)	(0.2022)
ATW × Duration × Skill Breadth				−0.1690***
				(0.0426)
ATW × Sq. Duration × Skill Breadth				0.0161***
				(0.0042)
Sales		−0.0018**	−0.0021	−0.0016
		(0.0008)	(0.0014)	(0.0012)
No. of CVs		−0.0003**	−0.0002	−0.0004**
		(0.0001)	(0.0002)	(0.0002)
Firm Age		0.0065**	0.0026	0.0022
		(0.0029)	(0.0026)	(0.0026)
Constant	0.0306***	−0.0333	0.0100	0.0209
	(0.0034)	(0.0241)	(0.0217)	(0.0201)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	999	999	999	999
R-squared	0.637	0.668	0.673	0.698
Number of startups	222	222	222	222

Note: Robust standard errors, clustered by firm, in parentheses.
**$p < 0.05$.
***$p < 0.01$.

number of CVs) and age are included (cf. column 2), there is no statistically significant effect of the interaction of ATW and partnership duration on multihoming. Because this linear term will not capture the nonlinear effects of learning discussed in Hypothesis 1, we next proceed to examine the estimates showing the impact of partnership duration and its squared term in columns 3 and 4.

Column 3 shows the results, including partnership duration and its square, but without its interactions with Skill Depth and Breadth. It corresponds to Equation (1), Section 5.4. Following Haans et al. (2016), we use these estimates as the basis for our test of the inverted U-shape relationship detailed in Hypothesis 1. The coefficient on *ATW X Duration* is positive (0.0777, *p*-value <0.01), while the coefficient on *ATW X Sq. Duration* is negative (−0.0075, *p*-value <0.05). Taken together, these results are in line with Hypothesis 1.

Tables 4 and 5 summarize other tests that are recommended in Haans et al. (2016) to test for an inverted U-shape relationship. We find that the marginal effect of duration, or slope, is significantly steep at both ends of our

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TABLE 4 Turning point analysis.

Quantity	Estimate	Method	95% CI	Remarks
Turning point[a]: $-\beta_1/2\beta_2$, where β_1 and β_2 are coefficients on Duration and Duration^2 from col. 3, Table 3	5.18	Analytical (point estimate); Confidence Interval (CI) via Bootstrap (1000 reps)	[4.61, 5.76]	Lies within observed duration range (0–10)
[As above]	5.18	Confidence Interval using Fieller method (Lind & Mehlum)	[4.57, 6.59]	Robust CI from U-test confirms inverted U-shape
Marginal effect at duration = 0	0.078***	Delta method	[0.021, 0.134]	Significant positive slope at lower bound
Marginal effect at duration = 10	−0.072***	Delta method	[−0.131, −0.013]	Significant negative slope at upper bound
Linear term significance	0.0777	Regression	$p = 0.007$	Strong positive slope at low durations
Quadratic term significance	−0.0095	Regression	$p = 0.010$	Strong support for curvature (inverted U-shape)

[a]Turning point = value of duration (5.18), where the relationship with multihoming probability peaks (inverted-U).
***$p < 0.01$.

TABLE 5 Inverted U-shaped relationship—Test criteria.

Test step	Criteria met?	Results
1. Significant squared terms	Yes	Negative and statistically significant
2. Marginal effect is significantly steep at both ends of data range	Yes	Marginal effect at duration = 0 is 0.078, marginal effect at duration = 10 is −0.072, both statistically significant
2. Turning point within data range	Yes	All CIs (delta, bootstrap, Fieller) fall within 0–10
3. Delta, Bootstrap, and Fieller methods used	Yes	Confidence intervals computed via multiple methods
4. U-test confirms shape	Yes	Lind & Mehlum U-test confirms inverted U ($p = 0.0083$)

Note: Fully consistent with Haans et al. (2016).

data range. The marginal effect at duration = 0 is 0.078 (with a confidence interval of [0.021, 0.134]), which is positive and statistically significant. In the context of our linear probability model, these estimates imply that a one unit increase in duration at duration = 0 leads to a 7.8 percentage point increase in the likelihood of multihoming. In contrast, the marginal effect at Duration = 10 is −0.072 (with a confidence interval of [−0.131, −0.013]), which is negative and statistically significant.

Next, we evaluate whether the point at which the slope turns from positive to negative, or the turning point, lies within the range of our data. The estimate for the turning point, which in Equation (1) can be computed from the ratio $-\beta_1/2\beta_2$, is equal to 5.18. Following Haans et al. (2016) and Lind and Mehlum (2010), we compute the confidence interval for the turning point using alternative approaches to the Delta method to account for finite sample bias and to correct for biases caused by departure from normality. First, we use bootstrap computations with 1000 iterations, yielding a 95% confidence interval of [4.61, 5.76], within our observed duration range of 0–10. We also

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follow Hirschberg and Lye (2005) and use the Fieller method (Fieller, 1954) to compute a confidence interval of [4.57, 6.59]. Together, these results establish an inverted-U relationship (Haans et al., 2016).

The last column in Table 3, model (4), serves as the basis for our tests of Hypothesis 2, which states that complementors with a broader skill base exhibit a flatter inverted U-shaped curve. We again follow Haans et al. (2016) to guide our tests. The coefficient on *ATW X Sq. Duration X Skill Breadth* (β_6 in Equation 2) is positive with a value of 0.0161 and statistically significant (p-value <0.01), consistent with a flattening curve.

We assess the flattening magnitude graphically in Figure 1a, plotting predicted probabilities of multihoming during the Oracle acquisition window across different levels of partnership duration and skill breadth.[16] At low levels of skill breadth, the relationship between partnership duration and multihoming follows an inverted-U pattern. Predicted probabilities initially increase with duration, consistent with the accumulation of transferable learning, but eventually decline as platform-specific learning and investments become more pronounced. As skill breadth increases, this pattern changes. The decline in multihoming at longer durations becomes progressively weaker, indicating that broader capability bases mitigate the dependence typically associated with prolonged platform relationships.

At the highest level of breadth, that is, when firms have all three skill sets, the predicted relationship differs substantially from that observed for narrow-breadth firms. Rather than exhibiting a pronounced decline at longer partnership durations, predicted multihoming probabilities remain comparatively stable and increase slightly at high durations. The overall pattern is thus consistent with the moderating effect predicted in Hypothesis 2 and with the formal tests reported in Table 3.[17] Together, the results suggest that broader skill bases help startups maintain strategic flexibility even after extended periods of collaboration with a home platform.

To formally assess whether the relationship becomes U-shaped at high levels of breadth, we follow Haans et al. (2016) and evaluate the slope of the relationship at the lower and upper bounds of the duration distribution. The results, reported in Table 6, provide evidence consistent with a U-shaped relationship at the highest level of skill breadth. Indeed, at duration = 0, the marginal effect of partnership duration is negative and statistically significant (-0.027, $p = 0.033$), while at duration = 10 it becomes positive and statistically significant (0.022, $p = 0.049$). Thus, the slope changes sign over the observed range of the data, satisfying the criteria proposed by Haans et al. (2016) for establishing a U-shaped relationship. The magnitude of the effect is modest, however, suggesting that breadth primarily attenuates the decline in multihoming associated with longer partnerships, while at very high levels of breadth it may also restore strategic flexibility at later stages of the platform relationship.[18]

Finally, to further unpack the moderating role of skill breadth, Figure 1b plots the first derivative of the probability of multihoming with respect to partnership duration together with 95% confidence intervals. Because Hypothesis 2 is fundamentally a prediction about how breadth changes the slope and curvature of the duration–multihoming relationship, the derivative plot provides a particularly direct test of the hypothesis. The results show that the marginal effect of partnership duration is strongly positive for low-breadth firms at short durations and strongly negative at long durations, whereas the effect progressively attenuates as breadth increases. The confidence intervals indicate clear separation across breadth levels at both low and high durations, providing graphical evidence consistent with the moderating effect reported in Table 3 and illustrated in Figure 1a.[19]

6.3 | Robustness checks

Nonlinear Model. We estimate a nonlinear model controlling for firm fixed effects to demonstrate that our results are not dependent on the use of the linear probability model that is used for our baseline specifications. We utilize the generalized estimating equation (GEE) approach (Wooldridge, 2001; Zeger et al., 1988), following the method outlined by Mundlak (1978) and Chamberlain (1980), to estimate binary response panel data models. The estimated regression coefficients provide information about the average response across firms ("population-averaged") by directly modeling the conditional distribution of the unobserved effects, with the mean assumed as a linear

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combination of the means of all independent variables. The estimates presented in Supplementary Material A (Table A2) provide information about the differential rate of multihoming for firms with different levels of breadth of skills at various stages of partnership duration. The GEE model's estimates are qualitatively similar to those in the baseline linear probability model.

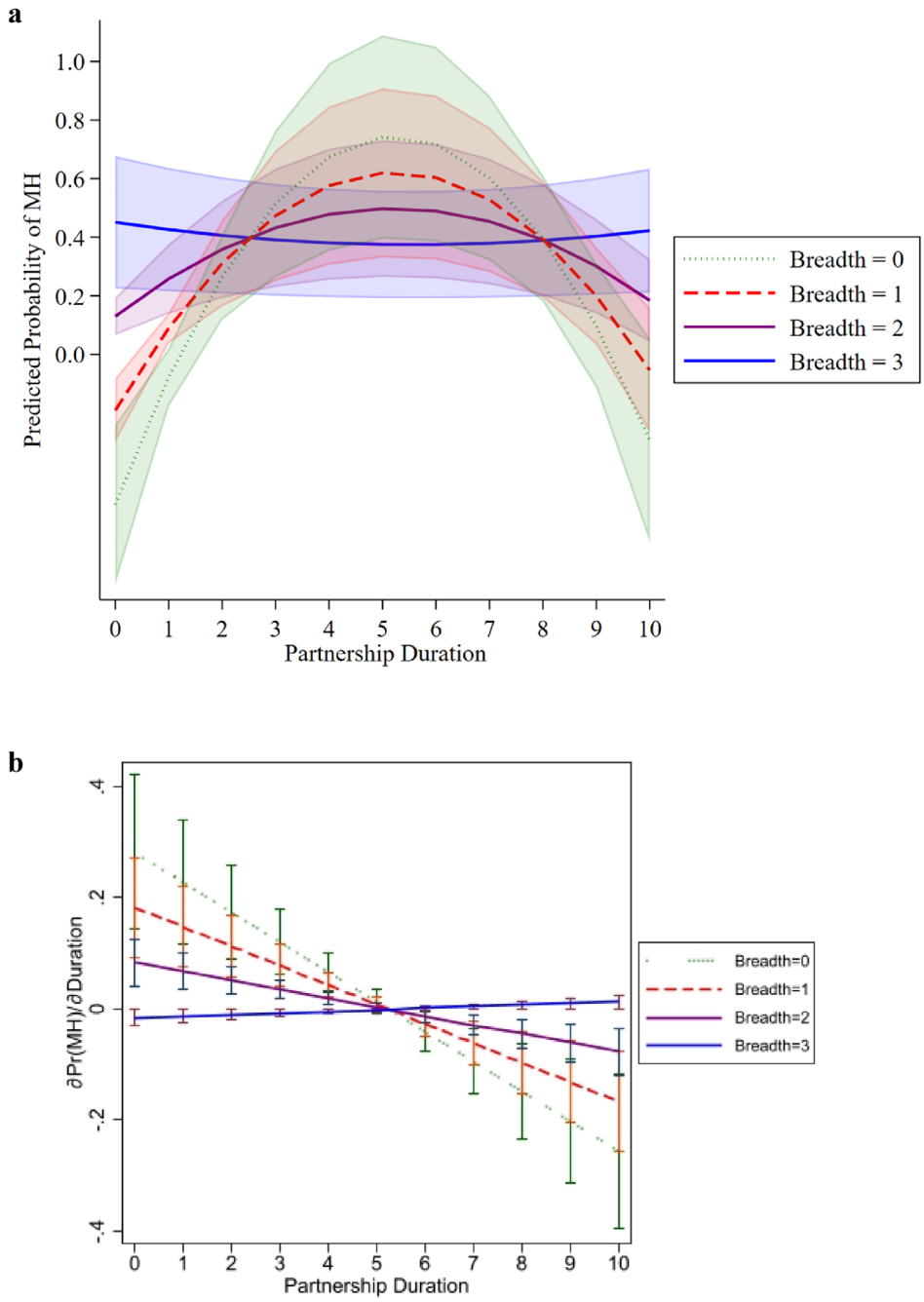


FIGURE 1 Legend on next page.

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TABLE 6 Evidence for U-shape at high breadth.

Duration	∂Pr(MH)/∂duration	Std. error	*t*	*p*-value	95% confidence interval
0 (low)	−0.027	0.013	−2.15	0.033	[−0.053, −0.002]
10 (high)	0.022	0.011	1.98	0.049	[0.0001, 0.043]

Alternative measures of learning and skills. In our development of Hypotheses 1 and 2, we emphasized the learning that occurred through repeated interactions with the platform owner and members of the platform ecosystem. However, we are unable to observe these interactions directly. Rather, our measure of learning is based on the duration of the partnership. Other types of learning could take place over time, facilitating enterprise software development. Repeated interaction in prior engagements can lead to better team learning (Reagans et al., 2005) and may facilitate codification of collective knowledge, enhancing the performance of repetitive tasks (Zollo & Winter, 2002).

Though this latter type of learning is not dependent on the length of affiliation with the platform ecosystem, it will increase over time. As a result, it may confound the interpretation of the estimated interaction effects between partnership duration and the measure of skill breadth. To address this concern, we conduct two robustness checks using alternative measures of internal firm learning. First, we include a variable for firm age at the start of the SAP partnership, which proxies for early-stage learning and accumulated organizational routines prior to joining the platform. We interact this variable (and its square) with ATW and with skill breadth (Model 1, Supplementary Material A, Table A3). Since this variable is time-invariant within firms, it cannot be identified directly in fixed-effects models and only enters via interactions with ATW. Second, we include the interaction between firm age and duration and skill breadth (Model 2). In both models, we include firm age as an un-interacted control, as in our baseline models, which is identified in fixed-effects estimation and helps isolate the effect of internal development from platform-specific dynamics. These specifications test whether ongoing internal learning prior to or during the partnership could explain our results.

The results of both models support our interpretation. Across specifications, the key interaction terms between partnership duration and skill breadth remain strong and statistically significant, consistent with our main hypotheses. In contrast, the interaction terms involving firm age, whether measured at the start of the partnership or as it evolves over time, are weak or insignificant.

Finally, in our analysis, we use a measure of *Skill Breadth* based on a minimum threshold across the three skill dimensions—technical, functional, and industry. We assess robustness using two alternative operationalizations (see Supplementary Material B3). First, we use a binary measure equal to one when the startup exceeds the threshold in all three domains simultaneously. Second, we use a Blau index based on the distribution of skills across domains, similar to measures used to capture diversity in startup teams (see Leatherbee & Katila, 2020).[20] Results using both

FIGURE 1 (a) Predicted probability of multihoming as a function of partnership duration. (b) First derivative of multihoming w.r.t. partnership duration. Figure 1a plots the predicted probability of multihoming during the Oracle acquisition time window (ATWt = 1) as a function of partnership duration with SAP (measured pre-shock) at four levels of pre-shock skill breadth: 0 (no domain covered), 1 (one domain covered), 2 (two domains covered), and 3 (all three domains covered: functional, industry, and technical). All other variables are held at their sample means. Predicted values are computed from the estimates of Equation (2) reported in Table 3, Model (4). Shaded areas indicate 95% confidence intervals. Figure 1b plots the corresponding marginal effect of partnership duration on the predicted probability of multihoming across the same range of duration values and skill-breadth levels. Error bars indicate 95% confidence intervals around the estimated marginal effects. Because both partnership duration and skill breadth are measured prior to the Oracle acquisitions, the figures illustrate how accumulated home-platform experience and pre-existing skill composition are associated with heterogeneous multihoming responses following the increase in multihoming opportunities created by the Oracle acquisitions.

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alternative measures are qualitatively consistent with our main findings (Supplementary Material A, Table A4), supporting the interpretation that breadth reflects the combination of ERP-relevant capabilities rather than overall skill depth alone.

7 | DISCUSSION AND CONCLUSIONS

We study entrepreneurship in platform ecosystems, examining how startup characteristics influence the decision to multihome. Specifically, we focus on two key factors: skill breadth and organizational learning that accumulates over the duration of startup-platform partnerships. We find evidence consistent with an inverted U-shaped relationship between partnership duration and the likelihood that a startup will multihome to alternative platforms. Importantly, we provide evidence that the breadth of capabilities moderates this temporal pattern. Broader capabilities mitigate the platform dependency that typically emerges in mature partnerships and, at very high levels, may even reverse the late stage decline in multihoming propensity, producing a U-shaped trajectory.

We contribute to the research stream on multihoming within the literature on platform ecosystems. While prior work has often emphasized demand-side drivers of multihoming (Corts & Lederman, 2009), more recent research highlights the role of learning and technological interdependencies, for example how multihoming can affect the quality of complements across platforms (Ozalp et al., 2018) or enhance offerings on the home platform through knowledge spillovers (Polidoro & Yang, 2024). We contribute to this work by highlighting how the dynamics of learning acquired during platform partnership are shaped by the breadth of skills at the complementor. Our finding that skill breadth conditions the relationship between partnership duration and multihoming complements recent work linking complementors' experience within the home platform to multihoming decisions (Chen et al., 2022b).

More broadly, our findings contribute to the platform governance literature by providing evidence that governance-induced learning and investment trajectories shape complementor behavior even in the absence of an explicit governance change (Chen et al., 2022a, 2022b; Zhang et al., 2022). While prior research emphasizes how platform owners' governance choices affect ecosystem outcomes, we show that prolonged exposure to a given governance regime can generate platform-specific dependence that shapes complementors' multihoming decisions when market conditions change. Relatedly, Thatchenkery and Katila (2023) show in Microsoft's enterprise infrastructure software ecosystem that weakening a dominant platform increased complementor patenting but left product introductions unchanged and reduced profitability, illustrating how dependence on platform-provided resources can limit complementors' ability to capitalize on new opportunities. Our findings complement this evidence by identifying another consequence of platform dependence: reduced flexibility to pursue opportunities across platforms, a constraint that is attenuated by skill breadth. Together, these studies underscore the distinctive features of enterprise software ecosystems, where platform-specific investments and skill breadth jointly determine startups' capacity to sustain flexibility and pursue growth across related platforms.

We also extend the literature at the intersection of entrepreneurship and platforms by demonstrating that, in platform ecosystems, startups need to align their capabilities to respond dynamically to ecosystem changes. This insight aligns with recent calls for more research examining entrepreneurship in the context of digital platform ecosystems (Nambisan et al., 2018, 2019). These ecosystems have become increasingly prevalent, with startups now commonly co-creating value through platform partnerships. We extend the entrepreneurship literature in platform ecosystems by highlighting how startups develop and apply capabilities over time, and the implications of these capabilities for responding to changing ecosystem opportunities (Argote et al., 2021; Combs et al., 2023).

Our study also contributes to the entrepreneurship literature by shifting attention from founding conditions to the growth phase, showing how accumulated capabilities can both enable and constrain strategic adaptation. We show that startup learning that arises from partnerships with a platform informs key growth-related decisions. Further, we extend work on the role of a startup skill base on growth (Grillitsch & Schubert, 2021; Symeonidou & Nicolaou, 2018) by highlighting the impact of skill breadth. By linking skill composition and learning to multihoming,

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we identify a capability-based mechanism that enables startups to preserve strategic flexibility under resource constraints.

Our results have implications for enterprise software startups deciding how to build capabilities. The evidence suggests that the longer a complementor co-creates value within a platform ecosystem, the greater the risk of becoming "locked-in" to the platform, reducing flexibility to respond to market or technological shifts. Cultivating breadth of skills across multiple domains mitigates this rigidity. Broad skillsets provide firms with a wider portfolio to adapt when external conditions change, whereas narrow specialization leaves them more vulnerable to lock-in. For managers, this implies that allocating resources to maintain and expand breadth, rather than concentrating narrowly, can provide greater strategic flexibility in dynamic platform markets.

Our empirical context of ERP platforms has both advantages and limitations. On the one hand, enterprise software ecosystems are a particularly valuable setting to study capability breadth because success requires the integration of technical, functional, and industry-specific knowledge. This makes ERP an ideal domain for examining how diverse skill bases condition learning and flexibility. Moreover, ERP represents a very large and economically significant sector, underscoring the importance of understanding entrepreneurial behavior in this space. At the same time, the specificity of the ERP context has limitations for generalization. Complements in ERP can begin as stand-alone products before affiliating with a platform, unlike more modular settings such as mobile apps or video games, where platform affiliation is mandatory from inception. Our measure of skill breadth, while capturing the three domains most central to enterprise software, may not reflect how breadth operates in other settings. While our measure fits the ERP context, future work should investigate whether the concept of breadth generalizes across different platform environments or manifests in context-specific ways.

These limitations suggest several directions for future work. Future studies could explore how the relationship between skill breadth, learning, and multihoming differs in more modular settings such as iOS or Android, where technical integration dominates and functional or industry-related skills may play a smaller role. They could also examine simultaneous multihoming, or contexts shaped by institutional or regulatory shocks, to assess whether capability shapes the implications of platform learning differently across settings.

Similarly, while our study focuses on ERP, the theoretical mechanism we identify may extend to other contexts in which software requires the integration of multiple domains of knowledge. The specific domains of skill breadth may vary, but the role of broad capabilities in shaping flexibility under platform dependence is likely to remain salient in settings that require the integration of technical, functional, and domain-specific knowledge. These reflect the broader point in business software about the need for combing multiple spheres of knowledge—in particular the context or domain in which the software is used—for firms to obtain value from their software investments.[21]

While the Oracle acquisitions represented a significant demand increase, there is no way to conclusively rule out all other forms of tacit strategic actions. We acknowledge that it is possible that at least some startups may have selected themselves into multihoming, and, hence, our estimates must be interpreted accordingly. In addition, while we attempt to disentangle platform-specific learning (proxied by partnership duration) from internal organizational learning (proxied by firm age), richer designs are needed to separate these effects more effectively. Finally, our study highlights that skill bases and prior platform partnerships shape startups' multihoming strategies; future research could extend this focus to other types of market opportunities and alternative mechanisms of sustaining growth across ecosystems. We look forward to additional research in this important area.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from National Establishment Time Series (NETS). Restrictions apply to the availability of these data, which were used under license for this study. Data are available from the author(s) with the permission of National Establishment Time Series (NETS).

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ORCID

Vijayaraghavan Venkataraman https://orcid.org/0000-0001-8962-8256

Marco Ceccagnoli https://orcid.org/0000-0002-7406-7596

ENDNOTES

[1] A detailed summary of the literature on multihoming is also available in Supplementary Material A, Table A1.

[2] For an overview of the platform governance literature, see Chen et al. (2022a).

[3] The terminology varies: Cennamo et al. (2018) describe them as co-specialized investments, Chen et al. (2022b) emphasize ecosystem-specific learning, and in ridesharing contexts, Chung et al. (2024) point to specialized assets such as driver ratings.

[4] Babak Varjavandi, the founder of Nakisa, noted that "Whenever there was a new technology, or if SAP wanted someone to be a ramp-up for certain kinds of integration, we'd volunteer." (Iansiti & Lakhani, 2009, p. 10).

[5] For example, in ERP ecosystems such as SAP's during our study period, platform evolution was guided by a deliberate strategy of backward compatibility. This continuity fostered stability for complementors but also increased their platform-specific lock-in, as their accumulated knowledge and tools were optimized for the evolving but path-dependent platform architecture (Kretschmer & Claussen, 2016).

[6] For example, the company IDC Scheer faced challenges when multihoming from SAP to Oracle because of differences in the needs of its primarily European customers for SAP with those of its larger share of US customers for Oracle (Ried, 2009).

[7] Here we provide details that shape our empirical research design. Further details are provided in Supplementary Material C.

[8] The acquisition of PeopleSoft by Oracle in 2004, initially valued at $11 billion, was one of the largest acquisitions in the IT industry at that time. While antitrust authorities scrutinized the acquisition in the US and Europe, in 2004, the US courts ruled in favor of Oracle and against the Department of Justice. A similar judgment soon followed in Europe.

[9] The term "high-function enterprise software" originates from the U.S. Department of Justice's market definition in United States v. Oracle Corp. and refers to large, integrated ERP systems serving complex organizational needs. Throughout the paper, we use the broader term "enterprise software" to refer to this class of platforms.

[10] https://www.cnet.com/tech/tech-industry/project-fusion-to-dominate-ellisons-calendar/.

[11] https://www.theregister.com/2025/01/02/twenty_years_since_oracle_bought_peoplesoft/.

[12] We validated our data source by comparing press release coverage in Factiva and Lexis Nexis for a 10% subsample. Factiva provided both broader coverage and greater precision, so we rely on Factiva for the analysis.

[13] Cf. "SAP Sheds M&A Shyness as Oracle Rivalry Moves to the Cloud Source: Bloomberg Business," Kjetland and Ricadela (2011), available at https://www.bloomberg.com/news/articles/2011-12-04/sap-sheds-m-a-shyness-with-successfactors-as-oracle-rivalry-moves-to-cloud. While Peoplesoft was the most significant ERP platform acquisition, the complete list of Oracle's acquisitions during the period is available at: Worthen (2009); https://www.wsj.com/public/resources/documents/st_ELLISON_20090211.html.

[14] Because many independent variables—such as skill breadth, depth, and partnership duration—are constructed as pre-shock, time-invariant measures, the relevant correlations reported mostly reflect cross-sectional relationships across the panel.

[15] In Supplementary Material A, Table A5, we estimated additional models where skill breadth and depth are entered separately, both with and without interactions with duration and its square term. Results suggest that while both measures are positively correlated, only breadth remains statistically significant as a moderator of the relationship between partnership duration and multihoming when both are included, further supporting our Hypothesis 2.

[16] With Breadth equal to 0 or 1, the predicted probability of multihoming is negative at zero duration, due to our use of a linear probability model. We present estimates of a nonlinear model in the robustness section, suggesting that our results are qualitatively consistent with estimates from the linear models.

[17] Figure 1a also reports 95% confidence intervals around the predicted probabilities. These intervals indicate that differences across breadth levels are most visible at low and high levels of partnership duration, while there is more overlap around intermediate duration values where the curves approach their turning points. For low-breadth firms, predicted probabilities follow a pronounced inverted-U pattern and the confidence intervals are wider around the middle of the duration range, where predicted multihoming is highest. For high-breadth firms, especially those with breadth equal to three, predicted probabilities are more stable across duration and do not show the same pronounced late-stage decline.

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We therefore interpret Figure 1a as descriptive evidence of the moderation pattern and rely on the formal interaction tests and derivative estimates for inference.

[18] Notably, the moderating effect of breadth operates primarily through changes in the curvature of the relationship rather than through shifts in the location of the turning point, which remains relatively stable across breadth levels.

[19] These estimates also help clarify how the combination of two pre-shock characteristics—skill breadth and accumulated SAP partnership duration—shape heterogeneous multihoming responses following the Oracle acquisitions. Figure 1a and the associated marginal effects from Figure 1b compare startups that differed in their pre-existing skill breadth and accumulated SAP partnership duration at the time of the shock. Consistent with our theoretical argument, firms with broader capability bases and relatively limited accumulated SAP experience exhibit a stronger propensity to multihome following the Oracle acquisitions. The effect of breadth is positive and statistically significant at low levels of partnership duration (0 years: 0.321, $p < 0.001$; 1 year: 0.168, $p = 0.001$). The relationship becomes negative at intermediate durations (4.6 years: −0.116, $p < 0.001$), before becoming positive again at longer durations (10 years: 0.238, $p = 0.003$), consistent with the U-shaped pattern for high-breadth firms shown in Figure 1a.

[20] We view our threshold-based measure as a better match with our theoretical framework. It captures whether startups possess meaningful competence across distinct skill domains—consistent with the notion of variety as presence of categories (Harrison & Klein, 2007). By contrast, the Blau index emphasizes evenness across categories and can assign high breadth scores to firms with very low overall skill endowments. In ERP ecosystems, where complementors must integrate technical, functional, and industry knowledge to deliver complete solutions, such "shallow breadth" is unlikely to confer the adaptability needed for multihoming. As a result, Blau-based breadth measures risk conflating breadth with insufficient depth and must be explicitly controlled for depth to yield meaningful interpretations.

[21] The implications of this need for domain knowledge have been made in other settings such as traditional business data processing (Bresnahan, 2019), healthcare IT (Dranove et al., 2014) and more recently, applications of AI (Tambe, 2026).

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