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Both customer and innovation assets are important to firm performance. Prior research has mostly examined these assets at the firm level and has not distinguished between the effects of asset depth relative to competitors and asset breadth across different segments. Using configuration theory and the resource-based view of the firm, the authors propose that how these assets interact to influence performance depends on both depth and breadth because these features reflect whether the assets are likely to create and/or appropriate value when deployed. Empirical results from two studies—one using secondary data and another using primary data from a survey of senior managers—indicate that performance is highest when firms employ configurations using deep customer and broad innovation assets or deep innovation and broad customer assets. In contrast, firm performance variability decreases in the presence of deep–deep and broad–broad asset configurations. The effect of configuration strategies on firm performance also is typically greater in dynamic than in stable environments.

Keywords: configuration theory, resource-based view, marketing assets, asset breadth, asset depth, innovation

Effects of Customer and Innovation Asset Configuration Strategies on Firm Performance

> The business enterprise has two and only two basic functions: marketing and innovation. Marketing and innovation produce results; all the rest are costs. (Drucker 1954, p. 144)

This often-cited quotation, offered more than half a century ago, still rings true among academics and business managers who recognize the importance of customer and innovation assets that often emanate from marketing activities (Srivastava, Shervani, and Fahey 1998). Yet neither form of assets appears on a firm's balance sheet because they are intangible and often difficult to measure. As a result, firms continue to struggle to understand and document the link between assets and firm performance to provide support for the necessity of marketing investments (Srinivasan et al. 2009). Most research has examined these assets at the firm level, even though a few recent studies have demonstrated that disaggregating product pipeline portfolios or technical knowledge into "depth" and "breadth" dimensions provides important insights into the underlying mechanisms for how intangible assets create shareholder value (Grewal et al. 2008; Prabhu, Chandy, and Ellis 2005). We build on these studies by developing and testing a model that proposes that how customer and innovation assets interact to influence performance depends on both depth and breadth because these features reflect whether the assets are likely to create and/or appropriate value when deployed. Thus, the research question we study is how a firm's configuration of customer and innovation assets influences the firm's financial performance and performance variability.

To develop our conceptual model, we rely on two theoretical perspectives used to understand the link between assets and firm performance—the resource-based view

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(RBV) of the firm (Barney 1991; Conner 1991) and configuration theory (Siggelkow 2002; Vorhies and Morgan 2003). The RBV offers a framework for understanding how firm assets generate sustainable competitive advantages (Barney 1991), and configuration theory provides a perspective for understanding how the arrangement of organizational assets (internal fit) and alignment of those assets with the environment (external fit) affect performance (Siggelkow 2002); thus, we study environmental dynamism as a moderator.

Consistent with extant research in both theoretical domains regarding the importance of the focus and scope of a firm's assets in building sustainable competitive advantage, we disaggregate customer and innovation assets into two categories that we posit are critical for understanding assets' ability to create and/or capture value (Grewal et al. 2008; Prabhu, Chandy, and Ellis 2005): depth and breadth. Asset depth refers to the focus and intensity of an asset and is critical for creating value because deep assets tend to be rare, unique, and hard to duplicate. Asset breadth captures the diversity and scope of the asset, and in addition to creating value, it is especially important for capturing value over time because broad assets provide diverse, expansive contexts for extracting value from unique offerings.

If the depth and breadth of customer and innovation assets represent the "fundamental building blocks" of assets, firm performance may depend on the internal arrangement or "architecture" of those assets, as well as their fit with the environment (Siggelkow 2002; Teece, Pisano, and Shuen 1997). We refer to the architecture of customer and innovation assets as the firm's "asset configuration strategy." Our theoretical framework and empirical results suggest that "a more is better" view toward assets is not optimal; rather, customer and innovation assets must be viewed from a configuration or portfolio perspective that recognizes the underlying mechanisms that operate among these assets, as well as their fit with the environment.

We evaluate the effects of asset configuration strategies on firm performance and performance variability in two studies. In Study 1, we test our model using secondary data and integrate customer depth and breadth measures with innovation depth and breadth measures, which we then link to firm performance and performance variability. In Study 2, we test our model using multi-item measures of key constructs in a survey of senior managers, which increases confidence in the underlying theoretical rationale of our predictions.

We find that customer and innovation assets interact and have differential effects on performance and performance variability. Therefore, different asset configuration strategies function better to improve performance than to reduce performance variability. Specifically, deep innovation–broad customer and deep customer–broad innovation asset-leveraging strategies lead to the best firm performance. In contrast, firm performance variability decreases for asset diversification (broad–broad) and asset concentration (deep–deep) configuration strategies. Our analysis also demonstrates the use of configuration theory as a lens for viewing the influence of assets on performance. Both internal fit among assets and their fit with the external environment affect performance and performance variability. For example, a deep customer–broad innovation asset configuration strategy has a greater impact on performance, and an asset diversification configuration strategy has a greater suppression effect on performance variability when environmental dynamism increases. These results suggest the effects of some configuration strategies on outcomes increase in dynamic environments.

Finally, our research extends extant literature on marketing and technology linkages (Dutta, Narasimhan, and Rajiv 1999; Moorman and Slotegraaf 1999) by examining how different aspects of customer and innovation assets lead to different performance outcomes. Our results reveal the importance of disaggregating assets into the depth and breadth components of both customer and innovation assets to understand how marketing activities affect firm performance and performance variability through their interdependent value-creating and value-capturing mechanisms. Component-level interactions would be difficult, if not impossible, to detect at higher levels of aggregation (e.g., firm level). We also build on Vorhies and Morgan's (2003) use of configuration theory, in that we apply a similar perspective to understand the effect of internal fit among asset components and their external fit with the environment on outcomes.

CONCEPTUAL BACKGROUND

Linking Assets and Firm Performance: The RBV and Configuration Theory

In the past decade, research in marketing has demonstrated that a firm's assets—that is, any items of value owned or controlled by a firm capable of creating value (Barney 1991), such as brands (Rao, Agarwal, and Dahlhoff 2004) and customer relationships (Palmatier 2008), have a direct influence on financial outcomes. However, focusing solely on performance is less meaningful for employees and customers, who are also interested in firm survival and performance variability. Consistent with classic cash flow arguments and financial theory (Markowitz 1987), we investigate a firm's financial performance and performance variability.

We attempt to determine the influence of two of the most important assets of a firm—customer and innovation assets—on firm performance (Drucker 1954; Srivastava, Shervani, and Fahey 1998). We are particularly interested in how the configuration of assets affects firms' financial outcomes. We rely on the RBV of the firm to provide insights into the link between a firm's assets and performance; this well-recognized framework indicates how firm assets generate sustainable competitive advantages (Barney 1991). Specifically, when firms have assets or bundles of assets that are valuable, rare, inimitable, and nonsubstitutable (VRIN), they can generate competitive advantages and above-average financial performance.

Consistent with extant RBV research (Prabhu, Chandy, and Ellis 2005), we propose that customer and innovation assets typically have positive effects on firm performance because, even as stand-alone assets, they often meet VRIN criteria, but additional refinements could help clarify the underlying mechanisms by which they create and capture value. We propose that customer and innovation assets should be disaggregated across depth and breadth dimensions to isolate their underlying value-generating mechanisms and relative effects on performance.

Asset depth refers to the focus and intensity of an asset and is critical for creating value because deep assets tend to be rare, unique, and hard to duplicate (Szulanski 1996). For example, firms with deep customer assets often have, compared with the competition, closer customer relationships, greater loyalty, and deeper knowledge about customer's desires and behaviors, which is typically reflected in a higher share of sales in their served market segments (Palmatier 2008). A close customer-to-firm relationship is difficult for competitors to copy because it takes time and effort and because it is difficult for firms to gain access to key decision makers (Colgate and Danaher 2000). Similarly, firms with deep innovation assets often have unique knowledge in their innovation space and technology-specific expertise regarding product applications and process insights, which in many industries is reflected in a substantial patent presence in their core technology areas (Prabhu, Chandy, and Ellis 2005). This technology-specific knowledge and related link to applications and processes make it difficult (e.g., due to patent protection) for competitors to offer substitutes (Dierickx and Cool 1989).

Asset breadth captures the diversity and scope of the asset, and in addition to creating value, it is especially important for capturing value over time because broad assets provide diverse, expansive contexts for extracting value from unique offerings (Bierly and Chakrabarti 1996). Asset breadth can help a firm generate a competitive advantage through performance enhancements by combining unique knowledge or capabilities from diverse customer segments or technology areas, which can result in hard-to-duplicate insights (Barney 1991). For example, a firm with broad customer assets may have unique access to and knowledge across different customer segments, enabling the firm to identify a common trend or need across multiple segments that may not be noticeable or even economically viable to a "single-segment" competitor, thus allowing the firm to be the first to launch a new product across these multiple segments.

Moreover, while a firm's deep customer or innovation assets can create value by satisfying the VRIN criteria through unique combinations of diverse perspectives, asset breadth may be more important in terms of enhancing performance by helping firms appropriate the value created from deep assets. For example, a new product technology created by a firm as a result of its deep innovation assets, while beneficial to the firm in the space for which it was developed, could generate additional benefits if the firm could sell the new technology to multiple customer segments as a result of its broad customer asset base.

Thus, disaggregating customer and innovation assets across depth and breadth dimensions both isolates the dimension of an asset most critical to enhancing performance (depth or breadth) and helps explain how these dimensions work together in creating and appropriating value. More specifically, if we consider asset depth and breadth as underlying building blocks that represent a firm's key value creation and appropriation mechanisms, configuration theory holds that performance ultimately depends on their arrangement (Siggelkow 2002). Extending configuration theory to our asset framework, we suggest that an optimal arrangement of assets creates (1) internal fit between innovation and customer asset depth and breadth and (2) external fit between the arrangement of innovation and customer asset depth and breadth and the environment. A firm must create both internal coherence, or fit among its innovation and customer assets, to create and appropriate value and external fit with the environment to capture value because the value creation and value-capturing mechanisms of assets are not independent but rather interact and are contingent on the external environment (Kabadayi, Eyuboglu, and Thomas 2007).

For descriptive and expositional purposes, we identify four asset configuration strategies, which we propose have differential effects on a firm's performance and performance variability (see Figure 1): (1) deep customer–broad innovation asset-leveraging strategy, (2) deep innovation–broad customer asset-leveraging strategy, (3), asset diversification strategy (broad–broad), and (4) asset concentration strategy (deep–deep). However, we also note that asset depth and breadth are continuous variables, and firms fall on continua across the four configuration strategies.

HYPOTHESES

Effect of Configuration Strategies on Firm Performance

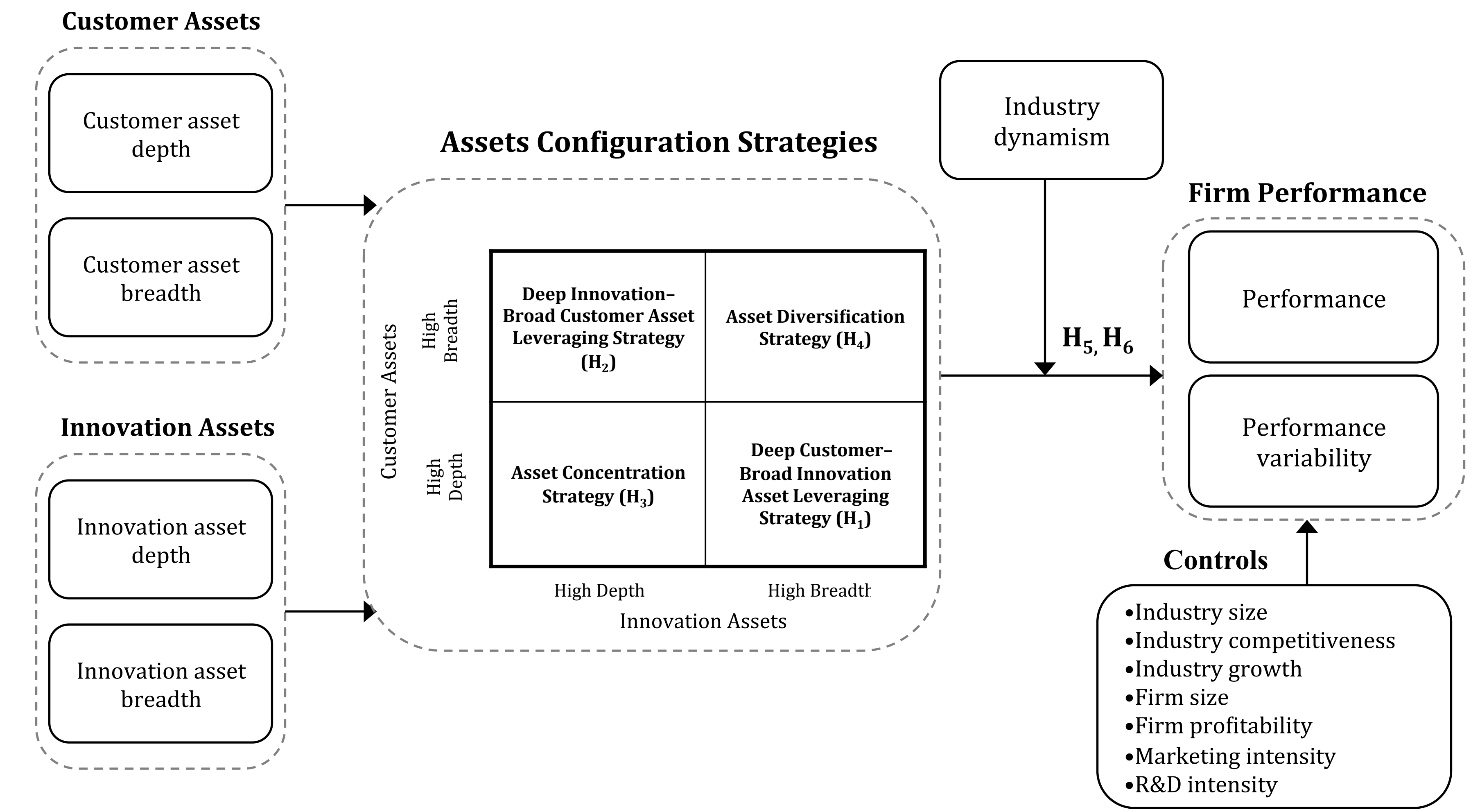
Deep customer–broad innovation asset-leveraging strategy. We propose that deep customer and broad innovation assets should have complementary effects on performance. Deep customer assets lead to an in-depth understanding of customer demands and preferences, which provide firms with ideas about unique ways to develop and deliver value to customers. For example, firms with an above-average share in a specific market segment (deep customer assets) gain a valuable, rare, and hard-to-duplicate position that enables them to understand the segment's trends and product needs, as well as gain feedback about new products/services. Such knowledge benefits generate performance enhancements through new product insights, quicker adaptation to changing conditions, and more successful product launches.

A firm may leverage or capture knowledge benefits created from deep customer assets better when it also possesses broad innovation assets. Firms with a breadth of innovation assets can better evaluate, assimilate, and respond to the opportunities that stem from their deep customer assets because innovation asset breadth provides them with broad and diverse technology portfolios from which they can draw (Sorescu, Chandy, and Prabhu 2003). In turn, a firm can deploy its diverse technology portfolio to create diverse products/services, as well as unique or customized products/services that meet idiosyncratic customer needs, which will help the firm achieve greater sales, lower price sensitivity, and higher profit margins (Sorescu, Chandy, and Prabhu 2003). In contrast, if a firm learns about some new requirement of a specific customer segment but lacks the technologies to address this need, it cannot meet this emerging customer need.

We propose that a firm can leverage deep customer assets, which results in valuable and unique knowledge, when those assets are complemented with broad innovation assets, thus increasing sales and profit margins by matching customers' needs with new and improved technology solutions. For example, Apple enjoys enhanced performance by pursuing a deep customer–broad innovation asset-leveraging strategy in which it consistently provides new and unique

Figure 1

EFFECTS OF CUSTOMER AND INNOVATION ASSET CONFIGURATION STRATEGIES ON FIRM PERFORMANCE



products to an entrenched group of existing customers by leveraging its broad technology portfolio (e.g., hardware, wireless, software).

Deep innovation–broad customer asset-leveraging strategy. Similarly, deep innovation assets and broad customer assets should have complementary effects on performance. Deep innovation assets reflect an intense knowledge and understanding of specific technologies and provide firms with rare and hard-to-duplicate insights into technological capabilities, trends, and trade-offs in a specific technology area. Extant research has expounded on a wide range of benefits resulting from innovation asset depth, including enhanced abilities to manage innovation effectively, to deploy technologies at lower cost, and to create value (Bierly and Chakrabarti 1996; Prabhu, Chandy, and Ellis 2005). Moreover, innovation asset depth helps firms avoid investing in projects that will not succeed (i.e., better ability to filter bad projects).[1]

A firm might best leverage or capture the benefits of deep innovation assets when it combines them with a broad and diverse customer portfolio because deep knowledge of a specific technology can create a competitive advantage and performance enhancements only if it produces products and services that are aligned with actual customer needs. Matching deep innovation assets with broad customer assets enables the firm to increase its sales by applying its deep innovation assets to match demand from diverse customer segments and to reduce its costs and increase profit margins by exploiting common technology assets across different segments. In contrast, a firm that pushes the boundary in a specific technology area and develops a new offering with unique performance capabilities may be unable to extract value (sales and profits) if it has only a narrow portfolio of similar customers, who may not need the application of the unique technology. Thus, we propose that a firm can leverage its deep innovation assets, which results in valuable and unique technological insights, when it complements them with broad customer assets by matching its specific technology portfolio to a broad, diverse set of customers. For example, Canon pursues a deep innovation–broad customer asset-leveraging strategy in which it offers better, unique products by leveraging its deep sensor technology knowledge across a broad and diverse set of customers in the copier, digital camera, and industrial product markets.

Both deep customer–broad innovation and deep innovation–broad customer asset-leveraging strategies represent complementary configurations, in which the internal fit between different components of assets (i.e., rare and hard-to-duplicate deep assets with multiple contexts through broad assets) work together to generate and capture value; thus, firms that pursue these configuration strategies should perform better than the firms that pursue other configuration strategies.

H_1: The interaction between customer asset depth and innovation asset breadth increases firm performance.

H_2: The interaction between customer asset breadth and innovation asset depth increases firm performance.

[1]We thank an anonymous reviewer for this suggestion.

Effect of Configuration Strategies on Firm Performance Variability

Asset diversification strategy. Research supports the premise that performance variability decreases as firms broaden either customer or innovation assets because firms hedge risks through such diversification (Evans 1991). For example, a loss of sales to one customer can be offset by an increase in sales to another customer; similarly, a failure in one technology area can be mitigated by a success in another area. However, we advance this argument by proposing that firms gain additional variability suppression benefits when they broaden different asset bases rather than the same asset base. We refer to broadening across both customer and technology areas as an asset diversification strategy.

The interaction between customer and innovation breadth may suppress performance variability because the two asset classes are relatively independent, so changes in customers and innovations are more likely to be compensatory than changes within the same asset class (Markowitz 1987). For example, Microsoft experiences minimal performance variability because it uses an asset diversification strategy with both broad customer and broad innovation assets. A fundamental shift in information technology could negatively affect much of Microsoft's technology portfolio, but the compensatory diversification benefits from Microsoft's broad customer base would be relatively unaffected.

Asset concentration strategy. Similarly, deep customer and deep innovation assets can work together to reduce performance variability. Increasing asset depth provides firms with more knowledge about and insight into future trends, which helps them make better decisions by anticipating and adapting to changing conditions, resulting in less performance variability (Srivastava, Shervani, and Fahey 1998). However, deep insight into just one asset area (e.g., customer) offers no protection against unforeseen changes in a different area (e.g., technology), so firms remain susceptible to dramatic performance shifts. However, if a firm has both deep customer and deep innovation assets, it possesses insight and foresight for both major sources of uncertainty. We propose that firms that can monitor, evaluate, and triangulate across both sources of uncertainty are better at anticipating and adapting, which should smooth their performance variability by improving their decision making. For example, firms often develop new products and services by predicting and matching future customer trends with the likely trajectory of different technologies (Christensen 1997). The likely success of this match of external customer needs with internal technologies depends mainly on the accuracy and depth of the firm's relevant knowledge across the two domains. We expect an interactive effect: Specifically, with external and internal insights, the firm's offering is more likely to succeed, but good technology insights can easily be undermined by poor customer insights, and vice versa (Day and Nedungadi 1994).

A deep–deep asset configuration strategy, or asset concentration strategy, mirrors Mark Twain's risk-reduction advice: "Put all your eggs in the one basket and—watch that basket" (Stevenson 1948, p. 672). By reducing risk through in-depth attention, the firm can anticipate and minimize the effects of change. For example, Boeing focuses its innovation assets predominantly on aerospace technologies to serve a narrow group of airline customers. Thus, Boeing does not reduce risk by diversifying across customers and technologies but rather centers its attention on and uses its resultant insights for anticipating and adapting to potential changes in either.[2]

H_3: The interaction between customer asset breadth and innovation asset breadth reduces firm performance variability.

H_4: The interaction between customer asset depth and innovation asset depth reduces firm performance variability.

Effect of Industry Dynamism on the Configuration Strategies and Firm Outcome Links

We capture the effects of external environmental changes using "industry dynamism," which we define as the extent to which industry demand changes rapidly and unpredictably (Jaworski and Kohli 1990). Configuration theory argues that a strategy's effect on performance depends on its fit with the external environment (Siggelkow 2002). Similarly, the RBV suggests that the effects of specific asset bundles or asset configurations on performance are best leveraged in dynamic environments (Teece, Pisano, and Shuen 1997).

The positive effect of deep customer–broad innovation and deep innovation–broad customer asset-leveraging strategies on firm performance should be greater in dynamic than in stable environments. As we have argued, the positive effect of deep–broad complementary asset configurations stems from the combination of value created from the knowledge benefits of deep assets and the value extraction benefits of broad assets. Because dynamic industries are characterized by frequent, difficult-to-predict changes in customer needs and technologies, dynamic environments provide firms that have deep–broad asset configurations with more opportunities to match their deep knowledge across broad contexts to enhance performance. In a stable industry, even firms without deep insights can copy the market leader's offering, so deep–broad configurations offer relatively small advantages in stable markets. However, in dynamic environments with constantly changing customer needs, there are many opportunities for leveraging deep insights across diverse situations (Jaworski and Kohli 1990), which provide an advantage to firms with deep–broad asset configurations because they can achieve more new offerings from unique customer–technology matches.

The variability suppression benefits described for firms that use an asset diversification strategy also should pay higher dividends in dynamic than in stable environments. Dynamic environments present more and greater magnitudes of contingencies than stable environments, so building redundancies through broad customer and broad innovation portfolios to reduce performance swings should be more significant in dynamic industries (Evans 1991). Compared with a stable environment, in a dynamic environment, a firm without deep insight into customers or technologies may be blindsided by rapidly changing customer needs or technology trends. We propose that the variability suppression benefits of the asset concentration strategy (deep–deep) derived from in-depth knowledge and attention, which allows the firm to anticipate and minimize the effects of change, is more effective as industry dynamism increases.

H_5: The positive effect of (a) deep customer–broad innovation and (b) deep innovation–broad customer asset-leveraging strategies on firm performance increases with industry dynamism.

H_6: The negative effect of (a) asset diversification and (b) asset concentration strategies on firm performance variability increases with industry dynamism.

STUDY 1

We test our conceptual model in two complementary empirical studies. In the first study, we collected data from a variety of secondary sources, including COMPUSTAT, the Center for Research in Security Prices (CRSP), and patent data, to capture the depth and breadth measures of customer and innovation assets, as well as measures of financial performance and variability. The sampling frame included firms that compete predominantly in the high-tech industries, such as software development (Standard Industrial Classification [SIC] 7374), semiconductor (SIC 3672), computers and related products (SIC 3571–3577), and electronic equipment (SIC 3600), during 1990 to 2005.

In the second study, we measured the key constructs using multi-item measures in a survey of senior managers from high-tech firms. Thus, while both studies test the same conceptual model (Figure 1), Study 1's use of secondary data increases the external validity of our results, while Study 2's use of multi-item scales increases the internal validity of our findings. In Table 1, we describe the constructs, definitions, measures, and data sources for both studies.

Measures

Firm performance and performance variability. To measure firm performance and performance variability, we relied on stock prices, which are forward looking, integrate multiple performance dimensions (sales, cash flow), and are difficult for managers to manipulate (Fang, Palmatier, and Steenkamp 2008). In particular, we used stock market returns as a measure of firm performance and idiosyncratic risk as a measure of performance variability (Srinivasan and Hanssens 2009). In equilibrium, systematic risk reflects the extent to which a stock's return changes when the overall market changes; it cannot be eliminated through diversification. The amount of risk that remains after accounting for systematic risk equals idiosyncratic risk.

With Equation 1, we used a four-factor model to calculate shareholder returns using daily stock return data (Srinivasan and Hanssens 2009). The four-factor capital asset pricing model recognizes many factors that may affect stock valuations, such as differences in returns between large-cap and small-cap portfolios (size risk factor) and between high versus low book-to-market stocks (value risk factor), as well as a systematic risk factor (beta) and a momentum factor:

[2]We only offer hypotheses for the effect of configuration strategies on performance and performance variability when we have a specific theoretical rationale to support an interaction effect. For example, we do not have a theoretical rationale to expect deep–broad or broad–deep asset configurations to influence performance variability, because there is no mechanism for leveraging the variability-reducing effects of diversification and information access across these two configurations. However, for completeness, we report the results of these nonhypothesized interactions.

Table 1
CONSTRUCTS, MEASUREMENTS, AND DATA SOURCES

Constructs	*Definitions*	*Study 1 Measures (Data Sources)*	*Study 2 Measures (Data Sources)*[a]
Performance	Overall firm performance	Shareholder return (CRSP and Kenneth French data library)	Three-item measure of firm profit margin/return on assets/return on equity (customer survey)
Performance variability	Variability in firm performance	Idiosyncratic risk (CRSP and Kenneth French data library)	Three-item measure of stability of firm profit margin/return on assets/return on equity (customer survey)
Customer asset breadth	Diversity and scope of the firm's customer portfolio	Entropy measure of firm sales revenue in different business segments (COMPUSTAT Business Segment)	Four-item measure of customer-asset breadth (customer survey)
Innovation asset breadth	Diversity and scope of the firm's technology portfolio	Entropy measure of granted patents in different national classes (Delphion Patent Database)	Four-item measure of innovation-asset breadth (customer survey)
Customer asset depth	Focus and intensity of the firm's customer portfolio	Average ratio of sales revenue to industry sales across different business segments (COMPUSTAT Business Segment)	Four-item measure of customer-asset depth (customer survey)
Innovation asset depth	Focus and intensity of the firm's technology portfolio	Average ratio of granted patents to all patents in each national class across different national classes (Delphion Patent Database)	Four-item measure of innovation-asset depth (customer survey)
Industry competitiveness	Intensity of competitive rivalry within an industry	Herfindahl index of firm's primary industry sales revenue (COMPUSTAT)	Five-item measure adapted from Jaworski and Kohli (1993) (customer survey)
Industry dynamism	Intensity of change and environmental turbulence within an industry	The standard deviation of sales in firm's primary industry across the prior five years, divided by mean value of industry sales for those years (COMPUSTAT)	Five-item measure adapted from Jaworski and Kohli (1993) (customer survey)
Industry growth	Rate of sales growth of an industry	Slope coefficient of sales in firm's primary industry across the prior five years, divided by mean value of industry sales for those years (COMPUSTAT)	Three-item measure of industry growth (customer survey)
Marketing intensity	Relative level of spending on sales and marketing within a selling firm	Marketing expenditure/total asset (COMPUSTAT)	Percentage annual marketing investment to firm total assets (customer survey)
R&D intensity	Relative level of spending on R&D by the firm	R&D expenditure/total asset (COMPUSTAT)	Percentage annual R&D investment to firm total assets (customer survey)
Firm size	Number of people employed by the firm	Log-transformation of number of employees (COMPUSTAT)	Log-transformation of number of employees (customer survey)

[a]See the Appendix for the scale items used in the survey.

$$(1)\quad R_{i,t} - R_{f,t} = a_0 + \beta\,(R_{m,t} - R_{f,t}) + spSMBt + hpHMLt + upUMDt + e_{i,t},$$

where $R_{i,t}$ is the stock return for firm i in month t, $R_{f,t}$ is the risk-free rate of return in month t, $R_{m,t}$ (market factor) is the average market rate of return in month t, SMBt (size factor) is the return on a value-weighted portfolio of small stocks less the return of big stocks in month t, HMLt (value factor) is the return on a value-weighted portfolio of high book-to-market stocks less the return on a value-weighted portfolio of low book-to-market stocks at month t, and UMDt (momentum factor) is the average return on two high-prior-return portfolios less the average return on two low-prior-return portfolios at month t.

The data source for the four-factor financial model was Kenneth French's Web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/). We obtained data for R_{it} from the University of Chicago's CRSP database. Thus, we estimated a four-factor model for each firm in each year to capture shareholder returns as α_0 (alpha) and idiosyncratic risk as the variance of $e_{i,t}$.

Customer assets. To determine the breadth (diversity and scope) and depth (focus and intensity) of a firm's customer assets, we used data from the COMPUSTAT Business Segment database, which provides firm sales revenues for different business operating segments, defined by their four-digit SIC codes. We used five-year windows to calculate the customer asset measures. For example, customer assets for 2005 depended on the firm's sales revenues in its specific business operating segments and the overall industry sales revenues of the pertinent four-digit SIC for 2001–2005.

The calculation of customer asset breadth, as we show in Equation 2, uses $p_{j,c} = n_{j,c}/\Sigma n_{j,c}$ to represent the proportion of a firm's sales revenue in segment j relative to overall sales revenue. We squared each p and took the sum over all business segments. Customer asset breadth equaled 0 when a firm's sales all occurred in a single business segment (low customer asset breadth) but moved toward 1 when the firm spread its sales over many business segments (high customer asset breadth), indicating greater diversity and scope in the firm's customer portfolio:

$$\text{(2)} \qquad \text{Customer asset breadth} = 1 - \sum_{j=1}^{c} p_{j,c}^2.$$

We measured customer asset depth as the average ratio of a firm's sales revenue to the industry's overall sales revenue across each operating segment. For example, Hewlett-Packard operates in multiple segments (imaging and printing group [SIC 3577], personal systems group [SIC 3571], services [SIC 7373], and financial services [SIC 6141]). For each of these segments, we calculated the ratio of Hewlett-Packard's revenue to the overall sales revenues in the segment across all firms and then averaged these ratios across its multiple segments. Thus, the measure provided an indication of the focus or intensity of the firm's customer assets.

Innovation assets. To measure a firm's innovation asset depth and breadth, we relied on a secondary data source that summarized patents granted to firms. In high-tech industries, firms often use patents to protect their innovation knowledge; therefore, patents offer good proxies of innovation assets. We obtained patent data from Thomson Scientific Delphion. Furthermore, we considered patents granted by the U.S. Patent and Trademark Office from 1990 to 2005. We used a five-year window to measure the firm's innovation assets, so to capture innovation assets in 2005, we examined the firm's granted patents filed between 2001 and 2005, inclusive. Finally, to construct a meaningful measure of innovation assets, we deleted firms with insufficient granted patents (i.e., fewer than ten).

To calculate innovation asset breadth, we relied on principles underpinning concentration index measures, such as the Herfindahl index, and the granted patent's national classes. The patent record contained primary national classes, which the U.S. Patent and Trademark Office uses to categorize patents into different subject areas. For firm i's breadth measure in year t, we calculated the number of national classes (c) of patents it filed between (t – 4) and t and denoted the number of times its patents fell into national class j as $n_{j,c}$ (j = 1, …, c). Then, $p_{j,c} = n_{j,c}/\Sigma n_{j,c}$ represented the proportion of national class j compared with the cumulative occurrence of all patents. We squared each p and took the sum over all national classes. Because we were interested in an index of breadth, not concentration, we subtracted this sum from 1 (see Equation 3). Innovation asset breadth equaled 0 when a firm's granted patents all occurred in a single class and moved toward 1 when the firm spread its patents over many national classes. Similar to customer asset depth, the innovation asset depth measure used the average ratio of a firm's filed patents in each national class to the overall number of patents in that class across all national classes.

$$\text{(3)} \qquad \text{Innovation asset breadth} = 1 - \sum_{j=1}^{c} p_{j,c}^2.$$

As a robustness check for using patent data as an indicator of innovation assets, we collected data about firm innovativeness from *Fortune*'s "Most Admired Company" list. We were able to match 432 observations with our data set and run regressions of innovation asset depth and breadth, firm size, profits, industry dynamism, and competition, on firm innovativeness obtained from the *Fortune* database. The results indicated that both innovation depth and breadth had positive effects ($p < .01$) on firm innovativeness, increasing our confidence in our measures.

Industry dynamism. To calculate industry dynamism, we divided the standard deviation of sales in the firm's product industry (four-digit SIC code) across the prior five years by the mean value of industry sales for those years (Fang, Palmatier, and Steenkamp 2008).

Control variables. We included several time-varying control variables in our model. At the industry level, we controlled for industry competitiveness, growth, and size. For industry competitiveness, we used a Herfindahl index, in which we squared each firm's market share and took the sum over all firms in the industry. Because we were interested in industry competitiveness, not concentration, we subtracted the sum from 1 for our measure. Industry growth represented growth in sales for the overall industry during the previous five years. Finally, we measured industry size as the log-transformation of overall sales in the firm's primary industry.

At the firm level, we controlled for marketing and research-and-development (R&D) intensity, firm size, and firm profitability. Marketing intensity was the firm's marketing expenditure divided by its total assets. For R&D intensity, we divided the firm's R&D expenditures by its total assets. Firm size was the log-transformation of the number of employees; firm profitability was the return on sales.

Analysis

To link a firm's customer and innovation assets to performance and performance variability, we used a one-year time lag between measures to control for endogeneity (Boulding and Staelin 1995). We obtained 2857 observations that represented an unbalanced, cross-sectional (n = 348) time series (t = 11). (Because we used five-year periods to create the innovation and customer assets and a one-year lag, we lost six years of data.) In Table 2, we summarize the descriptive statistics for all measures, pooled across firms and time. We mean-centered all variables to aid interpretations. The variance inflation factors for all variables were less than 3.5.

Our data reveal a panel structure, with a time series of observations for multiple firms, so we paid special attention to several estimation issues. First, shareholder return and idiosyncratic risk may be nonstationary, which could bias estimates. However, the statistically significant panel unit root test ($\chi^2 = -12.12$, $p < .01$) indicated that shareholder return was stationary (Cameron and Trivedi 2005). Idiosyncratic risk also was stationary, according to the statistically significant panel unit root test ($\chi^2 = -19.15$, $p < .01$). Second, we checked for first-order serial correlation in errors; the tests rejected the hypothesis of no first-order serial correlation ($p < .01$) for the estimations of shareholder returns and idiosyncratic risk, in support of our inclusion of an autoregressive (AR1) disturbance term. Third, we checked for cross-sectional dependence among error terms by employing a CD test (for shareholder return, 24.46, $p < .01$; for idiosyncratic risk, 19.20, $p < .01$) and Frees's test (for shareholder return, 6.87, $p < .01$; for idiosyncratic risk, 5.63, $p < .01$), both of which rejected the null hypothesis of cross-sectional dependence. Consistent with Chandy, Prabhu, and Antia (2003) and Morgan and Rego (2006), we also com-

Table 2
DESCRIPTIVE STATISTICS AND CORRELATIONS

	M		*SD*		*Correlations*											
Constructs	*Study 1*	*Study 2*	*Study 1*	*Study 2*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*
1. Performance	.0005	4.88	.0022	1.02	1.00	–.22	.24	.20	.17	.19	–.09	–.14	.23	–.07	.14	.20
2. Performance variability	.0009	4.12	.0016	1.14	.16	1.00	–.16	–.21	–.17	–.23	.14	.04	.06	–.13	–.05	.04
3. Customer asset breadth	.34	4.29	.22	1.11	.04	–.09	1.00	.09	.39	.22	–.09	.10	.09	.19	.03	.14
4. Innovation asset breadth	.49	4.03	.18	.98	.08	–.02	–.03	1.00	.11	.42	–.04	.08	.14	.17	.09	–.03
5. Customer asset depth	.05	4.55	.08	1.03	.13	–.03	.29	.05	1.00	.18	–.11	.05	.10	.20	.08	.12
6. Innovation asset depth	.02	5.01	.03	1.32	.01	.03	.06	.23	–.02	1.00	.05	–.07	.11	.13	.19	.09
7. Industry competitiveness	.72	5.35	.23	1.27	–.02	.04	.03	.06	–.11	.08	1.00	.21	.10	.02	.04	–.09
8. Industry dynamism	.14	5.25	.10	1.15	.01	.03	.01	–.03	.01	.07	.14	1.00	.28	–.10	.05	.06
9. Industry growth	.13	5.01	.19	1.17	.02	.04	–.08	.09	.06	–.03	.10	.06	1.00	.03	.06	–.10
10. Marketing intensity	.19	.10	.30	.38	.02	.20	.07	.10	–.03	.03	.02	.04	.03	1.00	.16	–.11
11. R&D intensity	.14	.09	.22	.24	.07	.18	.03	–.02	.19	.17	.04	.08	.05	.25	1.00	–.03
12. Firm size	2.46	2.03	1.01	.44	–.15	–.50	.25	.15	.19	.21	.09	.02	.05	–.18	–.14	1.00

Notes: Correlations for Study 1 (2) are reported below (above) the diagonal. Study 1 (2) $r > .03$ (.13), significant at $p < .05$.

puted the White test statistic and Breusch–Pagan statistics; both tests fail to reject the null hypotheses of no heteroskedasticity, indicating that heteroskedasticity is not a problem for either performance or performance variability.[3]

Fourth, in estimating the time-series cross-sectional data, we controlled for unobserved firm-specific effects. Including firm-specific effects also reduces serial correlation in the errors (Cameron and Trivedi 2005). Therefore, we conducted Hausman's test to determine whether we should model the unobserved effects as fixed or random effects. Hausman's test was significant ($p < .05$), so we estimated the fixed-effects model for performance and performance variability using a least square dummy variable estimator. The specification of this fixed effects AR1 model is as follows:

$$
\begin{aligned}
(4)\ & \text{Performance/Performance variability}_{i,t+1} = \\
& \upsilon + \alpha_i + \beta_1\text{Customer asset breadth}_{it} + \beta_2\text{Innovation asset breadth}_{it} \\
& + \beta_3\text{Customer asset depth}_{it} + \beta_4\text{Innovation asset depth}_{it} \\
& + \beta_5\text{Customer asset depth}_{it} \times \text{Innovation asset breadth}_{it} \\
& + \beta_6\text{Innovation asset depth}_{it} \times \text{Customer asset breadth}_{it} \\
& + \beta_7\text{Customer asset breadth}_{it} \times \text{Innovation asset breadth}_{it} \\
& + \beta_8\text{Customer asset depth}_{it} \times \text{Innovation asset depth}_{it} \\
& + \beta_9\text{Industry dynamism}_{it} \times \text{Customer asset depth}_{it} \\
& \times \text{Innovation asset breadth}_{it} + \beta_{10}\text{Industry dynamism}_{it} \\
& \times \text{Innovation asset depth}_{it} \times \text{Customer asset breadth}_{it} \\
& + \beta_{11}\text{Industry dynamism}_{it} \times \text{Customer asset breadth}_{it} \\
& \times \text{Innovation asset breadth}_{it} + \beta_{12}\text{Industry dynamism}_{it} \\
& \times \text{Customer asset depth}_{it} \times \text{Innovation asset depth}_{it} \\
& + \beta_{13}\text{Industry competition}_{it} + \beta_{14}\text{Industry dynamism}_{it} \\
& + \beta_{15}\text{Industry growth}_{it} + \beta_{16}\text{Marketing intensity}_{it} \\
& + \beta_{17}\text{R\&D intensity}_{it} + \beta_{18}\text{Firm size}_{it} + \varepsilon_{it},
\end{aligned}
$$

where υ is the overall constant; α_i are firm-specific fixed effects; ε_{it} = error term, such that $\varepsilon_{it} = \rho\varepsilon_{i(t-1)} + v_{it}$, and v_{it} is iid normal distributed with a mean of zero.

Results

We report the results of Study 1 in Table 3. For both performance and performance variability, as hypothesized interactions are added to the models, incremental R-square indicates a significant improvement in variance explained (i.e., Models 1–3; Models 4–6). Furthermore, for both models, we found support for performance persistence as indicated by the autocorrelation coefficient for performance ($\rho = .21$, $p < .01$) and performance volatility ($\rho = .21$, $p < .01$). With regard to the effects of asset configuration strategies on performance, the results of Model 3 indicated that the interaction between deep customer and broad innovation assets had positive effects on firm performance ($\beta = .14$, $p < .10$), providing marginal support of H_1. We found support for H_2 because the interaction between deep innovation and broad customer assets had a positive effect on firm performance ($\beta = .16$, $p < .05$). In terms of the effects of configuration strategies on firm performance variability, the results in Model 6 indicated that the interaction between deep customer and deep innovation assets had a negative effect on firm performance variability ($\beta = -.18$, $p < .05$), in support of H_4. However, we must reject H_3 because the interaction between broad innovation and broad customer assets was not significant.

Regarding the moderating effect of industry dynamism, we found support for H_{5a}; the interaction between the deep customer–broad innovation configuration strategy and industry dynamism positively affected the performance ($\beta = .20$, $p < .01$). However, H_{5b} did not receive support; the interaction between the deep innovation–broad customer configuration strategy and industry dynamism was not significant. We found support for H_{6a} in the increased negative effect of an asset diversification strategy on performance variability when dynamism increased ($\beta = -.25$, $p < .01$). In contrast, the interaction between asset concentration strategy and dynamism was not significant, in conflict with H_{6b}. Overall, our final models explain approximately 10.1% of the variance in firm performance (shareholder return) and approximately 42.1% in performance variability (idiosyncratic risk). Note that our model explains about four times more variance in performance variability versus performance, which, while consistent with previous research (e.g., Tellis and Johnson 2007), suggests that shareholder return is affected by many other factors besides idiosyncratic risk. Further research should explore additional variables to increase the explanatory power of these models.

Robustness Analysis

To enhance confidence in our results, we conducted several robustness tests to evaluate (1) a two-year lag between independent and dependent variables, (2) alternative measures of firm performance and performance variability, (3) an alternative measure of customer asset depth, and (4) two alternative measures of innovation asset depth and breadth. As we detail in the Web Appendix (see http://www.marketingpower.com/jmrjune11), the overall patterns held across these additional analyses, adding to our confidence in the results.

STUDY 2

Primary Survey Data Collection

As a supplement to Study 1, in Study 2, we relied on primary survey data to validate our model. Rather than using secondary data such as sales and firm patents as proxies for customer and innovation assets, we measured the key constructs using multi-item measures in a survey of senior managers to increase confidence in the underlying theoretical rationale of our predictions. The small sample size and large number of parameters to be estimated means that we cannot test the moderating role of dynamism on the linkage between asset configurations and performance.

The sampling frame consisted of 450 firms in a variety of high-tech industries. We obtained the names and contact information of senior executives from two commercial mailing lists and then contacted and prequalified each executive by telephone. Of this initial list, 268 executives met

[3]As Greene (2003) suggests, we also used a White heteroskedasticity consistent covariance estimator with ordinary least squares estimation to control for heteroskedasticity; the results are consistent.

Table 3

RESULTS: EFFECTS OF CUSTOMER AND INNOVATION ASSET CONFIGURATION STRATEGIES ON FIRM PERFORMANCE AND PERFORMANCE VARIABILITY (STUDY 1)

		Performance (Shareholder Return)			*Performance Variability (Idiosyncratic Risk)*		
Constructs	*Hypotheses*	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 5*	*Model 6*
Effects of Customer and Innovation Assets							
Customer asset breadth		.02 (.25)	.01 (.14)	.01 (.10)	–.23 (–2.93)***	–.20 (–2.35)**	–.18 (–2.12)**
Innovation asset breadth		.20 (2.57)***	.18 (2.23)**	.17 (2.00)**	–.10 (–1.22)	–.06 (–1.00)	–.06 (–.92)
Customer asset depth		.18 (2.24)**	.17 (1.80)**	.16 (1.74)**	.06 (1.07)	.05 (.86)	.05 (.82)
Innovation asset depth		.01 (.14)	.02 (.17)	.02 (.16)	–.04 (–.78)	–.04 (–.67)	–.03 (–.64)
Effects of Asset Configuration Strategies							
Deep customer–broad innovation asset-leveraging strategy	H_1 (+)		.17 (1.82)**	.14 (1.62)*		–.06 (–1.13)	.05 (.81)
Deep innovation–broad customer asset-leveraging strategy	H_2 (+)		.21 (2.86)***	.16 (1.77)**		–.01 (.13)	–.02 (–.28)
Asset diversification strategy (broad–broad)	H_3 (–)		.06 (1.07)	.06 (.92)		–.13 (–1.51)*	–.06 (–1.05)
Asset concentration strategy (deep–deep)	H_4 (–)		.07 (1.11)	.06 (.96)		–.18 (–2.25)**	–.18 (–2.07)**
Moderating Effects of Industry Dynamism							
Deep customer–broad innovation asset leveraging strategy × industry dynamism	H_{5a} (+)			.20 (2.56)***			
Deep innovation–broad customer asset leveraging strategy × industry dynamism	H_{5b} (+)			–.01 (–.03)			
Asset diversification strategy (broad–broad) × industry dynamism	H_{6a} (–)						–.25 (–3.50)***
Asset concentration strategy (deep–deep) × industry dynamism	H_{6b} (–)						.02 (.29)
Control Variables							
Industry competitiveness		–.14 (–1.60)*	–.15 (–1.63)*	–.15 (–1.69)**	.04 (.66)	.04 (.62)	.03 (.57)
Industry dynamism		–.11 (–1.29)	–.12 (–1.32)*	–.12 (–1.32)*	.24 (3.02)***	.21 (2.83)***	.10 (1.30)
Industry growth		.04 (.89)	.04 (.84)	.05 (.86)	.08 (1.21)	.07 (1.10)	.11 (1.47)*
Industry size		.02 (.64)	.02 (.63)	.03 (.65)	–.02 (.05)	–.03 (.08)	–.03 (.06)
Marketing intensity		.02 (.63)	.02 (.54)	.02 (.53)	.03 (.49)	.04 (.58)	.05 (.71)
R&D intensity		.04 (.85)	.04 (.86)	.03 (.72)	–.19 (–2.11)**	–.17 (–1.81)**	–.20 (–2.53)***
Firm size		–.61 (–6.17)***	–.60 (–5.58)***	–.58 (–5.10)***	–.33 (–3.99)***	–.30 (–3.43)***	–.36 (–4.21)***
Firm profitability		.22 (2.79)***	.22 (2.78)***	.22 (2.51)**	–.12 (1.21)	–.09 (1.19)	–.06 (.77)
Firm sales growth		.10 (1.21)	.09 (1.09)	.10 (1.15)	.21 (2.75)***	.18 (2.23)**	.17 (1.96)**
R^2		.09	.09	.10	.36	.40	.42
Incremental R^2 test *p*-value			.02	.02		.00	.00
F-statistics		7.56***	6.89***	6.58***	19.20***	17.15***	15.85***

*$p < .10$.
**$p < .05$.
***$p < .01$.

Notes: Standardized coefficients are reported with t-values in parentheses. We found support for performance persistence in both models because the autocorrelation coefficients for performance ($\rho = .21$, $p < .01$) and performance volatility ($\rho = .21$, $p < .01$) were significant.

the prescreening criteria and agreed to participate. Each qualified executive received a cover letter, a survey questionnaire, and a stamped return envelope. After follow-up telephone calls and a second wave of mailing two weeks after the first wave, we received 182 responses, of which 167 were usable after we eliminated responses with too many missing values (more than 5%) or inadequate levels of informant knowledge or involvement in the firm's strategic decision processes (less than 4 on a seven-point scale). The average knowledge level of respondents was 6.1, and the average involvement level was 5.7, both on seven-point scales. Our response rate was 37.1%, and the respondents included vice presidents of marketing, senior vice presidents, senior marketing managers, project managers, and product managers. We found no significant differences between early versus late respondents.

Measurement

The firm performance measure assessed return on assets, return on equity, and profit margins; the performance variability measure included the stability of the firm's return on assets, return on equity, and profit margins during the previous five years (reverse coded). In the Appendix, we provide a complete list of the measurement items for Study 2.

We used four seven-point Likert scale items, anchored by "strongly disagree" (1) and "strongly agree" (7), to assess customer and innovation asset depth and breadth. We again included several control variables. First, we controlled for industry competiveness, dynamism, and growth with multi-item measures. Second, we asked the respondents to indicate the percentage of their marketing and R&D expenditures relative to their firm's overall assets to control for marketing and R&D intensity. Third, we controlled for firm size.

We assessed the validity of our multi-item measures in two steps. First, we estimated our measurement model by restricting each item to load on its a priori specified factor and allowing the factors to correlate. The overall model indicated acceptable fit indexes: $\chi^2_{(108)} = 243.04$, normed fit index = .95, goodness-of-fit index = .93, confirmatory fit index = .96, and root mean squared error of approximation = .04. As we report in the Appendix, each factor loading was positive and significant at the .01 level, and all constructs indicated acceptable coefficient alphas. Thus, our measures displayed acceptable unidimensionality and convergent validity.

Second, we used a series of nested confirmatory factor model comparisons between pairs of constructs in the model to assess whether chi-square differences existed when we freed the correlations between the latent variables compared with when we constrained them to 1.0. The various chi-square difference tests were all significant and provided evidence of discriminant validity. In addition, the average variance extracted was greater than the squared correlation between the two constructs, in further support of discriminant validity. Because both our independent and dependent variables came from the same source, common method bias could pose a potential threat (Podsakoff et al. 2003); thus, we conducted Harman's single factor test. The largest factor accounted for 28% of the variance; furthermore, the rotated factor loading matrix showed that the items for each latent construct loaded on a single factor while items for different constructs loaded on different factors (e.g., the four items for customer asset breadth loaded on one latent construct, the items for customer asset depth loaded on the second latent construct). We also confirmed that none of the significance levels of correlations among independent and dependent variables changed when we partialed out common method bias using an unrelated "marker variable" (Lendell and Whitney 2001). Thus, on the basis of these tests, we do not believe that common method bias is a serious issue. Note that our multimethod approach helps further alleviate this common methods concern.

Analysis and Results

We used a moderated regression analysis to test our hypotheses with least squares; we mean-centered all variables to improve the interpretability of regression coefficients. We verified the standard regression assumptions using the RESET test and heteroskedasticity using the Breusch–Pagan test. In addition, the variance inflation factor statistic was less than 4.

We summarize the results from Study 2 in Table 4. First, the interaction between customer asset depth and innovation asset breadth (deep customer–broad innovation asset-leveraging strategy) was positively associated with firm performance ($\beta = .21$, $p < .05$), in support of H_1, and the interaction between innovation asset depth and customer asset breadth (deep innovation–broad customer asset-leveraging strategy) was positively associated with performance ($\beta = .27$, $p < .01$), in support of H_2. The interaction between customer asset breadth and innovation asset breadth (asset diversification strategy) was negatively associated with performance variability ($\beta = -.15$, $p < .05$), in support of H_3, but the negative association of the interaction of customer and innovation asset depth (asset concentration strategy) and performance variability was only marginally significant (H_4; $\beta = -.12$, $p < .10$). Thus, the results were consistent with Study 1.

DISCUSSION

Building on Drucker's (1954) astute observation that marketing and innovation are critical for generating current and future economic rents, we investigated how customer and innovation assets operate together to generate and appropriate value and ultimately influence firm performance. Our research focuses on the effect of asset configurations by developing and testing a framework that disaggregates assets to capture the depth and breadth of customer and innovation assets, thereby increasing the understanding of how marketing may affect firm performance and performance variability. We test the effects of asset configuration in two studies: a longitudinal study based on secondary data and a cross-sectional survey study that uses primary data. In this section, we contrast the results from both of the studies, discuss the implications of our research, and elaborate on the limitations and future research opportunities.

Overview and Comparison of Findings in Study 1 and 2

We offered six hypotheses, two that suggest a positive link between deep–broad asset configuration strategies and firm performance (H_1 and H_2), two that suggest a negative link between concentration and diversification asset configuration strategies and performance variability (H_3 and H_4),

Table 4

RESULTS: EFFECTS OF CUSTOMER AND INNOVATION ASSET CONFIGURATION STRATEGIES ON FIRM PERFORMANCE AND PERFORMANCE VARIABILITY (STUDY 2)

Constructs	*Hypotheses*	*Performance*		*Performance Variability*	
Effects of Customer and Innovation Assets					
Customer asset breadth		.14 (.10)	.11 (.13)	–.17 (.10)**	–.20 (.13)*
Innovation asset breadth		.22 (.10)**	.24 (.12)**	–.22 (.10)**	–.27 (.15)**
Customer asset depth		.27 (.08)***	.33 (.11)***	.04 (.07)	.07 (.10)
Innovation asset depth		.11 (.09)	.08 (.11)	–.11 (.10)	–.09 (.15)
Effects of Asset Configuration Strategies					
Deep customer–broad innovation asset leveraging strategy	H_1 (+)		.21 (.10)**		–.09 (.09)
Deep innovation–broad customer asset leveraging strategy	H_2 (+)		.27 (.09)***		.05 (.09)
Asset diversification strategy (broad–broad)	H_3 (–)		.09 (.11)		–.15 (.07)**
Asset concentration strategy (deep–deep)	H_4 (–)		.14 (.09)*		–.12 (.07)*
Control Variables					
Industry competitiveness		–.22 (.58)	–.25 (.62)	.05 (.09)	.06 (.09)
Industry dynamism		–.09 (.10)	–.11 (.12)	.14 (.08)**	.12 (.09)
Industry growth		.22 (.12)**	.20 (.11)**	–.14 (.10)	–.10 (.13)
Marketing intensity		–.12 (.37)	–.15 (.31)	.16 (.17)	.16 (.18)
R&D intensity		.26 (.40)	.21 (.43)	.18 (.18)	.17 (.19)
Firm size		.04 (.23)	.06 (.29)	–.25 (.11)**	–.28 (.12)**
R^2		.17	.19	.15	.17
F-statistics		3.62***	2.58***	3.12***	2.17***

*$p < .10$.
**$p < .05$.
***$p < .01$.
Notes: Unstandarized coefficients are reported with standard errors in parentheses.

and two that focus on the moderating effect of industry dynamism (H_5 and H_6). While Study 1 tests all the hypotheses, Study 2 tests only the first four hypotheses. As Table 5 shows, the findings are largely consistent between the two studies. Specifically, H_1, H_2, and H_4 are either marginally ($p < .10$) or strongly ($p < .05$) supported in both studies. However, for H_3, we only find support in Study 2.

These differences in the results, while slight, deserve some scrutiny. The differences in results between the two studies can arise because of (1) differences in the context, (2) differences in the way data were collected, and (3) differences in model specification. Both studies were in high-tech industries, suggesting minimal contextual differences. In Study 1, we rely on data from multiple secondary sources, and Study 2 uses survey data; thus, if anything, the results of Study 2 should be stronger as a result of common method issues. Contrary to this premise, H_4 is marginally supported in Study 2 ($p < .10$) and strongly supported in Study 1 ($p < .05$). However, because we are only able to include industry dynamism as a moderator in Study 1, model specification may account for the differences in results between the two studies. This conjecture is supported by comparing the results in Table 3 before adding industry dynamism's interaction term (i.e., firm performance–Model 2 and performance

Table 5

OVERVIEW OF FINDINGS BETWEEN TWO STUDIES

Asset Configuration Strategies	*Hypotheses*	*Direction of Hypotheses*	*Moderator: Industry Dynamism*	*Dependent Variable*	*Study 1 Results*	*Study 2 Results*
Deep customer–broad innovation asset leveraging strategy	H_1	Positive	Not applicable	Firm performance	Marginally supported	Supported
Deep innovation–broad customer asset leveraging strategy	H_2	Positive	Not applicable	Firm performance	Supported	Supported
Asset diversification strategy (broad–broad)	H_3	Negative	Not applicable	Performance variability	Not supported	Supported
Asset concentration strategy (deep–deep)	H_4	Negative	Not applicable	Performance variability	Supported	Marginally supported
Deep customer–broad innovation asset leveraging strategy × industry dynamism	H_{5a}	Increases positive effect	Increasing dynamism	Firm performance	Supported	Not tested
Deep innovation–broad customer asset leveraging strategy × industry dynamism	H_{5b}	Increases positive effect	Increasing dynamism	Firm performance	Not supported	Not tested
Asset diversification strategy (broad–broad) × industry dynamism	H_{6a}	Increases negative effect	Increasing dynamism	Performance variability	Supported	Not tested
Asset concentration strategy (deep–deep) × industry dynamism	H_{6b}	Increases negative effect	Increasing dynamism	Performance variability	Not supported	Not tested

variability–Model 5) with those in Table 4, in which the first four hypotheses are all significant in both studies ($p < .05$ or .10). Thus, the slight differences in final results appear to be driven by the inclusion of industry dynamism in Study 1, which represents a more complete specification, so we use Study 1 to draw implications for theory and practice.

Implications for Theory

The primary theoretical implications from our research are in two areas: (1) asset configuration strategies and (2) risk–return trade-offs. Our results suggest that while customer and innovation assets can have a direct effect on performance, the largest effect on performance occurs when these assets are optimally configured to both generate and appropriate value. For example, deep customer–broad innovation and deep innovation–broad customer asset-leveraging strategies resulted in the highest firm performance in our samples. Specifically, the benefits generated from rare and hard-to-duplicate deep assets are leveraged when matched with multiple contexts offered by broad assets, leading to above-average firm performance.

Support for our conceptual model has some important theoretical implications for applying the RBV and configuration theory to marketing assets. Identifying when customer and innovation assets are VRIN may offer guidance regarding their impact on building sustainable competitive advantage (Barney 1991). However, decomposing assets into depth and breadth components may be critical to understanding when the asset provides a unique, rare, and hard-to-duplicate benefit (depth) versus when it also offers a context or opportunity to capture value from the unique asset (breadth). Thus, depth and breadth may be fundamental units of analysis for evaluating such assets, and better than the aggregated measures of assets that typically appear in extant literature. Our finding that an appropriate configuration of customer and innovation assets influences performance builds on the RBV and configuration theory, which assert that the architecture of assets is critical to performance. For example, Conner (1991, pp. 134, 138, italics in original) makes a compelling argument that a "bundle of *linked*" assets that are "specific" to a firm and not "purchasable" creates causal ambiguity and superior long-term performance.

Furthermore, it seems that the payoffs from deep customer–broad innovation asset configuration increases as industry dynamism increases, which is consistent with theory in that both internal fit (between bundles of assets) and external fit (between firm asset configurations and the environment) are key to business success.

Our results also demonstrate a consistent risk–return trade-off, in which high-return configuration strategies come at the price of increases in performance variability, which suggests the need to adopt a risk-adjusted return approach when evaluating the effectiveness of these assets. For example, the best-performing configurations typically exhibited the highest variability. Parallel to financial theory, diversifying customer and innovation assets by increasing the breadth (scope and diversity) of a firm's customers and technologies reduces performance variability, both individually and synergistically, in that asset breadth has negative direct effects on variability, and the interaction of asset breadth also suppresses variability.

Less intuitive is the reduction in performance variability suggested by the interaction of customer and innovation asset depth (similar variability suppression as achieved by the asset diversification strategy), which stems from the alignment of deep customer knowledge with deep knowledge about focal technologies.

Implications for Practice

To draw implications for practice, we conducted a post hoc analysis to clarify the effect of asset configuration strategies on firm outcomes by splitting (median) the sample by both customer and innovation depth and breadth to generate a 2 × 2 matrix and determining the means of firm financial performance and performance variability for the four strategies (we used data from Study 1 for this presentation; see Figure 2). This approach enabled us to evaluate actual firm performance in our sample, independent of the model specification. The best configuration strategy in terms of firm performance was the deep customer–broad innovation asset-leveraging strategy, in support of positive direct and interaction effects of deep customer and broad innovation on performance. The asset diversification (broad–broad) configuration showed the worst performance; firms without a unique or rare asset have difficulty attaining a competitive advantage, consistent with the RBV's requirements (i.e., VRIN) for rent-generating assets.

Thus, managers should adopt a nuanced view of their customer and innovation assets and understand that customers and technology portfolios are performance-enhancing assets, but performance improves even further when deep assets (unique and rare) align with broad assets (opportunity). For example, firms with deep customer assets may seek partners and acquisition candidates with broad technology portfolios to generate significant returns. Performance-minded firms should be conscious of the need to balance their resource investments across customer and innovation asset domains if they hope to take advantage of potential synergies.

Figure 2

COMPARISON OF THE EFFECTS OF CUSTOMER AND INNOVATION ASSET CONFIGURATION STRATEGIES ON PERFORMANCE

Customer Assets	Innovation Assets: High Depth	Innovation Assets: High Breadth
High Breadth	**Deep Innovation–Broad Customer Asset Leveraging Strategy** High performance (1.6) High performance variability (.7)	**Asset Diversification Strategy** Lowest performance (.9) Lowest performance variability (.4)
High Depth	**Asset Concentration Strategy** Low Performance (1.2) Low performance variability (.5)	**Deep Customer–-Broad Innovation Asset Leveraging Strategy** Highest performance (1.7) High performance variability (.7)

Notes: These post hoc results indicate the means of the subgroups formed by median splitting the Study 1 sample on the basis of customer and innovative asset depth and breadth. The average of each cell's performance is the daily stock return (1000s), and the performance variability is the daily stock idiosyncratic variance (1000s).

Managers should also take a risk–return or portfolio perspective when making asset decisions; some asset configuration strategies are better at increasing performance, but such increases come at the cost of variability. Diversification through broader marketing assets seems to help suppress risk, though at some loss of performance.

Limitations and Further Research

Using two different methodologies and samples increases confidence in our results, but each approach has its own weaknesses. Study 1 used secondary data as proxies for our theoretically based constructs, though it also benefited from the strong external validity obtained by using firms' actual measures over time. Study 2 used theoretically precise and internally valid measures but relied on managers' reports and thus may have suffered from common method bias. The cross-sectional design of Study 2 prevents us from establishing causality and only allows us to establish associations. However, the consistent results between the two studies, robustness analyses, and post hoc tests helped undermine the specific issues of any one approach.

In Study 1, we use patent data to calculate measures of innovation asset depth and breadth, which has limitations. For example, a firm's innovation assets may be largely unpatented because they are unpatentable or because a firm chooses not to patent. However, researchers have argued that codified (patented) innovation assets and uncodified innovation assets are "highly complementary," such that patents should "function as a partial, noisy indicator of its unpatented technological resources" and thus, if anything, "the coefficients of (using patents) will be biased downward" (Silverman 1999, p. 1113).

We recognized that it is the configuration of assets that helps firms accomplish performance objectives and that industry dynamism plays a critical role in determining the efficacy of the configurations. Further research is needed to refine and continue to develop these asset configuration strategies. Such research could proceed in at least three directions. First, researchers could study other firm assets, such as relational assets emanating from supplier relationships and assets related to internal organizational business processes. Second, in addition to industry dynamism, researchers could study other contextual factors, such as technological intensity and resource dependency. Third, researchers could study the effect of asset configuration from a competitive rivalry perspective. For example, in an oligopoly setting (e.g., Komatsu and Caterpillar) in which firms compete in multiple markets, firms may have more opportunities for levering assets across market and technology spaces.

In conclusion, using configuration theory and the RBV of the firm, we have determined how asset configuration strategies drive firm performance and performance variability. Empirical results from two studies suggested that performance is highest when firms employ complementary configurations that generate value from rare and hard-to-duplicate deep assets and capture value across multiple contexts through broad assets. In contrast, firm performance variability decreases in the presence of deep–deep and broad–broad asset configuration strategies. The results suggest that the effect of configuration strategies on performance is greater in dynamic than in stable environments.

Appendix

CONSTRUCT MEASURES FROM STUDY 2

	Loadings
Performance	
During the last five years, how do you rate your firm's overall level of performance in: ("low/high")	
1. Profit margin	.73
2. Return on assets	.72
3. Return on equity	.79
Performance Variability	
During the last five years, how do you rate your firm's stability (reverse coded) of performance in: ("stable/unstable")	
1. Profit margin	.80
2. Return on assets	.69
3. Return on equity	.72
Customer Asset Breadth (During the last five years...)	
1. Our firm has developed very diverse customer knowledge.	.70
2. Our firm has developed customer segments with distinctive customer characteristics.	.80
3. Our firm has established relationships with very diverse channel members.	.72
4. Our firm has acquired customers with different profiles and behavior patterns.	.73
Innovation Asset Breadth (During the last five years...)	
1. Our firm has developed a diverse technology portfolio.	.71
2. Our firm has established a broad knowledge base of new technologies.	.75
3. Our firm has accumulated extensive know-how regarding new product and service development.	.66
4. Our firm has developed extensive knowledge of engineering management across different industries.	.82
Customer Asset Depth (During the last five years...)	
1. Our firm has developed deep knowledge about our customers' profiles and behavior patterns.	.78
2. Our existing customers have indicated high levels of customer loyalty to our products and/services.	.69
3. Our firm has established strong relationships with our existing customers.	.70
4. Our firm has established strong relationships with our existing channel members.	.81
Innovation Asset Depth (During the last five years...)	
1. Our firm has developed a deep innovation portfolio.	.76
2. Our firm has accumulated profound understanding of our existing technologies.	.65
3. Our firm has established thorough know-how regarding our product and service offerings.	.80
4. Our firm has developed deep understandings of engineering management in our industry.	.76
Industry Competitiveness (During the last five years...)	
1. Competition in our industry was cutthroat.	.77
2. There were many "promotion wars" in our industry.	.74
3. Anything that one competitor can offer, others could match readily.	.80
4. One hears of a new competitor move almost every day.	.71
5. Our competitors were relatively weak.	.76
Industry Dynamism (During the last five years...)	
1. In the market, customers' preferences have changed quickly over time.	.75
2. Market demand and consumer tastes have been unpredictable.	.72
3. Actions of consumers and distributors have been highly unpredictable.	.78
4. The industry has been changing very rapidly.	.69
5. It was very difficult to forecast where the technology would be in the next five years.	.67
Industry Growth (During the last five years...)	
1. Customer demand has increased significantly in the industry.	.70
2. The industry has experienced significant sales growth.	.68
3. We have seen significant growth in overall industry sales revenue.	.69

Appendix
CONTINUED

	Loadings
Marketing Intensity (During the last five years...)	
What has been the approximate percentage of your annual marketing investment to firm total assets?	N.A.
R&D Intensity (During the last five years...)	
What has been the approximate percentage of your annual R&D investment to firm total assets?	N.A.
Firm Size	
What is the approximate number of employees in your firm?	N.A.

Notes: All items use seven-point scales anchored by 1 = "strongly disagree" and 7 = "strongly agree," unless otherwise indicated. N.A. = not applicable.

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