Within-Industry Diversification and Firm Performance—An S-shaped Hypothesis

Niron Hashai

Jerusalem School of Business Administration
The Hebrew University

Mt. Scopus, Jerusalem 91905
Israel
Tel: +972-(0)2-5883110
Fax: +972-(0)2-5881341
e-mail: nironH@mscc.huji.ac.il

Key words: within-industry diversification, adjustment costs, coordination costs, firm performance, high technology SMEs.

Abstract

This study shows that the interplay between “adjustment costs”, "coordination costs” and within-industry diversification benefits, results in an S-shaped relationship between within-industry diversification and firm performance. At low levels of within industry diversification, coordination costs are negligible but “adjustment costs” are higher than the synergy benefits of a limited product scope, hence leading to negative performance outcomes. At moderate levels of within within-industry diversification synergies between related product categories substantially increase and outweigh the rise in adjustment and coordination costs, resulting in positive performance outcomes. Yet, extensive within-industry diversification gives rise to considerable coordination costs, which, coupled with adjustment costs, outweigh synergy effects and hamper performance. The study further shows that a greater change rate of within-industry diversification results in negative performance outcomes.

This article has been accepted for publication and undergone full peer review but has not been through the copyediting, typesetting, pagination and proofreading process, which may lead to differences between this version and the Version of Record. Please cite this article as doi: 10.1002/smj.2290

Many firms focus their operations on a limited number of products within their core industry (Li and Greenwood, 2004; Stern and Henderson, 2004; Tanriverdi and Lee, 2008; Zahavi and Lavie, 2013). *Given Imaging* (GIVN), an innovative medical-device company, demonstrates such within-industry diversification nicely. While operating only in the medical-device industry, *Given Imaging* offers very different product categories including: capsule endoscopy (a specialized capsule that allows visualization and detection of disorders of the GI [GastroIntenstinal] tract through an embedded camera), pH-monitoring systems (providing a catheter-free ambulatory pH test), high-resolution manometry systems (pressure-sensitive measurement devices), GI-function testing devices, and reflux ambulatory monitoring systems.

The evidence on the relationship between within-industry diversification and firm performance is mixed and inconclusive (Zahavi and Lavie, 2013). This may be the outcome of the fact that the performance implications of within-industry diversification are often masked by the effect of the level of sales in each product category, which, in turn, is usually correlated with both firm and industry stages of development. Given that within-industry diversification often occurs in parallel to firm and industry development, it is likely that for many firms these effects are confounded. A potentially important strategic question is therefore: *How does within-industry diversification affect performance, regardless of firm and industry development?*

The current study presents a novel theory regarding the costs and benefits of within-industry diversification and empirically investigates the performance implications of within-industry diversification and its rate of change, while controlling for firm and industry stages of development. I hypothesize and empirically demonstrate an S-shaped relationship between a firm's core-industry diversification level and its performance. This S-curve association results from two types of costs: 1) adjustment costs, representing the inefficiencies in transferring and adapting resources to different product categories; and 2) coordination costs, representing the complexities of sharing and creating effective linkages between different product categories, and the interplay of these costs with the synergy benefits of within-industry diversification at different levels. At low levels of within-industry diversification, firm performance actually declines with increases in product scope. Since coordination costs are still negligible at such levels, adjustment costs predominately trigger this decline, where they outweigh the modest synergy effects on performance at low within-industry diversification levels. At moderate levels of within-industry diversification, the relationship between within-industry diversification and performance becomes positive, where scope economies lead to greater synergy realization, which outweighs the rise in adjustment and coordination costs. Finally, at extensive levels of within-industry diversification, performance declines again due to the considerable rise in coordination costs, which, coupled with adjustment costs, outweigh the positive effects of within-industry diversification synergy on performance. I further argue that a greater change rate of within-industry diversification intensifies adjustment and coordination costs, thus resulting in negative performance outcomes. These predictions find broad support in an analysis of the within-industry diversification of a sample of Israel-based high technology firms when both firm and industry stages of development are taken into account. The sample has the advantage of including firms operating in several core industries, indicating that the S-shaped relationship holds in different industry settings. The study makes an important distinction between "adjustment" and "coordination" costs. These two concepts have long been central parts of the strategic management literature (Jones and Hill, 1988; Penrose, 1959) but have rarely been treated jointly. The theoretical framework treats the two concepts together, while distinguishing between their independent effects, arguing that adjustment costs are more dominant determinants of performance decline at low levels of within-industry diversification, while coordination costs gain dominancy at high levels. Importantly, the study shows that coordination costs are not only significant in the case of inter-industry diversification (Rawley, 2010; Zhou, 2011), but are already meaningful in the case of within-industry diversification.

The remainder of this study is organized as follows: the next section presents a theoretical framework that predicts an S-shaped pattern in the within-industry diversification-performance relationship and highlights the predicted effect of the within-industry diversification rate of change on performance; the following section describes the data and methods; the subsequent section presents the results; and the final section discusses the results and draws conclusions as well as theoretical and managerial implications.

BACKGROUND AND THEORETICAL FRAMEWORK

The relationship between within-industry diversification and performance

The extant literature on the relationship between within-industry diversification and firm performance varies substantially in its findings and the performance measures studied. One set of studies concentrates on sales growth as a performance measure. Nobeoka and Cusumano (1997) find that the rate of within-industry diversification is positively correlated with sales growth due to economies of scope in technology sharing. Tanriverdi and Lee (2008) show that software firms' within-industry diversification of "platform" scope (i.e. the range of operating systems that applications serve) and the within-industry diversification of "product market" scope (i.e. the range of applications the firm offers) are both negatively associated with sales growth. These negative performance implications arguably result from greater costs of search and adaptation to effectively match the firms' platform and product market scopes. Only firms pursuing the within-industry diversification of both their platform and product market scopes witness sales growth, which results from the ability to exploit complementarities between the two types of diversification. Recently, Zahavi and Lavie (2013) reported a U-shaped relationship between within-industry diversification and sales growth, contending that "negative transfer effects" trigger an imperfect replication of activities between highly similar, yet sufficiently different products, leading to a reduction in sales at low within-industry diversification levels. Economies of scope and greater product dissimilarity allow sales to increase as the firm further expands its product scope.

Other studies examine the relationship between within-industry diversification and profitability measures. Kekre and Srinivasan (1990) find that increases in firm profitability are associated with broader product lines, while Li and Greenwood (2004) find no significant relationship between within-industry diversification and returns on assets (ROA). Using market share as a performance outcome, Kekre and Srinivasan (1990) find that increases in market share are positively associated with broader product lines. Yet, Tanriverdi and Lee (2008) show that a firm's within-industry diversification of its platform scope is negatively associated with market share, but that the combination of platform- and product-market within-industry diversification positively affects market share.

Finally, another set of studies focuses on market exit and firm survival. In a study of the computer workstation industry, Sorenson (2000) reports that greater product scope reduces the likelihood of a firm's market exit. In a similar vein, Stern and Henderson (2004) find that, in the personal computer industry, the degree of within-industry diversification as well as the introduction rate of new products are both negatively correlated with firm failure rates (defined as market exit or death). On the other hand, Cottrell and Nault (2004) find that, for software firms, greater product- and greater category scopes (i.e. number of different applications) are negatively associated with firm survival, while platform scope is positively associated with firm survival. They also find that a greater introduction of new products increases the likelihood of survival, but a greater entry rate to new categories or platforms decreases it.

Importantly, the expansion of within-industry product scope often occurs in parallel to firm and industry development. It follows that both industry and firm stages of development may influence the relationship between within-industry diversification and firm sales if they occur concurrently. At the industry level, population ecology literature (Caroll and Hannan, 2000; Hannan and Freeman, 1984) essentially suggests that firms first face “liabilities of newness” that are likely to hamper their performance, then gain legitimization, which may allow performance increase, but finally face “liabilities of aging” and inertia, which reduces performance once again. Likewise, the industry life cycle literature (Abernathy and Utterback; 1978; Dosi, 1982; Klepper, 1996) predicts that at early phases of development, industry-level firm performance is usually low due to the low demand and uncertainty regarding technological paradigms. Once a dominant design is established in the market, sales and performance increase and finally decline when the product becomes technologically obsolete and demand slackens.

At the firm level, the literature has ascribed to several generic stages in a firm’s development. These stages include: conception and development of a product category, initial commercialization of the product category, rapid sales growth following the acceptance of the new product category in the market, and finally, stability as the firm exhausts the market potential for its product category (Kazanjian, 1988). Clearly, these stages are also likely to affect firm performance, which is expected to be low at early stages of firm development, increase as the firm grows, and then stabilize at some point.

To sum up, the evidence on the relationship between within-industry diversification and firm performance often highlights industry specific contingencies and is not fully consistent. Furthermore, since none of the past studies has controlled for the possible effect of the industry and firm stages of development, it remains unclear whether within-industry diversification can independently affect performance and under what conditions it does so. A more complete theorization is needed for the relationship between within-industry diversification and performance, where the full range of benefits and costs at different levels and change rates of within-industry diversification are taken into account.

Benefits of within-industry diversification

Within-industry diversification may be considered a more refined way of looking at related diversification (Li and Greenwood, 2004; Tanriverdi and Lee, 2008) and hence is likely to share benefits similar to those occurring in related diversification in terms of firm performance.

The initial impetus for within-industry diversification often comes from the opportunity to exploit market imperfections in the use of indivisible, intangible assets (Penrose, 1959; Teece, 1980). Thus, single-business firms can exploit firm-specific excess assets, especially intangible ones, across multiple product categories (Kor and Leblebici, 2005; Li and Greenwood, 2004; Zahavi and Lavie, 2013). As such, within-industry diversification may allow firms to leverage specific knowledge on technologies, the firm's customer base, its sales and distribution facilities or its experience with existing products, to enhance their performance as well as penetrate additional product categories within their core industry (Stern and Henderson, 2004; Tanriverdi and Lee, 2008).

Engaging in multiple product categories within the same industry can also help enhance the firm's technological knowledge base, capabilities and competitiveness through intra-firm knowledge diffusion (Stern and Henderson, 2004). Each specific product market has its own unique resource endowments and specific advantages, which might not be available for other product categories. Such advantages can be used by firms to augment their competitiveness in both existing and new product markets. Within-industry diversification further helps to increase the firm's revenues by strengthening its market power over competitors, suppliers, distributors and customers (Li and Greenwood, 2004), as well as reducing fluctuations in revenue by spreading investment risks over different product categories. Taken together, within-industry diversification therefore enables firms to realize multiple economies of scope by exploiting synergies between different product categories as a means to increase their performance (Tanriverdi and Lee, 2008; Zahavi and Lavie, 2013).

Costs of within-industry diversification

When diversifying within their industry managers contend with the need to *transfer* indivisible resources to new product categories as well as the need to *share* resources between different product categories (Helfat and Eisenhardt, 2004), which respectively leads to two major types of costs: “adjustment costs” and “coordination costs.” Adjustment costs are stimulated by the need to *transfer* and *adapt* resources to different product categories, while coordination costs result from the need to *share* and *create effective linkages* between the resources used for different product categories. In essence, adjustment costs relate to the imperfect utilization of resources in specific domains, whereas coordination costs relate to the simultaneous use of resources across domains. Both types of costs imply a suboptimal utilization of firm resources where within-industry diversification is concerned.

To a large extent, the two types of costs are shaped by an important attribute of resources, that is whether resources are “scale free” or “non-scale free” (Levinthal and Wu, 2010; Wu, 2013). Scale-free resources are resources whose use for a given task is independent of their use for other tasks. In many respects such resources constitute a within firm “public good.” Technological knowledge is a typical example of this kind of resources. On the other hand, non-scale free resources are those whose use for a specific task comes at the expense of another. The use of non-scale free resources implies the existence of opportunity costs, as it is likely to impose a shortage in resources for alternative tasks. Managerial time and attention, which according to Penrose (1959) are firm-specific resources that cannot be readily hired from outside the firm, are typical examples of non-scale free resources.

Adjustment costs: The concept of “adjustment costs” builds on Penrose's notion of a “dynamic adjustment cost” (Kor and Mahoney, 2000; Mahoney and Pandian, 1992; Penrose, 1959; Tan and Mahoney, 2006), which, in the context of within-industry diversification, specifically refers to the costs of transferring and adapting a firm's existing resources to other areas of operation.

There are many challenges relating to the launch and running of additional product categories, such as the purchase and installation of facilities, the employment of staff, and the establishment of internal management systems and external business networks. When non-scale free resources are transferred from their existing use to other areas of operation, the firm is likely to: 1) bear the expenses of moving people and equipment between different businesses (Helfat and Eisenhardt, 2004); and 2) face a shortage in critical resources required to conduct current tasks and thus the disruption of existing operations (Kor and Mahoney, 2000; Tan and Mahoney, 2006).

Furthermore, an important part of adjustment costs results from the need to adapt existing (scale free and non-scale free) resources to new areas of operation. Firms can be viewed as unique bundles of resources (Barney, 1991) that need to be adjusted to new domains of activity when the firm expands its product scope (Anand, 2004; Anand and Singh, 1997). Such adjustments may often be imperfect and costly as they are constrained by the range of existing routines (Nelson and Winter, 1982; Teece, 1987) and limited knowledge base of the firm (Cohen and Levinthal, 1990).

Given the fact that a diversifying firm is not fully familiar with new product categories, diversification into a new product category increases the likelihood of making mistakes in various business decisions, which leads to the inefficient allocation of resources to new operations (Fernhaber and Patel, 2012). For instance, since sales forces develop specific buyer relationships during long periods of time and embody tacit knowledge about specific product market conditions (Capron and Hulland, 1999), their use in other product markets may be impaired and costly.

Indeed, challenges can be experienced in any new product category, but there are difficulties specific to new product categories that are too close to a given firm's original business. These mostly concentrate around the imperfect replication of the firm's activities in product categories, which are similar yet sufficiently different, rather than pursuing a more nuanced management of operations in different product categories within the same industry (Zahavi and Lavie, 2013). In sum, the disruption of existing operations due to the shortage in resources coupled with the inappropriate redeployment of resources that may support operations in existing products, but not in in less familiar product categories, pave the way to the rise of adjustment costs.

Coordination costs: Within-industry diversification is also expected to lead to costs related to sharing and creating effective linkages between different product categories (Jones and Hill, 1988; Rawley, 2010; Zhou, 2011). The sharing of resources between new and existing product categories entails costs when non-scale free resources are involved. Sharing non-scale free resources between existing and new product categories implies, by definition, the existence of opportunity costs, and requires the coordination of resources between multiple product categories to assure the effective management of every product category (Fernhaber and Patel, 2012; Kor and Leblebici, 2005). For instance, the capacity limits to managerial attention (Ocasio, 1997) indicate that managers are more effective when focusing their managerial time, attention and efforts on a single product category relative to the case where they are required to split their time, attention and efforts between tasks related to multiple products (Ocasio, 1997). Engagement in multiple product categories is therefore likely to be associated with the costly and inefficient allocation of managers' time and efforts to the specific tasks demanded by different product categories.

Coordination costs are further stimulated by the need to create and maintain effective communication, information processing, and decision-making mechanisms to make joint planning and scheduling, design schemes for cooperation, as well as determine suitable procedures for sharing scale-free and non-scale free resources (e.g. setting transfer prices). Lack of coordination in managing multiple product categories may result, for instance, in the cannibalization of existing products by new ones (Cottrell and Nault, 2004). In fact, coordination costs may become detrimental for firm performance as they also affect non-shared resources since they often impose bureaucracies, which decrease the autonomy and incentives of specific product categories (Jones and Hill, 1988; Rawley, 2010).

As the number of internal transactions increases with the overall number of product categories developed, produced and marketed by the firm, the complexity of effectively coordinating linkages and interdependencies between product categories belonging to the same core industry as well as integrating intangible resources (such as diverse knowledge resulting from different product categories) can rise dramatically (Cottrell and Nault, 2004; Zhou, 2011). In fact, because product categories within the same core industry are likely to be highly related, their interdependencies are likely to be extensive, further increasing coordination costs (Zhou, 2011). Coordination costs across multiple related product categories may therefore lead to diseconomies in managing a large set of operations and impose ineffective control and governance mechanisms.

Performance across within-industry diversification levels

Given the above benefits and the costs of within-industry diversification, I can now specify how these benefits and costs vary across different levels of within-industry diversification. Figure 1 sums up the interplay of benefits and costs across different within-industry diversification levels.

[Insert Figure 1 about here]

Performance at low within-industry diversification levels: The benefits from within-industry diversification are expected to be quite modest for firms engaging in a very few product categories because of the limited potential to exploit economics of scope and their related synergies. While at low levels of within-industry diversification, coordination costs are expected to be negligible (as firms need to share resources and coordinate operations only between a few product categories), significant adjustment costs are likely to already occur. Such costs will likely center around the diversion of non-scale free resources from their current use and the imperfect adaptation of resources to new product categories. At low of within-industry diversification firms have virtually no supporting routines and knowledge base to efficiently transfer resources to new product categories (Fernhaber and Patel, 2012) and are further likely to bear the costs of imperfect replication of their existing operations in similar yet sufficiently different product categories within their core industry (Zahavi and Lavie, 2013). Taken together, as can be seen in the left hand side of Figure 1, at low levels of within-industry diversification, adjustment costs are likely to increase more rapidly than the modest increase in the benefits of within-industry diversification, leading to the hypothesis that:

> ***Hypothesis 1.*** *At low levels of within-industry diversification the relationship between within-industry diversification and performance is negative.*

Performance at moderate within-industry diversification levels: The benefits of within-industry diversification are expected to increase the more diversified firms are across a greater spread of product categories within their core industry. This results from the greater potential to exploit scope economies and synergies as the number and variety of product categories increases. While at moderate levels of within-industry diversification, coordination costs are still not expected to become acute, adjustment costs are expected to continue and increase the more diversified firms become within their core industry. This is due to the need to adapt resources to multiple new product categories as well as a greater diversion of resources from existing product categories to new ones. Yet, the increase in adjustment costs is likely to be moderated by the fact that some adaptation costs, such as those resulting from the imperfect adaptation of resources when replicating existing activities in similar yet different product categories, may in fact reduce. As firms become engaged in a greater number and variety of product categories, managers are more likely to realize the distinct resources required for different product categories and apply a more nuanced management of operations in different product categories (Zahavi and Lavie, 2013). Likewise, at such levels firms are likely to possess supporting routines and knowledge base to transfer resources to new product categories which may somewhat mitigate the rise in adjustment costs. Hence, relative to low levels of within-industry diversification, at moderate levels of within-industry diversification, I expect the increase in the benefits of within-industry diversification to be larger than the increase in adjustment costs. At moderate levels of within-industry diversification, the benefits of product scope expansion are therefore likely to be higher and increase more rapidly than the sum of corresponding adaptation and coordination costs, leading to performance increase. This view, portrayed in the center part of Figure 1, leads to the hypothesis that:

> ***Hypothesis 2.*** *At moderate levels of within-industry diversification, the relationship between within-industry diversification and performance is positive.*

Performance at high within-industry diversification levels: The benefits of within-industry diversification are unlikely to be infinite. At some level of within-industry diversification, such benefits may well reach the point of diminishing returns as there are limits to scope and synergy economies. This implies that the increase in within-industry diversification benefits is expected to cease at some level. At the same time, adjustment costs are likely to continue and increase with the level of within-industry diversification, and more importantly, coordination costs are likely to substantially intensify as the number of product categories in which firms engage grows. For firms operating an extensive range of product categories, resource sharing and the establishment and maintenance of effective linkages and interdependencies between product categories become complex, and coordination costs escalate (Jones and Hill, 1988; Rawley, 2010; Zhou, 2011). Taken together, at high levels of within-industry diversification, I expect the sum of adjustment and coordination costs to surpass the corresponding benefits of within-industry diversification, hence, reducing firm performance. I portray this view on the right hand side of Figure 1, and hypothesize that:

> ***Hypothesis 3.*** *At high levels of within-industry diversification, the relationship between within-industry diversification and performance is negative.*

Overall, the benefits of within-industry diversification are expected to increase up to a certain limit, adjustment costs are higher than the benefits at first but increase at a lower rate, while coordination costs are low at first but increase exponentially with within-industry diversification. Jointly, as portrayed in Figure 1, these costs result in a nonlinear S-shaped relationship between within-industry diversification and performance, with the slope being negative at low levels of within-industry diversification, positive at moderate levels, and negative again at high levels of within-industry diversification.

The effects of within industry diversification change rate

In addition to the level of within-industry diversification, the rate of change of firms' within-industry diversification may well affect the associated benefits and costs and their slopes and hence influence the performance outcomes of a within-industry diversification strategy. Firms penetrating additional product categories at a greater rate are likely to realize the synergies between these product categories earlier on and hence improve their performance (Nobeoka and Cusumano, 1997; Stern and Henderson, 2004). Yet a particularly high product scope expansion rate may also limit the firm’s managerial capacity to successfully identify complementarities and synergies, and hence, moderate their realization. In fact, both adjustment and coordination costs are likely to escalate when the rate of change in within-industry diversification increases.

In cases where firms enter new product categories quickly, time compression diseconomies (Dierickx and Cool, 1989) will likely arise, intensifying the costs resulting from a shortage in critical resources required for existing product categories and the inappropriate redeployment of resources in new product categories. When firms expand to more product categories at any given period, the need to divert non-scale free resources from their current use increases, and so does the shortage in such resources for existing operations and new ones (Kor and Mahoney, 2000; Tan and Mahoney, 2006). Expansion to a large number of product categories in a given period is further likely to require greater adaptation of resources and routines to new product categories, at any given point of time, which in turn is likely be more complex and costly (Dierickx and Cool, 1989; Mahoney and Pandian, 1992; Vermeulen and Barkema, 2002). Hence, the increase in the demand for resources, required for entering new product categories, and for their adaptation, is likely to be accompanied by convex adjustment costs—i.e., the costs of expansion may increase disproportionally to the benefits when the rate of expansion is accelerated (Knott, Bryce and Posen, 2003). Thus, entering a large number of product categories within a short period of time will likely infer greater adjustment costs and greater growth rate of such costs than a more moderate product scope expansion.

Greater rate of within-industry diversification is further expected to increase the coordination costs of managing multiple product categories. Once again the increase in the demand for sharing non-scale free resources and the increased requirement for linkages between different product categories are expected to escalate, the greater the rate of change at any given time period. Such escalation will likely result in greater complexity involved in such resource sharing and coordination (Dierickx and Cool, 1989; Vermeulen and Barkema, 2002), leading to an increase in coordination costs and their rate of growth (Zhou, 2011) relative to a more moderate product scope expansion.

Taken together, I expect that a greater rate of change in within-industry diversification will result in a moderate increase in benefits, which is likely to be outweighed by a more substantial increase in both adjustment and coordination costs. I therefore hypothesize that:

Hypothesis 4. *A greater within-industry diversification change rate is negatively related to firm performance.*

DATA AND METHODS

Sample

To test my hypotheses regarding the relationship between within-industry diversification and firm performance I need fine-grained data on the within-industry diversification of firms, which mostly operate in single core industries. Data regarding within-industry diversification is not readily available in traditionally used datasets, such as COMPUSTAT, which mostly comprises large, mature and substantially diversified firms (Stern and Henderson, 2004). Within-industry diversification has often been observed in small to medium-sized high technology firms (Stern and Henderson, 2004; Tanriverdi and Lee, 2008; Zahavi and Lavie, 2012) where such firms penetrate new product categories to sustain growth. However, the high costs and uncertainty involved in new technology development often lead these firms to a fairly limited expansion of their product categories' scope. This group of firms is also quite homogenous in terms of its strategic motivations for making product category expansions, hence increasing the likelihood of finding a systematic relationship between within-industry diversification and performance. This makes small and medium-sized high technology enterprises (SMEs) natural candidates for analyzing my predictions regarding the within-industry diversification—performance relationship.

I constructed a novel dataset containing specific data on the product scope expansion of a sample of Israel-based, mostly single-business, high technology SMEs. The extensive range of within-industry diversification within this sample of firms enhances the meaningfulness, reliability and variance of the relationships I wish to test. Israel is an appropriate setting for this type of sample because of the high number of Israel-based, high technology, single-business SMEs. Israel is ranked first in the world in the number of high technology start-up initiatives per capita (Bosma and Levie, 2009), and the contribution of the high technology sector, which is mostly composed of small and medium-sized firms, to Israel’s total industrial exports is above 50 percent (Central Bureau of Statistics, 2010).

My hypotheses were tested on a sample of randomly selected high technology private and public firms. The sample was derived from the full list of Israel-based, high technology firms constructed by Dolev and Abramovitz, Ltd. (D&A) consulting firm for the year 2007. Relevant data for the study were collected from multiple secondary and primary sources. D&A is a private company that collects information on the Israeli high technology sector. Its dataset covers information on firms back to the mid-1980s and it publishes periodical reports describing the high technology sector in Israel. The data from the D&A dataset were extensively supplemented with data from: the Israel Venture Capital

(IVC) dataset, annual financial reports, prospectuses and other written reports supplied by firms, press announcements from LexisNexis Academic, archives of leading Israeli financial newspapers such as *TheMarker* and *Globes*, NBER U.S. Patent Citations Data File, and the United States Patent and Trademark Office (USPTO) database (for patent data). The D&A and IVC datasets are both recognized as two comprehensive sources on Israeli high tech industries. Indeed, formal publications of the Israeli Central Bureau of Statistics concerning the high tech industries in Israel are based on the IVC dataset.

The 2007 D&A dataset represents the vast majority of high technology industries and includes 408 high technology firms that have reached the stage of selling their products. My data allows me to examine a sample of firms from several core industries and to test predictions on firms, each operating mostly in a single six-digit NAICS (North American Industrial Classification System) core industry. In that respect, the current study differs from past studies that have typically analyzed firms from a single industry (e.g. Stern and Henderson, 2004; Tanriverdi and Lee, 2008; Zahavi and Lavie, 2013). Data on sales, number of employees, firm age and attracted investments were collected from the D&A and IVC datasets as well as from annual financial reports and prospectuses, which are readily available for public firms. Access was granted to key figures in the financial reports of private firms, which represent 72 percent of the sample. Data on the product categories of the sampled firms were collected from LexisNexis Academic press announcements and the archives of leading Israeli financial newspapers such as *TheMarker* and *Globes*. These archival sources were used to identify announcements on existing and new product categories. Where deemed necessary, within-industry diversification data was supplemented and verified via web-based sources or by contacting the senior management of the firms themselves. These sources provided nearly complete information on the within-industry diversification of the sampled firms, making it possible to develop a relatively complete profile of the sample's within-industry diversification activities.

The number of new product category entries in which the sampled firms were involved (within their core industry) averaged 6.83 with a standard deviation of 3.35 (see Table 1). This range in within-industry diversification activity indicates that the sample captures firms with varying levels of within-industry diversification, as required to test my hypotheses.

Additional data that were unavailable from secondary sources were collected through a personal survey based on structured questionnaires, whereby 200 firms were randomly selected[1] and the senior management of these firms was asked to participate. Senior representatives of 165 firms agreed to participate in the survey and interview, which were carried out by one of the authors and a small group of master's students.[2] The interviews were conducted with two or three senior firm representatives whose replies were triangulated to ensure consistency. The interviewees were typically

[1] Approaching every second firm from a list of alphabetically sorted firms.
[2] Basic T-tests did not reveal evidence of interviewer-specific bias in the collected data.

chairmen, CEOs or senior vice presidents (VPs), where a prerequisite was that they had long enough tenure in the firm to effectively reflect on the firm's history as well as have access to supporting formal documentation.[3] The questionnaires covered a wide range of "hard data" including: number of product categories, stage of firm development, stage of industry development, number of employees, and market size. These data items often originated in written annual financial reports and prospectuses and could therefore be cross-checked for consistency.

Out of the 165 firms, I screened out 18 firms whose interviewees supplied incomplete data. This resulted in a sample of 147 firms. Basic T-test comparisons between the 147 participating firms and the 261 non-participating firms do not show evidence of any non-response bias in terms of the averages of firm sales, number of employees, age of firm, firm valuation or industrial classification (at the six-digit NAICS level). Overall, this procedure resulted in an unbalanced panel data of 896 firm-year observations for the 147 analyzed firms within the period 2000-2007. These firms operate in the following high technology NAICS sectors, including: Printing Machinery and Equipment, Semiconductor Machinery, Optical Instrument and Lens, Computer Terminal, Telephone Apparatus, Radio and Television Broadcasting and Wireless Communications Equipment, Semiconductor and Related Device, Electronic Components, Electromedical and Electrotherapeutic Apparatus, Surgical and Medical Instrument, Software, Custom Computer Programming, and Computer Systems Design.

Dependent and independent variables measures

Appendix Table 1 presents a detailed description of all measures and their sources.

I have used Returns on Sales (ROS) as my measure for *firm performance*. ROS is a highly acceptable measure for firm short-term economic performance (Goerzen and Beamish, 2005). To avoid potential problems that arise from different financing strategies, tax treatments and depreciation rules on different industries, I use firm earnings before interest, tax and depreciation, rather than net earnings.

For within-industry diversification, I developed a count measure for a firm's number of product categories in each year (within each firm's core six-digit NAICS industry). The term "product category" refers to products that differ in their technological specifications and design (Katila and Ahuja, 2002). First, I tracked down the number of product categories for each firm in the year 2000 based on firms' financial and/or own reports. Next, I used press announcements of new product category entries to identify entry to new product categories by each firms. The determination of what constitutes a new product category (rather than a new model of an existing product category) was conducted based on the guidelines of a panel of high technology industry experts. These industry experts first examined the product announcements independently (based on their experience, the data in the press announcement, and web-based information) and then discussed their classifications

[3] Fifty-five percent of the interviewees were at CEO level, 20 percent were at chairman level, and 25 percent were at senior management level (mostly CTOs, CFOs and VPs). The average firm tenure of interviewees was five years and a month, which is only nine months less than the average firm age in the sample.

together.[4] In cases where the industry experts were not in agreement in their individual classifications (less than 10 percent of the cases, reflecting an inter-rater reliability of 0.792), they reached a mutual agreement as to what constitutes a new product category and what is a new model of an existing product. In a few cases, the firms' senior management was contacted to request clarification on their different product categories. Overall, about 3,000 press announcements of new and existing product categories were examined for the sampled firms. These refer to both successful and unsuccessful product launches, because the latter are still exposed to many of the costs discussed in the theoretical section[5]. In addition, I used press announcement to identify cases where the sampled firms have withdrawn from specific product categories and each firm's number of product categories in each year was corrected accordingly.[6] The resulting number of product categories for each firm was then triangulated with the reported number of product categories (in each year), as provided by the firms themselves.[7] The correlation between the two alternative count measures was very high (r=0.931), thus corroborating the classification process.[8]

While this type of count measure has the drawback of not recognizing the size distribution of specific product categories, prior research has indicated that count measures are "among the most basic features of corporate portfolios" (Robins and Wiersema, 2003) and represent "pure diversification" (Kumar, 2009; Robins and Wiersema, 2003; Voss, Sirdeshmukh and Voss, 2008). The critical point here is that weighted diversification measures (such as Herfindahl or entropy) fail to distinguish between a firm's entry into new product categories and expansion within *existing* product categories.[9] A product category count measure may therefore provide a more accurate picture of the expansion of firms into *new* product categories as required for testing the predictions of my hypotheses.

Importantly, I used the linear measure of *within-industry diversification* to test Hypothesis 1, the squared measure of *within-industry diversification* to test Hypothesis 2, and finally added the cubed term of *within-industry diversification* to test Hypothesis 3.

My measure of the *within-industry diversification change rate* was the annual increase in the number of new product categories of a given firm divided by the total number of product categories in the preceding year. This measure was used for testing Hypothesis 4.

<u>*Control measures*</u>

[4] Each announcement was examined by two experts.

[5] Importantly, even in stages where firms still do not sell their products in the market, differences in performance for firms engaging in a different number of product categories are expected, due to adjustment and coordination costs in activities such as product development, design and prototype production.

[6] Less than 10 such cases were identified for the whole sample, which is not surprising given the fairly young age of the firms in my sample.

[7] These reports were either obtained from financial reports and/or the questionnaires.

[8] I used the self-reported product counts in robustness tests and got consistent results.

[9] The Herfindahl and entropy measures may thus indicate product scope expansion as a result of changes in the distribution of product counts across existing product categories, even in cases where no new product is introduced (Kumar, 2009).

The expansion of within-industry product scope often occurs in parallel to firm and industry development. The effects of both firm level and industry level stages of development may likely influence firm performance. Given that my theory regarding the interplay between the benefits and costs of within-industry diversification is independent of the effects of firm and industry stages of development, it is imperative to control for such effects when testing the within-industry diversification-firm performance relationship, in order to unfold confounding performance effects of development stages.

Some of the benefits and costs ascribed to within-industry diversification may intensify according to the firm's development stage. For instance, adjustment and coordination costs are likely to be more acute for firms in early developmental stages that are often limited in their resources (Penrose, 1959). Such firms do not always have the capabilities or the appropriate organizational structures to support the transfer and adaptation of resources between product categories and to coordinate increased product diversity. Over time, however, firms accumulate resources, and may learn to more efficiently adapt their resources into new product categories and coordinate multiple product categories. In turn, this may reduce the adjustment and coordination costs associated with within-industry diversification and hence lead to higher performance.

At the industry level, lack of legitimization at early industry phases (Caroll and Hannan, 2000; Hannan and Freeman, 1984) may likely affect the ability of diversifying firms to reap the benefits of such strategy. On the other hand, inertia in maturing industries may increase firms' adjustment and coordination costs when diversifying. Uncertainty regarding technological paradigms at early phases of industry development (Abernathy and Utterback; 1978; Dosi, 1982; Klepper, 1996) may not only affect the ability of firms to reap the benefits of within-industry diversification, but may also imply adaptation and coordination complexities, which in turn increase both adjustment and coordination costs (Zhou, 2011). While diversifying firms may leverage the benefits of within-industry diversification during the industry sales growth phase, at the decline phase, where technologies become obsolete and demand slackens, the realization of such benefits is hampered and so is firm performance.

I have therefore included controls for firm and industry development. For each firm, I identified its stage of development for each year. Following the classification used in the IVC dataset, in each year, a firm may be in one of the following stages: "*seed*," "*R&D*," "*initial revenue*," and "*revenue growth*." This classification, in essence, corresponds to stages of firm development identified in prior work (e.g. Kazanjian, 1988) and allows for comparable stages of firm development for all the firms in the sample. I am then able to relate to each firm's within-industry diversification while controlling for its stage of development. Firms classified at the "*seed*" stage are those in their early days of product development and fundraising. The "*R&D*" stage includes firms that have been able to reach the stage of discovery and application of new and improved products, processes and services. Typically, such firms already have prototypes of their products, but have not started selling them yet. Firms classified at the "*initial revenue*" stage are those that have started to establish their internal and external marketing and sales infrastructure. This period includes all firms whose yearly revenue does not exceed USD 10 million. Finally, firms belonging to the "*revenue growth*" stage are those that have entered the phase of further developing their sales efforts. This stage includes all firms whose yearly revenues exceed USD 10 million.

The industry development stage was measured in accordance with Abernathy and Utterback (1978), Klepper (1996) and others, to include the following stages: The *fluid phase* where new technological paradigms are launched, industry level demand is low, production systems are unsettled, and multiple technological and business concepts emerge (Abernathy and Utterback, 1978); the *growth phase*, which is characterized by the convergence of technological standards around a "dominant design" (Abernathy and Utterback, 1978; Anderson and Tushman, 1990), common industrial practices, and growth in demand; the *maturity phase*, which signifies a substantial slowdown in the industry growth rate. At this stage, technological, conceptual and operational paradigms have been established (Dosi, 1982) and the importance of economies of scale and scope comes to the forefront (Klepper, 1996). Finally, the *decline phase* is characterized by the shift in consumer preferences to new technologies, resulting in a decrease in the industry sales volume.

Another important control relates to each firm's technological assets, which allows me to control for the possible performance implication of an important type of scale free resource. Firms with more substantial technological assets should be able to generate higher abnormal benefits, enjoy greater scale and scope economies, and be more capable of exploiting market imperfections in the trade of intangible technological assets (Bettis, 1981; Teece, 1980; Robins and Wiersema, 1995). Hence, firm-level technological assets are expected to increase performance. My measure of intangible technological assets is the firm's R&D intensity (the ratio of R&D expenditures to sales). This measure of intangible technological assets is well accepted in the literature (Caves, 1996; Delios and Beamish, 1999; Morck and Young, 1991).[10]

In addition, it is equally important to control for the possible performance consequences of non-scale free resources by controlling for firm size and its fixed and financial assets. Firm size is measured as a logarithm of the number of employees. A logarithmic transformation of this measure is used to reduce skewness. To control for the effects of the firm's *tangible resources*, my models also include a measure of fixed assets. Another factor that may affect firm performance is financial investments made in the firm. I therefore control for the total investments (in USD million) that were made in each firm (up to a given year) by private investors, venture capital funds, corporate venture capital or through public offerings. Since investments were heavily skewed, I used a logarithmic transformation of this measure. I also control for a firm's extent of internationalization that makes competing demands on the managerial time and efforts of high technology firms (Delios and Beamish, 1999).

[10] The number of patent applications and the number of patent citations were used in the robustness tests as alternative measures for technological assets.

The extent of *internationalization* is operationalized by a count number for the number of countries in which each firm supplies its products or services.

Given that performance may be affected by the prior experience of the firm's top management, I include a dummy variable coded as "1" for firms that had, in a given year, members of their top management with *prior* managerial experience in other firms, and "0" otherwise.

Modeling procedures

I examined the effect of within-industry diversification on performance by using the firm-year unit of analysis. All independent variables and controls are lagged by one year, relative to the dependent variables, in order to facilitate causal inference. I further centered the variables on their means to minimize their colinearity. Following past studies (Contractor, Kundu and Hsu, 2003; Lu and Beamish, 2004), I test the S-shaped relationship, implicated from Hypotheses 1–3, by adding to the linear term of *within-industry diversification* its squared term and its cubic term.

I used Two Stage Least Squares (2SLS) regression models. The use of the 2SLS research design stems from the potential endogeneity between performance and diversification (Miller, 2006). In other words, it is unclear whether within-industry diversification is driven by performance or vice versa and whether some exogenous measure (such as the level of non-scale free resources) affects both measures. While lagged independent variables somewhat mitigate such a possible endogeneity, it is still important to rule it out.

2SLS regressions (Wooldridge, 2010) enable the testing of the relationship between two endogenous variables by using two stages where, in the first stage, one of the endogenous variables is estimated based on all other independent variables and then this estimation is used to predict the other endogenous variable. In the current study, following the reasoning of my hypotheses, the first stage variable predicts within-industry diversification, which is then tested in the second stage against the firm's performance.

The 2SLS technique enables accounting for the correlation in the disturbance term across equations, thereby producing more efficient estimates. A crucial condition for such estimation is the inclusion of an instrumental variable (IV), which is correlated with the second stage dependent variables only through its correlation with the first stage variable. The IV used for *within-industry diversification* is the number of technology domains to which the firm's patents are classified in each year. The front page of each patent provides information on the main three-digit technology domain to which the USPTO has assigned the invention. The number of technology domains therefore reflects the technological diversity of the firm. The measure, denoted as *technological diversity*, is likely to be positively associated with the product scope of firms, as different technology domains are often related to different product categories (Hagedoorn and Cloodt, 2003). In contrast, I do not expect to find a significant relationship between *technological diversity* and *performance*, other than through the effect of *within-industry diversification*, where the firm's product scope (resulting from a given level of technological diversity) is expected to directly impact performance. In other words, *technological diversity* is not likely to have a systematic association with the factors in the error term affecting *performance*. The variable *technological diversity* is indeed significantly correlated with *within-industry diversification*, but not with *Ln_sales* (see Table 1) and hence, meets the criteria for being a candidate for an IV. In addition to the linear term of *technological diversity*, I also use the squared and cubed terms of *technological diversity* and its annual rate of change as IVs in the 2SLS regression models.

Applying 2SLS between-firm models with clusters allows to test for inter-firm variance in their within-industry diversification—performance relationships. The cluster method assumes that there is a correlation between observations of specific groups (firms, in this case). Incorporation into a cluster implies that the observations are independent across firms, but not necessarily within firms. It calculates the variance in standard error for each firm separately and hence corrects for the possible deviation in standard error terms. I have further included industry-level fixed effects to test for inter-industry variance in performance that may not have been captured by the industry stage dummies. Industry fixed effects enable me to control for the impact of unobserved, time invariant, industry-specific effects on performance. Inter-temporal trends are controlled with year fixed effects.

RESULTS

Table 1 presents descriptive statistics and a correlation matrix of all the variables in my sample. The table indicates that the firms in the sample are, on average, less than six years old, enroll about 147 employees, have annual sales of about USD 42 million, and their R&D intensity is 0.23.

[Insert Table 1 about here]

Table 2 respectively presents the first-stage regression results for the linear, squared and cubic terms of *within-industry diversification,* and for *within-industry diversification change rate.* It can be seen that all IVs are highly significant in terms of their t-statistics. The F-values of excluded instruments are all larger than the critical number of ten proposed by Staiger and Stock (1997), thus corroborating the strength of the chosen IVs and the robustness of the first stage regressions.

[Insert Table 2 about here]

Table 3 reports the results of the second-stage regression models for *firm performance* (in terms of ROS) as a dependent variable. Model 1 is the baseline model that includes only the control variables. For firm development stages, the *seed* stage serves as the reference stage. It is noteworthy that *R&D* stage is insignificant, while the *initial revenue* stage is positively correlated with *firm performance* (at the five percent significance level) and the *revenue growth* stage has an even stronger positive association with *firm performance* (with a significance level of one percent). For industry development stages the *fluid phase* serves as the reference stage. It can be seen that the *growth phase* is positively associated with *firm performance* (at the five percent significance level), while the *mature phase* is not.[11] These correlations remain robust in models 2–4. Most of the other control variables are also significantly and positively correlated with *firm performance*, except *tangible resources*, and come out insignificant.

In model 2, I add the linear term of *within-industry diversification* as estimated by its IV (*technological diversity*) and the other control variables. Model 2 indicates that *within-industry diversification* is negatively correlated to *firm performance*, thus lending support to Hypothesis 1. In model 3 I add the squared term of *within-industry diversification* (as estimated by *technological diversity squared*). Model 3 indicates that *within-industry diversification squared* is indeed positively correlated to *firm performance*, as predicted in Hypothesis 2. Finally, in model 4 I add the cubed term of *within-industry diversification* (as estimated by *technological diversity cubed*). Model 4 indicates that *within-industry diversification cubed* is negatively correlated to *firm performance*, as predicted in Hypothesis 3.

Together with the predicted effects of *within-industry diversification* and *within-industry diversification squared*, the latter supports the S-shaped relationship between *within-industry diversification* and *firm performance*. Wald tests on the significance of the inclusion of each additional variable indicate that the inclusion of the squared and cubic terms significantly improves the model fit ($p<.01$).

In addition, it is noteworthy that the *within-industry diversification change rate* is also included as an independent variable in models 1-4 and is consistently negatively correlated with *firm performance* as predicted in Hypothesis 4. The second-stage regression results therefore also support Hypothesis 4.

[Insert Table 3 about here]

Figure 2 graphically depicts the relationship between within industry diversification and firm performance for the analyzed sample (based on model 4 in Table 3). The figure shows that the first inflection point occurs slightly above two and a half product categories (at 2.53 product categories). The second inflection point occurs at 9.6 product categories. Both these inflection points fall well within the range of my sample, thus corroborating the feasibility of my findings.

[Insert Figure 2 about here]

<u>*Robustness tests*</u>

I conducted several robustness tests. To further test the validity of the IVs, I conducted a Hansen/Sargan (Sargan, 1988) test for over-identification. Under the null hypothesis the IVs used are the appropriate ones and are uncorrelated with the disturbances (Hall and Peixe, 2003). The Hansen/Sargan test statistics came out strongly significant for all models ($p=.000$), hence verifying that the instrumental variables used are valid and that the models are not over-identified.

[11] None of the firms in the sample reached the industry decline stage in the analyzed time frame.

I further ran 2SLS within-firm fixed-effects models to test whether the results hold for intra-firm variance in within-industry diversification range (rather than for inter-firm variance). The results remained the same, albeit at a lower significance level (mostly $p<0.05$), indicating that the results also hold within specific industries. Another measure to ensure that industry specific profitability does not affect the results was to normalize ROS to the average of each 6 digit NAICS industry analyzed (on an annual basis. I have computed the average ROS per year and industry (typically using 7-11 industry-year observations) and then calculated a normalized ROS measure as: (ROS of firm i- Average ROS in industry j)/ Average ROS in industry j. Results have remained consistent also when using this normalized ROS.

In addition, I have replaced my performance measure with sales growth, which is often considered to be an effective performance measure for small to medium-sized high technology firms (Stuart, 2000; Tanriverdi and Lee, 2008; Zahavi and Lavie, 2013). Results have remained consistent also for this performance measure. I increased the lag structure to two years obtained consistent results, although the explained variance (the value of R^2) became smaller as performance lag increases and the significance levels of the explanatory variables typically reduced to five percent level.

I also used an alternative measure for *within-industry diversification*. The measure is a Herfindahl dispersion index, calculated as one minus the Herfindahl-Hirschman index (HHI) of each firm's number of specific products within each product category. Data for specific products within each product category was obtained from LexisNexis Academic and from the sampled firms, and the classification of product categories was approved by a panel of high technology experts. I assumed the measure to be zero in years where firms have not yet started selling their products, reflecting an index of one. The difference between this measure and the product-category count measure lies in the ability to capture the dispersion of activity across different product categories (according to the number of specific products in each such category) and not only to observe penetration into new product categories. I ran the same between firm 2SLS regressions, as reported in the main analyses, using *technological diversity* and its square and cubic values, as well as *technological diversity change rate* as IVs. The results of these regressions were similar to my main analyses, although at a somewhat lower significance level (around one percent for *within-industry diversification* and *within-industry diversification squared*, but only around seven percent for *within-industry diversification cubed*).

In addition, following Zahavi and Lavie (2013) each product life span was truncated at three years. Once again, results remained robust. Replacing the *R&D intensity* measure with two alternative measures for technological assets: the number of patents and the number of citations (the number of times a given patent was cited) for patents applied for in each year, by each firm, retained results at similar levels of significance and in the same direction.

Another important consideration in testing my models is the fact that my predictions regarding the within-industry diversification–firm performance relationship might suffer from selection bias if the same factors that influenced the change in firm product-scope boundaries also cause firms to fail and drop out of the sample. Failure can either be the death of a firm or its acquisition by another firm (since in the latter case acquired firms have mostly been integrated within much larger acquiring companies and have not retained independent operations, which precludes their separate analysis). Overall, I had 22 failure cases in my sample—15 firms that died out and seven acquired firms. To account for the possibility of survivor bias among the sampled firms, I used the technique described by Barnett (1994) and Henderson (1999). That technique entails the following calculation: $\lambda = [\varphi(\Phi^{-1}[F(t)]]/ [1- F(t)]$, where φ is the standard normal density function, Φ^{-1} is the functional inverse of the standard normal distribution, and F(t) is the cumulative hazard function, which is derived from failure rate models. These failure rate models use the discrete time event history analysis technique to predict failure based on the following variables: firm age, firm age squared, firm sales, market share and industry. In this case, once λ is calculated, it is included as a control in second-stage regression analyses, employing the Heckman (1979) correction. The results, when correcting for survivor bias, have not changed, indicating that the original 2SLS models are robust.

In additional analyses, I added the AR(1) parameter to account for autocorrelation across subsequent records of the same firm. Results indicate that the coefficients for that parameter are mostly insignificant and lower than 0.1, suggesting that such a correction may not be required. It seems that the use of year fixed effects in the model fully account for autocorrelation, so that the AR(1) parameter is redundant.

I further controlled for the fact that 36 percent of the firms in my sample had some activity outside their six-digit NAICS core industry[12] by adding a dummy to indicate whether a firm is operating in more than a single industry. Results did not change. Likewise, adding a dummy to indicate whether a firm is private or public (72 percent of the firms in the sample are private) did not have an effect on the observed S-shaped relationship. Adding a dummy to indicate whether or not a firm has acquired another firm in the time period between 1999 (one year prior to the first year in my panel data) and a given year did not yield any significant results. Likewise, testing whether my findings are affected by the board composition of the sampled firms, in terms of venture capital representation, private investor representation or corporate venture capital representation, did not reveal any significant results.

DISCUSSION AND CONCLUSIONS

This study examines the nature of the relationship between within-industry diversification and firm performance at different levels and change rates of within-industry diversification. The study therefore contributes to the emerging stream of research on within-industry diversification (Li and

[12] These firms can be considered dominant business unit firms (Rumelt, 1974) as the sales of these firms outside their core industry do not exceed 25 percent of their total sales.

Greenwood, 2004; Stern and Henderson, 2004; Tanriverdi and Lee, 2008; Zahavi and Lavie, 2013) with the aim of elucidating the performance implications of this strategy. The study underscores the complex curvilinear performance effects of within-industry diversification, while importantly, controlling for the possible confounding effect of firm and industry stages of development with regard to firm performance.

The study indicates that the emerging body of literature on within-industry diversification has to go beyond simple linear explanations. I find that within-industry diversification has a nonlinear relationship with firm performance. At low levels of within-industry diversification, greater within-industry diversification is associated with performance reduction. At moderate levels of within-industry diversification, greater within-industry diversification is accompanied by performance increase and then at high levels of within-industry diversification, is once again associated with performance reduction. A greater change rate of within-industry diversification reduces firm performance at all levels.

These findings are consistent with those of Zahavi and Lavie (2013) in terms of the decline in performance at low levels of within-industry diversification, but are at odds with Zahavi and Lavie in terms of the decline in performance at high levels[13]. One explanation for these contradictory findings may be the main measure for within-industry diversification, which, unlike that of Zahavi and Lavie (2013), captures only penetration into *new* product categories and not expansion within existing product categories to which the firm has diversified. Indeed, when I use a Herfindahl index as an alternative measure of within-industry diversification, the cubed measure of *within-industry diversification* becomes insignificant. The overall conclusion from these differences is that penetration into a new product category bears adjustment and coordination costs very different from those associated with expansion within existing product categories to which the firm has diversified. The greater adjustment and coordination costs a firm faces for a new product category penetration are likely to be attributed to the lack of experience and familiarity a firm has within such a penetration, relative to the case of expanding operations in a "non-core," yet more familiar, product category. In that respect, this study points to an important distinction between pure diversification into new areas (Kumar, 2009; Robins and Wiersema, 2003) and diversification that mainly consists of operation expansion in existing areas.

A key insight of this study is that firms with limited levels of within-industry diversification are likely to face lower performance than firms operating only with a single product. This result is at odds with most inter-industry diversification-performance studies, which predict an increase in performance for firms operating in closely related industries (Palich et al., 2000). One explanation for the differences in predictions between inter- and intra-industry diversification studies is that in the case of inter-industry diversification, decentralized organizational structures such as the M-form divisional

[13] Importantly, the results do not change also when using the same dependent variable that Zahavi and Lavie (2013) use.

structure (Bartlett and Ghoshal, 1993; Hoskisson, Harrison, and Dubofsky, 1991) are often used. Such structures may reduce the overall organizational complexity of managing multiple businesses through a better allocation of resources and decision-making and reduced coordination costs (Williamson, 1981; Bower, 1986). These organizational structures therefore support the shift from a single-business to a multi-business firm, where semi-autonomous divisions take charge of separate businesses. In contrast, in the case of within-industry diversification, such support of decentralized organizational structures often does not exist, making the emergence of coordination costs more likely.

Importantly, this study identifies two main cost drivers of within-industry diversification. Adjustment costs are stimulated by the need to *transfer* and *adapt* resources to new product categories, and coordination costs result from the need to *share* resources and *create effective linkages* between product categories. These two concepts have long been central parts of the strategic management literature (Jones and Hill, 1988; Penrose, 1959) but have rarely been treated jointly. The theoretical framework treats the two concepts together while highlighting the differences in the costs stemming from an adjustment to new product categories. Adjustment costs result from the diversion of non-scale free resources from their current use, shortage of non-scale free resources (Wu, 2013) in current product categories and the need to adapt scale free and non-scale free resources to new product categories. On the other hand, coordination costs result from the imperfect sharing of non-scale free resources between different product categories, as well as the investments required for creating effective interaction of both shared and non-shared resources (Rawley, 2010; Zhou, 2011) engaged in different tasks.

The theory regarding the role of adjustment and coordination costs in within-industry diversification gives scholars a better understanding of important factors shaping inter-firm performance differences. First, in bringing to the forefront the distinct resource demands at different levels of within-industry diversification. Second, in distinguishing between costs related to the simultaneous use of resources across domains (i.e. when sharing resources and creating linkages between them) and costs related to the imperfect utilization of resources in specific domains (i.e. when transferring and adapting resources). Third, in the distinction between costs related to scale-free resources relative to costs related to non-scale free resources. Evidently, coordination costs may not only arise in highly unrelated diversifying firms, as the extant literature often argues (Bergh and Lawless, 1998; Hill and Hoskisson, 1987; Hitt et al., 1997; Markides, 1992), or for related inter-industry diversifiers as has been recently argued (Zhou, 2011), but can also be prominent at extensive levels of within-industry diversification.

In addition, this study has the advantage of looking at relatively fine-grained diversification levels. In inter-industry diversification studies (see Palich, et al., 2000 for an extensive review of this literature stream), limited levels of diversification are unobserved as they are all compounded under the single industry classification, hence masking strategically important benefits and liability generating factors.

On the other hand, my results are consistent with the extant literature on the geographic diversification-performance relationship. This literature adopts the view that limited levels of geographic diversification decrease performance, moderate levels of geographic diversification increase performance, and extensive geographic diversification decreases performance once again, hence supporting an S-shaped relationship (Contractor, et al., 2003; Lu and Beamish, 2004). Similar to the case of within-industry diversification, this stream of literature is also able to observe limited levels of diversification (e.g. entry into a new foreign country). I contend that the ability to observe more fine-grained levels of diversification is critical as it enables the researcher to observe important relationships that are unobserved otherwise.

Practical implications

This study further offers practical guidance to managers in within-industry diversifying firms. Although care should be taken when interpreting the slopes, heights and inflection points identified in this study, my findings suggest that managers need to take a long-term view of within-industry diversification. At low levels of within-industry diversification, there might not be positive performance implications for within-industry diversification. At such levels, declining performance need not halt product-scope expansion efforts, provided the firm's top management devotes attention to rectifying adjustment costs to permit the intrinsic benefits of within-industry diversification to arise and increase performance. As well as being resolute at low levels of product expansion, managers need to be aware of the potential downside of overly excessive within-industry diversification and to be proactive in the design and implementation of within-industry diversification strategies by keeping the extent of within-industry diversification activities at an optimal level. Alternatively, and perhaps more importantly, management can extend the peak of performance and move the threshold of within-industry diversification to a higher level, by pursuing a slower rate of within industry diversification. As learning tends to be incremental (Levinthal and March, 1993), this, in turn, may allow managers engaging in within-industry diversification learn to adapt organizational structures and systems to handle adjustment and coordination complexities.

Limitations and future research

The most notable limitation of this study is that the empirical results are derived from a sample of Israeli high technology SMEs, thus raising the concern that the findings might be specific to the chosen sample. An implicit assumption in this study is that firms are actively engaged in within-industry diversification. While this assumption is often true, in some industries (often low-technology ones) single-business firms are fairly stagnant in their within-industry diversification. Such firms may be able to mitigate some of the negative performance consequences of low within-industry diversification over time. This is because over time, they are expected to learn how to overcome both adjustment and coordination costs. It follows that such firms may witness different relationships between the extent of their within-industry diversification and their performance. It is therefore important to replicate this study for firms that originate in other countries and operate in other industries to increase the external validity of my theory and findings. Furthermore, the potential effect of the external competitive environment on the within-industry diversification–performance relationship (Henderson and Stern, 2004; Li and Greenwood, 2004; Sorenson, 2000), should be accounted for as means to enrich our understanding of the contingencies affecting the relationship. Hence, future research should begin to explore how the sequence and intensity of within-industry diversification and the markets chosen for expansion (e.g. in terms of their competitiveness level), may affect the factors underlying the identified S-curve relationship and influence its slopes and inflection points. Likewise, adopting a more internal view of within-industry diversification, future research should examine the effects of internal organizational moderators, such as a firm's organizational design and its staffing (Bartlett and Ghoshal, 1993; Hoskisson, et al. 1991; Ocasio, 1997), on the extent to which adjustment and coordination costs arise and thereby on the relationship between within-industry diversification level and change rate and performance.

Conclusion

In developing a comprehensive model of the relationship between within-industry diversification and performance, this study not only makes an important contribution to the understanding of the strategic implications of within-industry diversification, but also allows a more fine-grained distinction between single-business firms as a means to explain their performance heterogeneity. The analyses demonstrate that the relationship between within-industry diversification and the performance of single-business firms varies with the extent of within-industry diversification. In fact, the observations made regarding the adjustment and coordination costs in handling a large number of product categories in the same core industry lead to speculations that these costs may be an important unexplored factor leading firms to diversify *across* industries. It may be that inter-industry diversification is driven by the desire to reduce the connectedness of operations by establishing separable organizational routines and structures that are responsible for the firm's operations in different industries. Inter-industry diversification may result from the reaction of firms witnessing a decrease in performance as their within-industry diversification becomes too excessive. This motivation, coupled with the challenge of simultaneously expanding across and within industries, is therefore an important subject for future inquiry.

Acknowledgements

I wish to thank Mike Hitt and Micki Eisenman for their thoughts and comments on previous versions of this paper and the Asper Center for Entrepreneurship at the Hebrew University for its financial support. An earlier version of this paper was nominated for the Best Paper Award in the SMS annual meeting 2012, at Prague.

REFERENCES

Abernathy W, Utterback J. 1978. Patterns of industrial innovation. *Technology Review* **80**(7): 40–47.

Anderson P, Tushman M. 1990. Technological discontinuities and dominant designs: a cyclical model of technological change. *Administrative Science Quarterly* **35**:604–633.

Ansoff HI. 1957. Strategies for diversification. *Harvard Business Review* **35**(5): 113–124.

Barnett WP. 1994. The liability of collective action: growth and change among early American telephone companies. In *Evolutionary Dynamics of Organizations*, Baum JAC, Singh JV (eds). Oxford University Press: New York: 337–354.

Bartlett CA, Ghoshal S. 1993. Beyond the M-form: toward a managerial theory of the firm. *Strategic Management Journal* **14**(S2): 23–46.

Bergh DD, Lawless MW. 1998. Portfolio restructuring and limits to hierarchical governance: the effects of environmental uncertainty and diversification strategy. *Organization Science* **9**:87–102.

Bettis RA. 1981. Performance differences in related and unrelated diversified firms. *Strategic Management Journal* **2**(4): 379–393.

Bosma N, Levie J. 2009. Global Entrepreneurship Monitor—2009 Global Report.

Bower JL. 1986. *Managing the Resource Allocation Process*. Harvard Business School Press: Boston, M.A.

Carroll GR, Hannan MT. 2000. *The Demography of Corporations and Industries*. Princeton University Press: Princeton, N.J..

Caves RE. 1996. *Multinational Enterprise and Economic Analysis*. Cambridge University Press: Cambridge.

Central Bureau of Statistics. 2010. *Israel Statistical Yearbook 2009*. Central Bureau of Statistics: Jerusalem.

Contractor F, Kundu SK, Hsu CC. 2003. The three-stage theory of international expansion: the link between multinationality and performance in the service sector. *Journal of International Business Studies* **34**(1): 5–18.

Cottrell T, Nault BR. 2004. Product variety and firm survival in the microcomputer software industry. *Strategic Management Journal* **25**(10): 1005–1025.

Delios A, Beamish PW. 1999. Geographic scope, product diversification and the corporate performance of Japanese firms. *Strategic Management Journal* **20**(8): 711–727.

Dierickx I, Cool K. 1989. Asset stock accumulation and sustainability of competitive advantage. *Management Science* **35**(12): 1504–1511.

Dosi G. 1982. Technological paradigms and technological trajectories, *Research Policy* **11**:147-162.

Fernhaber SA, Patel PC. 2012. How do young firms manage product portfolio complexity? the role of absorptive capacity and ambidexterity. *Strategic Management Journal* **33**(13): 1516–1539.

Hannan M, Freeman J. 1984. Structural inertia and organizational change. *American Sociological Review* **49**:149–164.

Heckman J. 1979. Sample selection bias as a specification error. *Econometrica* **47**(1): 153–61.

Henderson AD. 1999. Firm strategy and age dependence: a contingent view of the costs of newness, adolescence and obsolescence. *Administrative Science Quarterly* **44**:281–314.

Hill CWL, Hoskisson RE. 1987. Strategy and structure in the multiproduct firm. *Academy of Management Review* **12**:331–341.

Hitt MA, Hoskisson RE, Kim H. 1997. International diversification: effects on innovation and firm performance in product-diversified firms. *Academy of Management Journal* **40**(4): 767–798.

Hoskisson RE, Harrison JS, Dubofsky DA. 1991. Capital market evaluation of M-form implementation and diversification strategy. *Strategic Management Journal* **12**(4): 271–279.

Jones GR, Hill CWL. 1988. Transaction cost analysis of strategy-structure choice. *Strategic Management Journal* **9**(2): 159–172.

Katila R, Ahuja G. 2002. Something old, something new: a longitudinal study of search behavior and new product introduction. *Academy of Management Journal* **45**(6): 1183–1194.

Kazanjian RK. 1988. Relation of dominant problems to stages of growth in technology-based new ventures. *Academy of Management Journal* **31**(2): 257–279.

Klepper S. 1996. Entry, exit and innovation over the product lifecycle. *American Economic Review* **86**(3):562–583.

Knott AM, Bryce DJ, Posen HE. 2003. On the strategic accumulation of intangible assets. *Organization Science* **14**(2): 192–207.

Kor YY, Leblebici H. 2005. How do interdependencies among human-capital deployment, development and diversification strategies affect firms' financial performance? *Strategic Management Journal* **26**(10): 967–985.

Kor Y, Mahoney JT. 2000. Penrose's resource-based approach: the process and product of research creativity. *Journal of Management Studies* **37**(1): 109–139.

Kumar SMV. 2009. The relationship between product and geographic diversification: the effects of short-run constraints and endogeneity. *Strategic Management Journal* **30**(1): 99–116.

Levinthal DA, March JG. 1993. The myopia of learning. *Strategic Management Journal* **14**: 95–112.

Levinthal D, Wu B. 2010. Opportunity costs and non-scale free capabilities: profit maximization, corporate scope and profit margins. *Strategic Management Journal* **31**:780–801.

Li SX, Greenwood R. 2004. The effect of within-industry diversification on firm performance: synergy creation, multi-market contact and market structuration. *Strategic Management Journal* **25**(12): 1131–1153.

Lu J, Beamish PW. 2004. International diversification and firm performance: the S-curve hypothesis. *Academy of Management Journal* **47**:598–609.

Mahoney JT, Pandian JR. 1992. The resource-based view within the conversation of strategic management. *Strategic Management Journal* **13**(5): 363–380.

Markides CC. 1992. Consequences of corporate refocusing: ex ante evidence. *The Academy of Management Journal* **35**(2): 398–412.

Miller DJ. 2006. Technological diversity, related diversification and firm performance. *Strategic Management Journal* **27**(7): 601–619.

Morck R, Yeung B. 1991. Why investors value multinationality. *Journal of Business* **64**(2): 165–187.

Nobeoka K, Cusumano MA. 1997. Multiproject strategy and performance: the benefits of rapid design transfer in new product development. *Strategic Management Journal* **12**(8): 563–588.

Ocasio W. 1997. Towards an attention-based view of the firm. *Strategic Management Journal* **18**:187–206.

Palich LE, Cardinal LB, Miller CC. 2000. Curvilinearity in the diversification performance linkage: an examination of over three decades of research. *Strategic Management Journal* **21**(2): 155–174.

Penrose E. 1959. *The Theory of the Growth of the Firm*. Oxford University Press: New York.

Robins J, Wiersema MF. 1995. A resource-based approach to the multibusiness firm: empirical analysis of portfolio interrelationships and corporate financial performance. *Strategic Management Journal* **16**(4): 277–299.

Robins JA, Wiersema MF. 2003. The measurement of corporate portfolio strategy: analysis of the content validity of related diversification indexes. *Strategic Management Journal* **24**(1): 39–59.

Rawley E. 2010. Diversification, coordination costs and organizational rigidity: evidence from microdata. *Strategic Management Journal* **31**(8): 873–891.

Rumelt RP. 1974. *Strategy, Structure and Economic Performance*. Harvard University Press: Cambridge, M.A.

Staiger D, Stock JH. 1997. Instrumental variables regression with weak instruments. *Econometrica* **65**:557–586.

Stern I, Henderson AD. 2004. Within-business diversification in technology-intensive industries. *Strategic Management Journal*, **25**(5): 487–505.

Stuart TE. 2000. Interorganizational alliances and the performance of firms: a study of growth and innovation rates in a high technology industry. *Strategic Management Journal* **21**:791–811.

Tan T, Mahoney JT. 2006. Why a multinational firm chooses expatriates: integrating resource-based, agency and transaction costs perspectives. *Journal of Management Studies* **43**(3): 457–484.

Tanriverdi H, Lee CH. 2008. Within-industry diversification and firm performance in the presence of network externalities: evidence from the software industry. *Academy of Management Journal* **51**(2): 381–397.

Teece DJ. 1980. Economies of scope and the scope of the enterprise. *Journal of Economic Behavior and Organization* **1**(3): 223–247.

Voss GB, Sirdeshmukh D, Voss ZG. 2008. The effect of slack resources and environmental threat on product exploration and exploitation. *Academy of Management Journal* **51**(1):147–164.

Williamson OE. 1981. The economics of organization: The transaction cost approach. *American Journal of Sociology* **87**(3): 548–577.

Wooldridge JM. 2010. *Econometric Analysis of Cross Section and Panel Data*. MIT Press: Cambridge, M.A.

Wu B. 2013. Opportunity costs, industry dynamics and corporate diversification: evidence from the cardiovascular medical device industry, 1976–2004. *Strategic Management Journal* (forthcoming).

Zahavi T, Lavie D. 2013. Intra-industry diversification and firm performance. *Strategic Management Journal*, **34**(8): 978-998.

Zhou YM. 2011. Synergy, coordination costs and diversification choices. *Strategic Management Journal* **32**:624–639.

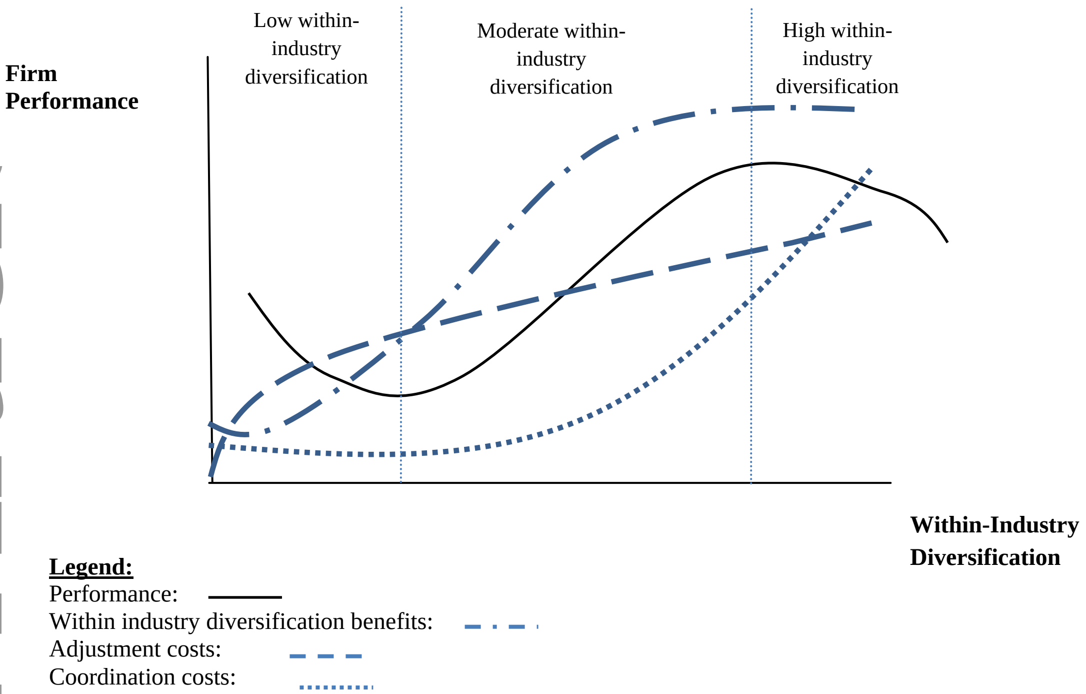

Figure 1 — The within-industry diversification—performance relationship

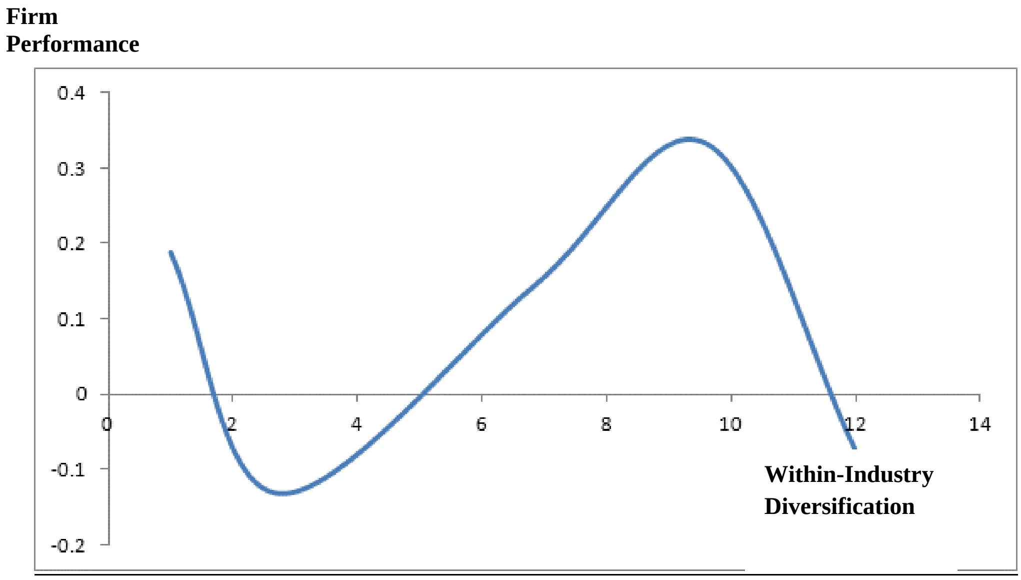

Figure 2 — Empirical estimation of the within-industry diversification—performance relationship (Intercept included)

Table 1 — Descriptive Statistics and Pearson Correlations (N=896)

Variable	Mean (Std. Deviation)	*1*	*2*	*3*	*4*	*5*	*6*	*7*
1. Firm performance	0.11 (0.26)	1						
2. Within-industry diversification	6.83 (3.35)	0.075*	1					
3. Within-industry diversification change rate	0.57 (1.25)	0.015	-0.026	1				
4. R&D intensity	0.23 (0.15)	0.187**	0.092*	0.035	1			
5. Firm size	147.28 (88.37)	0.231***	0.241**	0.038	0.170**	1		
6. Tangible resources (in USD millions)	53.44 (64.12)	0.098*	0.085*	-0.014	0.129**	0.245***	1	
7. Total investments (in USD millions)	29.45 (19.42)	0.234***	0.127**	0.190***	0.014	0.155**	0.016	1
8. Patents	12.26 (18.71)	0.246***	0.122*	-0.047	0.397***	0.020	-0.094*	0.087*
9. Internationalization	11 (6.18)	0.121**	0.164**	0.007	0.236***	0.147**	0.072*	0.075*
10. Firm age	6.12 (5.42)	0.265***	0.126**	0.014	0.133**	-0.166**	0.034	0.101*
11. Prior experience	0.49 (0.26)	0.113*	0.092*	0.076*	0.047	0.134**	0.026	0.038
12. Technological diversity	3.79 (5.20)	0.052	0.184**	0.081*	0.283***	0.077*	0.052	0.126**

*Notes: *** statistically significant at 0.1%; ** statistically significant at 1%; * statistically significant at 5%.*

Table 2 –First stage regression models for within-industry diversification

Dependent variable:	**Within industry diversification**	**Within industry diversification squared**	**Within industry diversification cubed**	**Within industry diversification change rate**
Technological diversity	0.234** (0.083)	0.198** (0.068)	0.205** (0.070)	0.104* (0.052)
Technological diversity squared	-0.004* (0.002)	0.009*** 0.004)	-0.009* (0.004)	0.002 (0.005)
Technological diversity cubed	0.012* (0.006)	-0.002 (0.017)	0.351* (0.178)	0.015 (0.022)
Technological diversity change rate	0.003 (0.013)	-0.004 (0.011)	0.006 (0.018)	0.314** (0.104)
R&D stage	0.053 (0.038)	0.028* (0.014)	0.004 (0.005)	0.211** (0.079)
Initial revenue stage	0.155* (0.078)	0.072 (0.066)	0.001 (0.004)	0.032 (0.025)
Revenue growth stage	0.142* (0.070)	0.052* (0.024)	0.008 (0.007)	0.041 (0.035)
Growth phase	0.175* (0.086)	0.141* (0.070)	0.099* (0.048)	0.024* (0.011)
Maturity phase	0.122** (0.039)	0.123* (0.060)	0.162* (0.080)	0.002 (0.006)
R&D intensity	0.132* (0.065)	0.142* (0.069)	0.034* (0.016)	0.354** (0. 113)
Firm size	0.226* (0.111)	0.021*(0.010)	0.018* (0.008)	-0.066 (0.009)
Tangible resources	0.174* (0.085)	0.058* (0.026)	0.044* (0.023)	0.029* (0.014)
Total investments	0.022* (0.011)	0.012* (0.005)	0.009* (0.004)	0.037* (0.018)
Internationalization	0.006 (0.007)	0.002 (0.005)	0.011 (0.009)	0.002 (0.004)
Prior experience	0.265* (0.131)	0.157* (0.076)	0.004 (0.005)	0.044* (0.021)
Firm age	0.235** (0.081)	0.315* (0.155)	0.004 (0.006)	0.131* (0.064)
Year	+	+	+	+
Industry	+	+	+	+
Adjusted R^2	0.235	0.212	0.172	0.183
F-statistic	22.55***	20.17***	16.37***	17.29***

Notes: Intercept is not shown. Standard errors in brackets.
**** statistically significant at 0.1%; ** statistically significant at 1%, * statistically significant at 5%.*

Table 3 — Second stage regression models for the relationships between within-industry diversification and firm performance 2000–2007 (N=896)

	Model 1	Model 2	Model 3	Model 4
Within-industry diversification		-0.503*** (0.103)	-0.514*** (0.099)	-0.487*** (0.105)
Within-industry diversification squared			0.084** (0.023)	0.096** (0.031)
Within-industry diversification cubed				-0.005* (0.002)
Within-industry diversification change rate	-0.167** (0.057)	-0.161** (0.055)	-0.158** (0.049)	-0.155** (0.050)
R&D stage	0.027 (0.021)	0.031 (0.025)	0.025 (0.019)	0.037 (0.028)
Initial revenue stage	0.023* (0.011)	0.025* (0.012)	0.031* (0.014)	0.042* (0.020)
Revenue growth stage	0.216** (0.072)	0.224** (0.075)	0.237** (0.077)	0.231** (0.076)
Growth phase	0.010* (0.005)	0.018* (0.008)	0.015* (0.007)	0.013* (0.006)
Maturity phase	0.012 (0.009)	0.013 (0.010)	0.014 (0.011)	0.010 (0.008)
R&D intensity	0.218** (0.071)	0.214** (0.069)	0.225** (0.067)	0.210** (0.065)
Firm size	0.332** (0.108)	0.351** (0.116)	0.378** (0.120)	0.396** (0.128)
Tangible resources	0.115* (0.055)	0.127* (0.062)	0.118* (0.057)	0.121* (0.059)
Total investments	0.151** (0.073)	0.152** (0.070)	0.153** (0.068)	0.152** (0.067)
Internationalization	0.354** (0.109)	0.325** (0.107)	0.337** (0.108)	0.339** (0.110)
Prior experience	0.011 (0.010)	0.020 (0.013)	0.018 (0.011)	0.032 (0.020)
Firm age	0.039* (0.018)	0.040* (0.019)	0.022* (0.011)	0.033* (0.015)
Year	+	+	+	+
Industry	+	+	+	+
Centered R^2	0.148	0.173	0.188	0.215
F statistic	14.34***	15.55***	16.02***	17.54***

Notes: Intercept is not shown. Standard errors in brackets.

**** statistically significant at 0.1%; ** statistically significant at 1%; * statistically significant at 5%.*

<u>Appendix Table 1 — Description of Variables and Measures</u>

Variable name	**Variable description**	**Data sources**
Firm performance	Ln (LAN) of the ratio of firm EBITDA (earnings before interest, tax and depreciation), in Million $ US, to its sales volume in year t, representing returns on sales (ROS)	Based on firms' financial reports, D&A and IVC datasets.
Within-industry diversification	Number of product categories (in core industry) of firm i in year t	Based on new product announcement data from LexisNexis Academic and Israeli financial newspaper archives (*Globes* and *The Marker*) cross-checked with firms' financial and own reports.
Within-industry diversification change rate	Number of product categories$_{i,t}$ minus number of product categories$_{i,t-1}$) / number of product categories$_{i,t-1}$	Based on new product announcement data from LexisNexis Academic and Israeli financial newspaper archives (*Globes* and *The Marker*) cross-checked with firms' financial and own reports.
R&D intensity	The ratio of R&D expenditures to sales in year t	Based on firms' financial reports.
Firm size	Ln (LAN) of number of employees in year t	Based on firms' financial reports, D&A and IVC datasets.
Tangible resources	Firm i's fixed assets in year t (in USD million)	Based on firms' financial reports.
Total investments	Ln (LAN) of total investments (in USD million) made up to a given year t	Based on firms' financial reports, D&A and IVC datasets.
Patents	Number of patents applied at year t (granted patents only)	NBER U.S. Patent Citations Data File complemented by USPTO website
Internationalization	Number of countries in which each firm is selling its products at year t	Based on firms' financial reports cross-checked with new product announcement data from LexisNexis Academic and Israeli financial newspaper archives (*Globes* and *The Marker*).
Firm age	Age of firm i in 2007	Based on firms' financial reports, D&A and IVC datasets.
Prior experience	A dummy measure where "1" indicates that members of firm i's top management have prior experience in other firms and "0" otherwise	Based on LexisNexis Academic, firm websites and firms' own reports.
Firm stage of development	A dummy measure indicating in which of the following four stages of firm development the firm is in year t: Seed stage; R&D stage; Initial Revenue stage; and Revenue Growth stage.	Based on firms' own reports and the IVC dataset.
Industry stage of development	A dummy measure indicating in which of the following four stages of industry development the firm is in year t: Fluid phase; Growth phase; Maturity phase; and Decline phase.	Based on firms' own reports cross-checked with industry level data obtained from Gartner and IDC.

Technological diversity	The number of three-digit technology domains to which a given firm's patents are assigned.	USPTO website.