Social Networks and Firm Performance:

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2014

Chapter 3

SOCIAL CAPITAL OF ENTREPRENEURS AND SMALL FIRM PERFORMANCE: A META-ANALYSIS OF CONTEXTUAL AND METHODOLOGICAL MODERATORS

ABSTRACT

Despite a surge of studies examining the role of social capital in the entrepreneurial process, no quantitative assessments exist of the empirical evidence to date. To resolve seemingly conflicting results, I conducted a meta-analysis of the link between entrepreneurs' personal networks and small firm performance and identify new moderators affecting this relationship. Analyses of 61 independent samples indicated that the social capital—performance link was positive and significant (r_c=.211). Effect sizes of weak ties were smaller than those of structural holes, while network diversity had the largest positive effect on performance. Results also showed that the social capital—performance link depends on the age of small firms, the industry and institutional contexts in which they operate, and on the specific network or performance measures used. Based on these findings, I develop recommendations for future research on the contingent value of social capital for small firms.

Keywords: networks, social capital, small firm performance, meta-analysis

3.1. Introduction

The relative scarcity of innovative, fast growing new ventures combined with their economic significance has stimulated a burgeoning stream of research exploring the determinants of new venture performance outcomes (see Gilbert et al., 2006). Although this work has identified numerous factors—including the characteristics of the entrepreneur (Baum et al., 2001), the venture's resources and strategy (Brüderl et al., 1992), and its external environment (Aldrich and Martinez, 2001)—one key factor that has received increased attention concerns the social capital embedded in the personal networks of entrepreneurs (Hoang and Antoncic, 2003; Stuart and Sorenson, 2007). Unlike traditional supply- and demand-based perspectives that have conceptualized entrepreneurs as either rational, autonomous actors or as "cultural dopes" without agency (Thornton, 1999), the network perspective maintains that 'entrepreneurship is embedded in a social context, channeled and facilitated or constrained and inhibited by people's positions in social networks' (Aldrich and Zimmer, 1986: 4). Social networks play a critical role in the entrepreneurial process as they may provide entrepreneurs with privileged access to knowledge, financial, reputational, and other types of resources that facilitate the discovery and exploitation of entrepreneurial opportunities (Hite and Hesterly, 2001; Stam and Elfring, 2008).

Although research examining the link between social networks and new venture performance has exploded over the last decade, and some conceptual reviews of this literature have emerged (Hoang and Antoncic, 2003; Jack, 2010; Stuart and Sorenson, 2007), few efforts have been undertaken to quantitatively assess the empirical evidence to date. Conducting such a review is important because disagreement persists in the entrepreneurship literature as to whether and when social networks have a positive impact on new venture performance. For instance, while Stuart and Sorenson (2007: 215) suggested that 'there is little doubt that entrepreneurship scholars believe that heterogeneity in social capital endowments give rise to performance differences across firms,' Watson (2007: 854) recently concluded that 'although the arguments in favor of networking appear compelling…there has been little empirical evidence to date of an association between firm performance and the owner's use of networks.' Indeed, studies have begun to examine the performance effects of different network characteristics and study potential contingencies that might condition their effects (Batjargal, 2010; Stam and Elfring, 2008). The relationship between entrepreneurial networks and performance appears complex and highly contingent, thus highlighting the need for a systematic assessment of existing empirical evidence to identify common patterns in, and potential moderators of, the link between entrepreneurs' personal networks and new venture performance.

Thus, I find broad agreement that entrepreneurs' social capital constitutes a key asset for small firms, but no consensus about the conditions under which certain network properties lead to enhanced business performance. To help reconcile these theoretical debates, this study employs meta-analytic methods to quantitatively evaluate existing empirical evidence. Meta-analysis is a powerful tool for advancing cumulative knowledge, enabling accumulation across studies to establish facts, and revealing the hidden meaning of research literature (Hunter and Schmidt, 2004: xxvii). Because it allows researchers to systematically combine and integrate published research results, meta-analysis has gained increasing prominence as a method in the entrepreneurship literature (e.g., Rauch et al., 2009; Unger et al., 2011). My meta-analysis builds on these prior studies by both identifying the average effect size of entrepreneurs' personal networks on new venture performance and examining potential moderators of this relationship. Specifically, I investigate whether the performance impact of social networks varies across different network dimensions (i.e., network structure, tie strength, and compositional diversity). I also test if the nature of a venture's life cycle stage, industry context, and institutional environment moderate the relationships between these network properties and new venture performance.

My meta-analytic review makes three important contributions. First, by assessing average effect sizes of the structural, relational, and resource properties of entrepreneurial networks on performance, I am able to assess both the absolute and relative magnitude of these effects. While past research has often focused on a few dimensions of entrepreneurs' personal networks, my study extends prior narrative reviews (e.g., Hoang and Antoncic, 2003; Stuart and Sorenson, 2007) by providing systematic evidence on the relative strength of the link between each network dimension and performance. Second, my study helps to reconcile some of the mixed findings noted in prior literature reviews (Elfring and Hulsink, 2003; Jack, 2010). By assessing potential firm, industry, and institutional level contingencies, I reveal how network performance effects may differ across ventures that are more or less established, operate in high or low technology industries, and reside in emerging or developed economies. In so doing, I respond to calls for more research that simultaneously considers linkages between entrepreneurial resources, contexts, and outcomes (Aldrich and Martinez, 2001; Welter, 2011). Third, my meta-analytic approach enables us to identify the impact of methodological choices on study outcomes. By examining how sampling and operationalization affect research results, I am in a position to also provide methodological recommendations for future research.

3.2. Theory and hypotheses

3.2.1. Social capital and small firm performance

Social capital entails the actual and potential resources accessible through an actor's network of relationships (Nahapiet and Ghoshal, 1998). The core intuition is that investments in social relations generate goodwill available to individuals and groups that can be mobilized to achieve certain goals (Adler and Kwon, 2002). Accordingly, social capital creates value by endowing well connected actors with privileged access to intellectual, financial, and cultural resources (Bourdieu, 1986). In the field of entrepreneurship, social capital has emerged as a contextual complement to theories focusing on individual traits by acknowledging that entrepreneurs are embedded in a social context that enables and constrains behavior (Aldrich and Zimmer, 1986). The popularity of network-based theorizing is reflected in the surge of studies examining networks and entrepreneurial outcomes at different levels of analysis including the role of social capital in the creation of new firms (De Carolis, Litzky & Eddleston, 2009), the performance of corporate strategic initiatives (Lechner et al., 2010), the innovativeness of regional clusters (Whittington et al., 2009), and the transformation of organizational fields (Van Wijk et al., 2012).

In this meta-analysis, I focus on the social capital embedded in the personal networks of entrepreneurs and its effects on small firm performance. Following Zhao et al. (2010), I define an entrepreneur as the founder, owner, and manager of a small firm. By personal network, I mean the family members, friends, and business contacts with whom an entrepreneur is directly connected and the indirect relations between them (Dubini and Aldrich, 1991). Although firms can be embedded in a multiplicity of networks, my focus on entrepreneurs' personal networks is consistent with the view that these ties are critical to the development of small firms (Maurer and Ebers, 2006). Compared to executives in large firms, entrepreneurs in small firms are more directly involved in daily firm operations, have greater discretion in decision-making, and more frequently perform key boundary-spanning roles (Hite and Hesterly, 2001). The individual-level social capital embedded in entrepreneurs' personal networks may thus importantly influence small firm performance. Research findings remain ambiguous, however, suggesting that a focused meta-analysis can clarify this important "micro-macro link" (Peng and Luo, 2000).

Although entrepreneurs' network relationships can be regarded an asset for small firms, there is no consensus on what properties of these networks constitute social capital. Prior narrative reviews suggest, however, that entrepreneurs' personal networks can be evaluated along three key facets, i.e. the relational, structural, and resource dimensions of social capital (Gulati, Lavie & Madhavan, 2011; Hoang and Antoncic, 2003; Nahapiet and Ghoshal, 1998).

Scholars examining the relational dimension of social capital consider the nature and quality of interactions between exchange partners, highlighting a possible trade-off between weak and strong ties. On the one hand, researchers have employed Granovetter's (1973) weak tie theory to argue that entrepreneurs can access more novel information through weak ties. This insight originates in homophily theory (McPherson et al., 2001), which holds that strong overlapping bonds tend to form among socially proximate individuals, making weak ties more likely to link people from distant social circles. On the other hand, scholars have stressed the benefits of strong ties by arguing that tie strength increases the willingness and ability of an entrepreneur's network contacts to provide needed resources (Batjargal, 2003). This argument dates back to research on embeddedness which has shown that frequent, close interactions facilitate trusted resource exchanges and tacit knowledge transfer (Uzzi, 1997).

Researchers focusing on the structural dimension of social capital have considered how the position of entrepreneurs in a structure of relationships creates advantage. One stream of research has employed Burt's (1992) theory of "structural holes," defined as the absence of direct relations among a focal actor's network contacts, to suggest that entrepreneurs obtain strategic benefits by forging ties to otherwise unconnected others (Batjargal, 2010). Based on a resource dependence logic (Pfeffer and

Salancik, 1978), this insight stems from the idea that mediating exchanges between actors who are not directly connected increases an entrepreneur's timely access to, and control over, external resources (Burt, 2005). By contrast, another stream of research has adopted Coleman's (1988) theory of network closure to emphasize the benefits associated with cohesive networks in which entrepreneurs' network contacts are directly connected and structural holes are absent (Hansen, 1995). Grounded in exchange theory (Blau, 1964), this perspective maintains that closed networks generate trust, social support and norms of reciprocity that enable cooperation among network members (Obstfeld, 2005).

Scholars have also begun to examine the resource dimension of social capital by directly considering the resources held by entrepreneurs' network contacts (Batjargal, 2003). Some have used social resource theory (Lin, 2001) to suggest that diverse networks, comprising members with different backgrounds, are beneficial because they enable entrepreneurs to quickly locate needed resources (Birley, 1985). This line of work has also drawn on institutional theory, arguing that the actual quality of small firms is difficult to observe directly such that entrepreneurs with diverse ties to prominent affiliates benefit from status transfer (Stuart et al., 1999). Others, however, have underscored the value of homogeneous networks. This research stream, grounded in theories of absorptive capacity (Hansen, 1999), argues that knowledge sharing occurs more readily when entrepreneurs and their network contacts have shared cognitions due to a common language or shared narrative (Nahapiet and Ghoshal, 1998).

The preceding discussion highlights two conflicting conceptualizations of social capital that might enhance small firm performance. On the one hand, the "bridging view" of social capital argues that entrepreneurs with large, diverse, and weakly connected personal networks identify more novel opportunities but face difficulties assembling resources to exploit them. On the other hand, the "bonding view" of social capital maintains that entrepreneurs with small, cohesive personal networks composed of strong ties can more effectively mobilize resources around new projects but lack access to fresh ideas. Given these contrasting perspectives found in the literature, I choose not to formulate competing hypotheses on the main effects of entrepreneurs' social capital on small firm performance. Instead, this meta-analysis seeks to statistically evaluate the extent of cumulative empirical support for the different theoretical perspectives that prevail in the literature and then examine the boundary conditions under which each theory is most predictive of small firm performance.

3.2.2. *Contingencies in the social capital—small firm performance relationship*

To reconcile the bridging and bonding views on social capital, researchers increasingly argue that each can be effective but in different contexts (Burt, 2000). The corresponding logic is that the value of a particular network depends on what actors seek to achieve through it, their abilities to utilize network resources, and prevailing cultural norms (Adler and Kwon, 2002). In the entrepreneurship literature, the value of adopting this emerging contingency perspective has been recognized, as shown by recent calls for 'research that further explores the contingencies under which social capital becomes an asset or a liability' (Maurer and Ebers, 2006: 290). Likewise, Elfring and Hulsink (2003), Witt (2004), and Martinez and Aldrich (2011) have theorized about possible moderators. The empirical evidence is still limited, however, as only few studies have tested moderator effects. Advancing this research stream, I examine three contingencies that may condition the value of entrepreneurs' social capital. In selecting suitable moderators, I only included those that have been subject to some debate in the literature, thus ensuring that the moderators are deemed relevant and will contribute to further theory development in the field.

Specifically, I build on the idea that small firms' network requirements might change over time (Lechner et al., 2006; Slotte-Kock and Coviello, 2010) and consider how the optimal form of social capital differs for new and old small firms. Doing so may help to reconcile competing theoretical perspectives. For instance, while Larson and Starr (1993) argue that the networks of small firms will become increasingly cohesive, Hite and Hesterly (2001) predict that new firms benefit when network density decreases over time. Since case study research has offered initial support for both views (Coviello, 2006; Elfring and Hulsink, 2007), a meta-analysis is warranted to better understand how firm age might alter the value of entrepreneurs' social capital.

I also acknowledge that networking effectiveness may depend on the environmental context of small firms (Witt, 2004) by contrasting the forms of social capital most valuable for entrepreneurs in low and high-technology industries, and those in emerging and established economies. Considering these moderators may address critical unresolved theoretical debates. For example, while Rowley, Behrens & Krackhardt (2000) suggest that networks rich in bridging social capital are more valuable in dynamic industries, Aral and Van Alstyne (2011) claim that such networks are less useful in turbulent information environments. Furthermore, some argue that bridging social capital can benefit small firms in emerging economies (Batjargal, 2010) while others argue that entrepreneurs must cultivate cohesive networks to prosper in these markets (Xiao and Tsui, 2007). My meta-analysis therefore considers both the industry and country level context of small firms to better understand environmental influences on network performance effects.

3.2.2.1. Firm age

The limited resource base of small firms renders it critical that entrepreneurs obtain resources through their personal networks. Yet potential resource providers will, in the case of new firms, typically be skeptical about the firm's prospects because it lacks legitimacy (Stinchcombe, 1965). Entrepreneurs also tend to possess superior information about the true value of their new firms, creating information asymmetries that hinder resource acquisition (Shane, 2003). This uncertainty makes that entrepreneurs must initially rely on strong ties with family, friends, and other close contacts to acquire resources. The trust, reciprocity, and 'shadow of the future' engendered in strong ties reduce concerns among potential resource providers that entrepreneurs may act opportunistically (Larson and Starr, 1993). Furthermore, frequent and close interactions help to lower information asymmetries through fine-grained knowledge transfer (Uzzi, 1997). When small firms mature, however, their improved legitimacy enables entrepreneurs to increasingly procure resources from weak ties (Hite and Hesterly, 2001). In this regard, strong ties can become a liability since they are costly to maintain and breed norms of reciprocity that may keep entrepreneurs tied to contacts that have lost their value (Gargiulo and Benassi, 2000). Weak ties, by contrast, entail less emotional attachment and thus provide entrepreneurs more flexibility to search for new and additional resources that can support continued firm growth (Coviello, 2006; Maurer and Ebers, 2006). Overall, this logic suggests the following hypotheses:

Hypothesis 1a. Strong ties in entrepreneurs' personal networks will be more positively related to small firm performance for new firms than old firms.

Hypothesis 1b. Weak ties in entrepreneurs' personal networks will be more positively related to small firm performance for old firms than new firms.

Heightened uncertainty and information asymmetries also render structural holes in entrepreneurs' personal networks less valuable for newly created small firms. Instead, for new firms, resource acquisition occurs more rapidly when entrepreneurs' personal networks lack structural holes and are densely connected (Hite and Hesterly, 2001). In this case, entrepreneurs and potential resource providers are tied to the same third parties. This curbs opportunism and induce cooperation because information about any misconduct quickly circulates throughout the network and sanctions are enforced (Coleman, 1988; Larson and Starr, 1993). Furthermore, lack of structural holes in entrepreneurs' personal networks speeds up communication and coordination, which should be particularly important for new firms (Batjargal, 2010). By contrast, when small firms become older, dense networks may create a "cognitive lock-in" (Maurer and Ebers, 2006) by insulating the firm from access to novel resources that facilitate further growth. Older firms often experience increasing inertia in their business operations, resulting in slow adaptation to the evolving environment (Hannan and Freeman, 1984). Given their information benefits (Burt, 2005), structural holes in entrepreneurs' personal networks will thus be particularly valuable for established small firms. Based on this logic, I hypothesize:

Hypothesis 1c. Structural holes in entrepreneurs' personal networks will be more positively related to small firm performance for old firms than new firms.

Network diversity, or connections to persons with different backgrounds and social positions, increases the scope of resources available to entrepreneurs. Direct accessibility of diverse resources is particularly valuable for newly created small firms, which face more uncertainty about which resources will be needed and where they might be located (Elfring and Hulsink, 2007). Entrepreneurs with diverse personal networks may resolve this uncertainty because they can directly identify others who may offer needed social, emotional, or material support (Renzulli et al., 2000). New firms, whose founders lack experience and face significant time constraints, especially benefit from network diversity through reduced search costs (McEvily and Zaheer, 1999). Entrepreneurs with diverse personal networks can quickly mobilize resources held by their network contacts instead of having to expend time searching for resources through indirect ties. Finally, diverse connections serve as a prism by enhancing a small firm's visibility and creating a broad, positive reputation among a wider set of constituencies (Podolny, 2001). Network diversity thus enables entrepreneurs to develop legitimacy for their small firms, which is more pertinent for new organizations. This reasoning suggests the following hypothesis:

Hypothesis 1d. Diversity of entrepreneurs' personal networks will be more positively related to small firm performance for new firms than old firms.

3.2.2.2. Low vs. high technology industries

Contingency theory views firm performance as a function of the fit between organizational structure and characteristics of the task environment (Lawrence and Lorsch, 1967). Given the distinct roles of strong ties and weak ties, this means that the industry context of firms may importantly influence whether strong or weak network relationships enhance small firm performance. In high-technology industries, which experience greater dynamism and technological turbulence, firms benefit from organic structures that facilitate flexibility, innovation, and fast decision-making (Jansen et al., 2006). In this regard, weak ties will be more effective because they enable broader, distant search behaviors that explore more alternatives in the environment (Hansen, 1999). Entrepreneurs can manage relatively many weak ties, ensuring balanced exposure to information on new products and technologies. By contrast, the time and emotional investments needed for strong ties imply that entrepreneurs' cognitive resources are consumed by only few relationships, resulting in more local, biased scanning of the environment (Rowley et al., 2000). The latter, however, can be beneficial for firms in low-technology industries. In such stable environments, small firms benefit from refining existing technologies and competencies (Jansen et al., 2006), which is facilitated by rich information exchanges through strong ties (Uzzi, 1997). Accordingly, I predict:

Hypothesis 2a. Strong ties in entrepreneurs' personal networks will be more positively related to small firm performance for firms in low-technology industries than firms in high-technology industries.

Hypothesis 2b. Weak ties in entrepreneurs' personal networks will be more positively related to small firm performance for firms in high-technology industries than firms in low-technology industries.

Industry conditions may also alter the value of structural holes for small firm performance. According to Zaheer and Zaheer (1997), firms operating in fast-moving and information-intensive environments derive competitive advantage from having superior capabilities to quickly sense and respond to rapid changes in markets and technologies. This means that, particularly in high-technology industries, small firms perform better when entrepreneurs have personal networks that facilitate alertness to emerging threats and opportunities. In this regard, Burt (2005) argues that information tends to flow more within than between groups, yielding a "vision advantage" to actors whose networks span structural holes between unconnected others. Connections to disparate social circles increase entrepreneurs' awareness of changing market conditions, making structural holes more valuable to small firms operating in the dynamic, uncertain environments that typify high-technology industries (Rowley et al., 2000). Besides increasing alertness to environmental changes, structural holes also facilitate small firms' capacity to quickly respond to those changes. In this regard, Kim, Oh & Swaminathan (2006) argue that cohesive networks may induce relational inertia that constrains actors in quickly reconfiguring their resources to fit with changes in the environment. By contrast, entrepreneurs whose personal networks span structural holes enjoy more autonomy and flexibility in proactively adapting their firms' strategic directions to take advantage of sudden environmental changes (Maurer and Ebers, 2006). Overall, these arguments suggest the following hypothesis:

Hypothesis 2c. Structural holes in entrepreneurs' personal networks will be more positively related to small firm performance for firms in high-technology industries than firms in low-technology industries.

The competitiveness of small firms operating in high-technology industries largely depends on the strength of their innovative capabilities (Rosenbusch et al., 2011). In these markets, knowledge is increasingly specialized and dispersed across industry participants, creating the need to access knowledge from a variety of sources (Powell, Koput & Smit-Doerr, 1996). Diverse personal networks will be particularly valuable for firms in high-technology industries since innovation entails the novel recombination of disparate ideas and resources (Schumpeter, 1934). In this regard, network diversity increases the number of unique knowledge elements that can potentially be recombined and thus enhances the likelihood that entrepreneurs identify highly innovative opportunities (Ruef, 2002). Exposure to people with distinct backgrounds challenges entrepreneurs' cognitive structures, promotes novel insights and solutions, and reduces pressures for conformity (Aldrich, 1999). By contrast, for small firms in low-technology industries, it will be more beneficial when entrepreneurs maintain less diverse personal networks. Individuals can more easily share and absorb knowledge when they have similar backgrounds and experiences (Reagans and McEvily, 2003), suggesting that network diversity increases the effort and resources entrepreneurs must expend to effectively coordinate and communicate with their network contacts. At the same time, small firms in low-technology industries obtain fewer performance benefits from innovation such that the novelty value of access to diverse knowledge is reduced. Together this means that, in low-technology industries, the costs of network diversity are more likely to outweigh the benefits. Accordingly, I hypothesize:

Hypothesis 2d. Diversity of entrepreneurs' personal networks will be more positively related to small firm performance for firms in high-technology industries than firms in low-technology industries.

3.2.2.3. Emerging vs. established economies

Emerging economies encompass countries characterized by rapid economic growth, increasing liberalization of markets, and vastly underdeveloped formal institutional infrastructures (Hoskisson et al., 2000; Puffer et al., 2010). To cope with the unique economic, political, and social context of emerging economies, entrepreneurs might need to configure their personal networks differently than in established economies. Since the absence of a reliable government and established rules of law renders market transactions costly and uncertain, entrepreneurs in emerging economies rely more on close personal relationships to procure resources and protect their small firms from arbitrary extortion or expropriation (Xin and Pearce, 1996). These relations are based on shared identification with family, hometown, region, school, or place of work and involve frequent exchanges of gifts as a sign of goodwill and respect (Peng and Luo, 2000). The trust embedded in these strong ties constitutes a critical informal governance mechanism through which entrepreneurs in emerging economies carefully navigate information-poor environments. Unlike in established economies, where reliable information is abundant and publicly available through impersonal channels, entrepreneurs in emerging economies depend on strong particularistic relations to obtain high-quality private information that is unavailable through weak ties (Luo, 2003; Uzzi, 1997). Together, these arguments lead to the following prediction:

Hypothesis 3a. Strong ties in entrepreneurs' personal networks will be more positively related to small firm performance for firms in emerging economies than firms in established economies.

Hypothesis 3b. Weak ties in entrepreneurs' personal networks will be more positively related to small firm performance for firms in established economies than firms in emerging economies.

If small firms in emerging economies cannot enjoy the structural support of formal institutions to govern market transactions, this increases the need for informal sanctioning mechanisms that can prevent wrongdoing by potential exchange partners (Li et al., 2008). In the emerging economy context, it is therefore more beneficial when entrepreneurs and their network contacts are densely connected through ties to the same third parties because deviant behavior will then be quickly noticed and sanctioned (Coleman, 1988). Entrepreneurs in emerging economies like Russia and China indeed often distrust outsiders who are not part of the same social group, thus limiting opportunities for entrepreneurs to bridge structural holes across communities (Batjargal, 2010). These tightly-knit groups tend to be based on long standing localized networks whose members seek protection through shared monitoring and social control (Aidis et al., 2008). Networks with few structural holes can thus be advantageous for small firms in emerging economies whose institutional inefficiencies increase entrepreneurs' reliance on cohesive personal networks to reduce market uncertainty and transaction costs (Luo, 2003). By contrast, political, economic, and regulatory institutions are often stronger and better enforced in established economies which reduce entrepreneurs' need for network governance (Xin and Pearce, 1996). In developed markets, then, structural holes are more advantageous because the presence of efficient institutions such as financial intermediaries and property protection enables entrepreneurs to capture more value from exploiting the opportunities created by spanning structural holes. Together, this reasoning suggests the following hypothesis:

Hypothesis 3c. Structural holes in entrepreneurs' personal networks will be more positively related to small firm performance for firms in established economies than firms in emerging economies.

It is well established that entrepreneurs in emerging economies cultivate personal networks to countervail uncertainty associated with unpredictable government regulation, rapid industrial growth, and increasing competitive intensity (Luo, 2003; Xin and Pearce, 1996). Despite this uncertainty, power and resources tend to be highly concentrated into the hands of a small group of high-ranking government officials and top managers at major state-owned enterprises (Peng and Luo, 2000). By contrast, in established economies, sources of resource dependence are much more dispersed because numerous external factor markets offer alternative channels for obtaining resources that are less governed by the state. Given these differences, small firms in emerging economies may perform better when entrepreneurs form less diverse personal networks by focusing their networking efforts on influencing key government officers and leaders at state-owned enterprises. By contrast, small firms in established economies face more uncertainty about potential sources of resource dependence and may therefore perform better when entrepreneurs build diverse personal networks. In this setting, small firms tend to operate in knowledge-intensive sectors that are “innovation-driven,” while small firms in emerging economies often operate in basic industries that are “efficiency-driven” (Bosma et al., 2012). Since entrepreneurs with more diverse personal networks are more likely to identify innovative opportunities (Ruef, 2002), network diversity will be particularly valuable for small firms in established economies. Accordingly, I hypothesize:

Hypothesis 3d. Diversity of entrepreneurs’ personal networks will be more positively related to small firm performance for firms in established economies than firms in emerging economies.

3.3. Data and methods

3.3.1. Search strategy and inclusion criteria

My aim was to collect the population of empirical studies that considered the relationship between the social capital of entrepreneurs and small firm performance. I employed several search techniques to locate relevant studies. First, I consulted computerized databases (ABI/Inform, EBSCOhost, EconLit, Elsevier Science Direct, Google Scholar, JSTOR, and PsycInfo), using combinations of keywords related to entrepreneurship (e.g. SME, new venture, entrepreneur, founding team), networks (e.g. social capital, personal networks), context (e.g. emerging economies, high-technology industries) and performance outcomes (e.g. firm growth, firm performance). Second, I manually searched the major entrepreneurship and management journals. To reduce publication bias, I also searched for unpublished studies in the databases of Social Science Research Network (SSRN), conference proceedings of the Academy of Management (1984-2009) and the Babson College Entrepreneurship Research Conference (1981-2009). Finally, I examined the references of located studies to find additional studies. Together these searches yielded a total of 148 studies including 15 unpublished studies.

To be included in my meta-analysis, studies had to meet four criteria. First, I only considered studies examining the personal networks of entrepreneurs. Studies focusing on interorganizational collaborative ties were thus excluded. Second, studies had to examine small firms which were defined as firms with less than 500 employees (Rosenbusch et al., 2011). Third, studies needed to report a correlation (or convertible equivalent) between a measure of social capital and a measure of firm performance. When this information was missing, I contacted the respective authors to obtain the information. Fourth, studies had to employ independent samples. As recommended by Geyskens et al. (2009), I computed the mean effect sizes across studies using the same sample and variables. If the same dataset was used more than once but included different variables, I maintained the effect sizes separately.

After applying these criteria, the final search resulted in 59 primary studies (of which 10 are unpublished) with 61 independent samples involving a total of 13,263 observations. The primary studies are marked by * and are listed in Table 4.

Table 4: Overview of studies included in the meta-analysis

Authors (year)	Sample size	Firm age	Industry	Country	Effect size[b]	Social capital construct labels[c,d]	Performance construct labels[c,e]
Acquaah (2007)	200	old	low-tech	Ghana	.44 (C)	Social capital with top managers, community leaders, and government officials (N,I)	Organizational performance (M,R)
Armanios et al. (2012)	94	new	high-tech	China	-.05 (C)	Government official ties (S,I)	Venture growth (G,R)
Atuahene-Gima and Li (2004)	373	new	high-tech	China	.02 (C)	Government ties, financial ties (N,I)	Sales growth (G,R)
Batjargal (2003)	75	new	mixed	Russia	.05 (L)	Network size and heterophily, strong and weak ties, resourcefulness (N,H,S,W,D,T)	Revenue growth, profit margin, ROA (G,P,A)
Batjargal (2010)	159	new	high-tech	multiple	-.05 (L)	Network size, structural holes (N,H,T)	Profit growth (G,R)
Bhagavatula et al. (2010)	107	old	low-tech	India	.01 (C)	Network size, network constraint, tie strength (N,H,S,T)	Opportunity recognition, resource mobilization (N,R)
Bradley et al. (2012)	201	old	low-tech	Kenya	-.15 (C)	Strong ties, weak ties (S,W,I)	Firm performance (P,R)
Bratkovic et al. (2009)	103	new	mixed	Slovenia	.11 (C)	Resource network intensity, contact intensity, friendship (S,T)	Firm growth (G,R)
Brink (2011)	93	old	low-tech	Denmark	.16 (C)	Number of connections (N,I)	Firm growth (G,R)
Butler et al. (2003)	100	old	low-tech	Thailand	.02 (C)	Ties to professionals, ties to family members (W,S,I)	Sales growth, profitability (G, P,R)
Cantner and Stuetzer (2010)	182	new	mixed	Germany	.02 (C)	Weak ties, strong ties (W,S,I)	Employment growth (G,A)
Capelleras et al. (2010)	647	old	mixed	multiple	.07 (C)	Network support (N,I)	Venture growth (G,R)
Chrisman et al. (2005)	159	new	low-tech	U.S.	.01 (C)	Guided preparation (S,I)	Sales, employment (G,R)
Dai and Liu (2009)	711	new	high-tech	China	.51 (C)	International business networks (D,I)	Business performance (M,R)
Davidsson and Honig (2003)	380	new	mixed	Sweden	.08 (L)	Parent/friends in business, encouragement, married, agency contact, business network (S,W,I)	Profit (P,R)
Filatotchev et al. (2009)	711	new	high-tech	China	.51 (C)	Global networks (D,I)	Export performance (N,R)
Florin et al. (2003)	275	old	mixed	U.S.	.22 (C)	Social resources (N,T)	Sales growth, ROS (G,P,A)
Ge et al. (2009)	177	old	mixed	China	.13 (C)	Networking intensity, networking range (S,D,I)	Venture performance (M,R)
Grandi and Grimaldi (2003)	40	new	high-tech	Italy	.50 (C)	Frequency of interaction with external agents (S,I)	Technological excellence (N,R)
Hanlon (2001)	50	old	mixed	Canada	.14 (C)	Support strength, diversity of supporters (S,D,T)	Employee growth (G,R)
Hansen (1995)	44	new	mixed	U.S.	.18 (C)	Action set size, degree, and frequency (N,H,S,T)	New organization growth (G,A)
Hmieleski and Carr (2008)	223	new	mixed	U.S.	-.10 (C)	Social capital (N,I)	New venture performance (G,A)
Honig (1998)	215	old	low-tech	Jamaica	.04 (C)	Semiweekly church attendance, marital status (S,I)	Monthly profit (P,A)
Hormiga et al. (2011)	130	new	mixed	multiple	.16 (C)	Relationships with customers and suppliers, informal network, connectivity and event attendance (N,S,D,I)	New business venture success (M,R)
Hsu (2007)	149	new	high-tech	U.S.	.23 (C)	High network recruiting (N)	Pre-money valuation (N,R)
Jensen and Greve (2002)	100	new	mixed	Norway	.27 (C)	Acquaintances, friends, network redundancy (W,S,H,T)	Revenues (G,R)
Kessler (2007)	756[a]	new	mixed	multiple	.06 (C)	Network importance, positive role models (N,S,I)	New venture success (M,R)
Lau and Bruton (2010)	134	old	high-tech	multiple	.39 (C)	Close ties with government and financial institutions, trade and policy committees, and board of directors (S,I)	Sales performance, new product performance, production efficiency (G,N,R)
Lee and Tsang (2001)	168	old	mixed	Singapore	.24 (C)	Communication frequency, breadth of communication (S,D,I)	Sales and profit growth (M,R)
Li and Atuahene-Gima (2001)	184	old	high-tech	China	.19 (C)	Political networking (S,I)	New technology venture performance (M,R)
Liao and Welsch (2003)	462	new	mixed	U.S.	.09 (L)	Family and friends have started new firms (S,I)	Revenue growth (G,R)
Lin et al. (2006)	125	new	high-tech	Taiwan	.00 (C)	Social capital (N,I)	New venture performance (N,R)
Ma et al. (2009)	250	new	low-tech	China	.10 (C)	Structural holes (H,T)	Strategic adaptive capability (N,R)
Manev et al. (2005)	160	new	low-tech	Bulgaria	.16 (C)	Client network, institutional network, strong ties, weak ties (N,S,W,T)	Performance index, growth (G,N,R)
Manolova and Manev (2006)	623	new	low-tech	Bulgaria	.18 (C)	Diversity of network (D,T)	External financing (N,R)
Manolova et al. (2010)	555	new	low-tech	Bulgaria	.11 (C)	Personal networking (D,T)	Internationalization (N,R)
McEvily and Zaheer (1999)	227	old	low-tech	U.S.	.03 (C)	Nonredundancy, infrequency of interaction (H,W,T)	Acquisition of competitive capabilities (N,R)
Minguzzi and Passaro (2001)	104	old	low-tech	Italy	.14 (C)	Participation in industry associations (N,I)	Revenue (G,R)

Table 4 *(continued)*

Authors (year)	Sample size	Firm age	Industry	Country	Effect size[b]	Social capital construct labels[c,d]	Performance construct labels[c,e]
Ndofor and Priem (2011)	103	new	low-tech	U.S.	.04 (C)	Coethnic and non-coethnic contact frequency (S,D,T)	Venture profits, entrepreneur returns (P,R)
Oh et al. (2004)	161	old	low-tech	Canada	.12 (C)	Network brokerage, network range (H,D,T)	Net income (P,R)
Ostgaard and Birley (1996)	159	old	low-tech	England	.03 (C)	Number of contacts and memberships, communication frequency, years known, ties to strangers (N,S,H,D,T)	Sales, employment, profit growth (G,P,R)
Owens (2003)	147	old	low-tech	U.S.	.14 (C)	Social networking (N,I)	Business performance (M,R)
Park and Luo (2001)	128	old	mixed	China	.25 (C)	Guanxi with business community and government (S,I)	Organizational performance (G,R)
Patel and Terjesen (2011)	452	old	low-tech	U.S.	.15 (C)	Network size, tie strength, network diversity (N,S,D,T)	Transnational venture performance (P,R)
Peña (2004)	114	new	mixed	Spain	-.05 (C)	Networking (N,I)	Sales, employment, and profit growth (G,P,R)
Peng and Luo (2000)	127	old	mixed	China	.24 (L)	Ties with top managers, ties with government officials (N,I)	ROA, market share (P,N,R)
Prajapati and Biswas (2011)	133	old	low-tech	India	.20 (C)	Network size, supportive network, density (N,S,I)	Enterprise performance (M,R)
Premaratne (2001)	303	old	low-tech	Sri Lanka	.15 (C)	Density of social networks and support networks (H,T)	Sales and profit growth (G,P,R)
Sawyerr et al. (2003)	150	old	high-tech	U.S.	.18 (C)	External networking (N,S,I)	Sales growth, ROA, net income (G,P,R)
Scholten (2006)	65	new	high-tech	Holland	.15 (C)	Network size, structural holes, tie strength, heterogeneity (N,H,S,D,T)	Employment growth (G,R)
Stam and Elfring (2008)	87	old	high-tech	Holland	.27 (C)	Network centrality, bridging ties (H,D,T)	New venture performance, sales growth (G,M,R)
Vissa and Chacar (2009)	470	new	high-tech	India	.36 (C)	Network constraint (H,T)	Revenue growth (G,A)
West and Noel (2009)	83	new	high-tech	U.S.	.39 (C)	Network frequency (S,I)	New venture performance (M,R)
Wright et al. (2008)	349	new	high-tech	China	.01 (C)	International networks (D,I)	Employment growth (G,R)
Xu (2008)	70	old	mixed	U.S.	.10 (C)	Social capital diversity (D,I)	New venture innovativeness (N,R)
Yang et al. (2011)	130	old	mixed	China	.62 (C)	Network scale, network strength (N,S,I)	New venture performance (M,R)
Zhao (2005)	205[a]	old	mixed	China	.05 (C)	Overall guanxi, weak guanxi, strong guanxi (N,W,S,I)	Sales growth, profit growth (G,P,A)
Zhou et al. (2007)	129	old	mixed	China	.14 (C)	Guanxi networks (D,I)	Sales growth, profitability growth (G,P,R)
Zou et al. (2010)	252	old	high-tech	China	.13 (C)	Strong ties, weak ties (S,W,I)	Profit, competitive advantage (P,N,A)

[a] Study contains two samples. [b] Effect is the study-level effect, and the codes indicate whether the research design was cross-sectional (C) or longitudinal (L). [c] Construct labels in the tables are those used to describe social capital and performance variables in the primary studies. [d] Codes in parentheses show how social capital constructs were coded into network size (N), strong ties (S), weak ties (W), structural holes (H), and network diversity (D). Codes also show if social capital was operationalized using tie-based measures (T) or scale items (I). [e] Codes in parentheses indicate whether small firm performance was operationalized using growth measures (G), profit measures (P), or nonfinancial measures (N). Composite measures (M) refer to aggregate measures that combine multiple performance indicators into one measure. Codes also show if performance was self-reported (R) or based on archival data (A).

3.3.2. Coding and measures

Table 4 shows the main constructs examined in the primary studies and the way I coded them. To improve coding reliability, the first and second author both coded the studies. In the few cases where there was disagreement, I resolved it through discussion.

3.3.2.1. Small firm performance

Firm performance is a multidimensional construct that has been measured using a variety of indicators. In this regard, Venkatraman and Ramanujam (1986) recommended that researchers distinguish between financial and nonfinancial performance measures. The former indicate the achievement of the economic goals of the firm, whereas the latter capture the firm's broader operational effectiveness. Furthermore, Zahra (1996) argued that there can be a trade-off between achieving growth and profitability, suggesting that both capture distinct facets of firm performance. Accordingly, I coded studies based on three types of performance: growth, profitability, and nonfinancial performance[1]. Growth measures included objective or perceived growth in sales, profit, employment, and market share. Measures of profitability included accounting-based indicators such as return on assets (ROA), return on equity (ROE), and return on sales (ROS) as well as self-reported

[1] Studies that use composite performance measures, containing performance indicators from more than one of the three categories, were coded into a separate category. These studies are denoted by (M) in Table 4 and are included in the calculation of the overall effect size of each social capital variable. However, they are excluded from effect size calculations for individual growth, profit, and nonfinancial performance measures. Composite measures contain multiple performance indicators, thus preventing us from coding the studies into one performance measure category.

assessments of profitability. Nonfinancial performance included various indicators of operational effectiveness such as technical excellence, competitive capabilities, productivity, and export performance. I excluded firm survival because past research suggests that the dissolution of small firms does not necessarily indicate weak business performance (Unger et al., 2011).

3.3.2.2. Social capital

I coded primary studies according to the properties of entrepreneurs' personal networks that were considered including network size, strong and weak ties, structural holes, and network diversity. As for network size, I included studies that either used tie-based measures or networking scales. Tie-based measures generally involve the use of a name generator or position generator to elicit the specific network contacts of the entrepreneur and then count the total number of relationships (e.g. Batjargal, 2003). Networking scales measure the extent to which entrepreneurs maintain extensive ties within a particular domain (e.g., managers at other firms, government officials) without capturing distinct relationships with individual persons or organizations (e.g. Peng and Luo, 2000).

Next, I classified studies into those examining strong ties and weak ties. Studies were assigned to the strong ties category when they considered entrepreneurs' personal connections with family and friends, whereas studies examining entrepreneurs' connections with distant business contacts and acquaintances were coded as weak ties (e.g. Batjargal, 2003; Davidsson and Honig, 2003). Some studies have also used a continuous measure of tie strength, capturing the frequency of interaction between the entrepreneur and her network contacts and/or the emotional closeness of these relationships (e.g. Patel and Terjesen, 2011). I classified these studies into the strong ties category. To check the robustness of my findings I also ran separate analyses for studies using a continuous tie strength measure, which yielded very similar results to those for strong ties reported in this paper.

I considered studies to focus on structural holes when they used a measure of network structure that indicates the extent to which entrepreneurs' network contacts are connected to each other. The more connections exist, the fewer structural holes between the contacts. A commonly used measure is network density which captures the number of ties among the entrepreneur's network contacts relative to the maximum possible number of ties that could exist (e.g. Hansen, 1995). Another popular measure of structural holes is Burt's (1992) constraint score. It measures the extent to which the entrepreneur has invested resources in relationships with redundant contacts who are also indirectly connected to the entrepreneur via her other contacts. Since network density and constraint capture the *lack* of structural holes in a network, some studies measured structural holes as one minus network density or one minus network constraint (e.g. Batjargal, 2010). When studies did not apply such a transformation (e.g. Vissa and Chacar, 2009), I recoded effect sizes (i.e. an effect size of .20 for network density was recorded as -.20) to ensure that all effect sizes measured the presence, not the absence, of structural holes in entrepreneurs' personal networks.

Finally, I considered studies to focus on network diversity when they examined the extent of heterogeneity in the attributes of entrepreneurs' personal network contacts. Commonly used measures include proportion of kin relations, occupational or demographic diversity, variety of memberships in associations, range of contacts in different industries, and range of international connections (e.g. Batjargal, 2003; Renzulli et al., 2000).

3.3.2.3. Theoretical moderators

I classified small firms as new firms if they on average existed for less than 6 years, and as old firms if they were 6 years or older. This cut-off point ensured a balanced distribution of new and old firms in my sample. Because researchers disagree about when new firms "grow old" I experimented with alternative cut-off points and found similar results to those reported below.

Next, I coded studies according to the sampled industries. Following Rauch et al. (2009), sectors classified as high-technology industries included biotechnology, Internet, software, electronics, computer equipment, and technology consulting services. Low-technology industries included food, restaurant, hotel, agriculture, manufacturing, construction, fashion, and retail.

Finally, I classified studies into those that consider emerging economies and those that examine established economies. To code the studies, I employed the list of 64 countries that were identified by Hoskisson et al. (2000) as emerging economies. Although some of these have recently become more established, I still use Hoskisson et al.'s (2000) overview because it provides a consistent and widely accepted definition over time. As the mean publication year of the primary studies was 2006, this classification scheme also appears valid for my sample.

3.3.2.4. Methodological moderators

My meta-analysis evaluates whether the effect size of entrepreneurs' social capital on small firm performance varies across different network properties and performance outcomes. To offer further insights into how construct measurement and research design may influence research findings, I also coded several other study characteristics.

First, I coded whether studies were published or unpublished to examine potential publication bias. Second, I classified studies into those using longitudinal data, in which performance was measured at a later point in time than social capital, and those employing cross-sectional data wherein both were measured concurrently. Third, I classified studies into those using objective, quantitative measures of small firm performance (e.g. sales growth), and those that employed subjective measurement scales (e.g. performance relative to competitors). Fourth, I coded whether studies employed archival data of small firm performance or self-reported performance data. Fifth, I classified studies into those measuring social capital using tie-based measures and those employing scale measures. Tie-based measures often employ "name generators" to elicit entrepreneurs' specific network contacts, while scale items tend to ask respondents to directly assess some characteristic of their networks. Sixth, I coded the network content for each study, distinguishing between studies that consider the general advice networks of entrepreneurs and studies that define the network more specifically by asking entrepreneurs to report ties to specific entities such as managers at other firms or government officials.

3.3.3. Meta-analytic procedures

Following the widely used meta-analytic procedures developed by Hunter and Schmidt (1990, 2004), I first estimated mean effect sizes (r_w) based on the Pearson product-moment correlations reported by each study, weighted by the study's sample size to correct for sampling error. When studies reported multiple correlations for a given relationship, I combined them into a single correlation. Next, I adjusted the estimates for measurement error, yielding a corrected effect size (r_c). Since only 25 of the 59 primary studies reported reliability estimates I reconstructed the missing reliabilities for both the independent and dependent variables using the mean of available alpha's (.74 for social capital and .76 for performance), as recommended by Hunter and Schmidt (2004). To facilitate hypothesis testing, I then calculated the 95% confidence interval around the sample-size weighted mean correlation and considered effect sizes to be significant when the confidence interval did not include zero (Whitener, 1990).

To assess potential publication bias, I used two techniques. First, I used Rosenthal's (1979) "file-drawer" method which calculates the number of unpublished studies (fail-safe N) with null results that is needed to render each mean effect size statistically insignificant. As shown in Table 5, all fail-safe N values exceeded Rosenthal's (1979) criterion (i.e., 5 * number of studies + 10). For instance, the fail-safe N for the overall effect size of social capital was 1,256, which exceeded the threshold value of 315. Given that my initial search returned 148 studies including 15 unpublished studies, it is unlikely that 1,256 unpublished studies remain undetected. Second, I compared effect sizes between published and unpublished studies in my sample. As shown in Tables 7 and 8, the effect sizes did not differ significantly from each other, suggesting that although publication bias cannot be ruled out, it is unlikely to be severe.

I used multiple techniques to examine the presence of moderators, as recommended by Cortina (2003). I first examined the homogeneity of each correlation by applying the 75% rule (Hunter and Schmidt, 1990). According to this rule, effect sizes are considered homogeneous if more than 75% of the observed variance is due to sampling error. If this number is below 75%, then moderators are likely to exist. A disadvantage of the 75% rule, however, is that it may overestimate the likelihood of heterogeneity (Geyskens et al., 2009). I therefore also examined the presence of moderators by constructing 95% credibility intervals around each mean-corrected effect size, using the corrected standard deviation around the mean. When a credibility interval is wide (exceeding .11) or contains zero, moderators are likely to be present (Geyskens et al., 2009; Whitener, 1990).

I tested the significance of the hypothesized moderating effects using bivariate subgroup analysis, which is well suited for categorical moderators (Geyskens et al., 2009). For each moderator, I divided the sample into relevant subgroups and then calculated Z-scores to assess the statistical significance of between-group differences in sample-weighted mean effect sizes. Furthermore, I checked if the average residual variance of moderator subgroups was lower than the residual variance of the overall effect, which would indicate a moderation effect (Hunter and Schmidt, 2004). A limitation of this method, however, is that it does not control for the influence of other moderators. I therefore also conducted multivariate meta-regressions in which the overall effect size of social capital on performance constitutes the criterion and the predictors are the moderators.

3.4. Results

3.4.1. Main effects of entrepreneurs' social capital on small firm performance

Table 5 reports the meta-analytic results for the link between entrepreneurs' social capital and small firm performance. As shown in Table 5, the overall relationship between social capital and small firm performance was positive and significant. The sample size weighted and reliability corrected effect size was r_c=.211 which, according to Cohen (1977), can be considered as moderately large. Furthermore, the 95% confidence interval did not include zero, indicating that the overall effect size was statistically significant. Yet the effect did exhibit heterogeneity, as the percent of variance attributed to sampling error (17.64%) was well below the threshold value of 75% needed for assuming homogeneity. The credibility interval was also relatively large and included zero, indicating the presence of moderators.

Table 5:

Results of meta-analysis on social capital and small firm performance

Variable	k	N	Rw	Sampling error (% variance)	Corrected *r* (c*r*)	95% Confidence Interval	95% Credibility Interval	Fail-safe *N*
Overall relationship[a]	61	13,263	.157	17.64	.211	.105 to .208	-.053 to .475	1,256
Network size[b]	28	5,925	.125	22.95	.167	.098 to .151	-.081 to .285	576
Growth measures	16	2,696	.072	26.17	.093	.050 to .094	-.138 to .324	125
Profit measures	9	1,407	.125	60.49	.168	.111 to .138	.058 to .278	128
Nonfinancial measures	5	1,291	.161	77.19	.214	.109 to .221	.144 to .284	125
Strong ties[b]	35	6,131	.121	28.87	.162	.063 to .179	-.064 to .388	668
Growth measures	18	2,220	.106	52.89	.141	.028 to .193	-.017 to .299	238
Profit measures	12	2,142	.132	74.47	.176	.093 to .174	.108 to .243	193
Non-financial measures	5	943	.166	34.85	.221	.107 to .224	.012 to .430	130
Weak ties[b]	11	1,882	.064	48.43	.085	.052 to .075	-.062 to .197	82
Growth measures	7	822	.086	77.14	.121	.016 to .155	.025 to .217	78
Profit measures	7	1,213	.041	48.26	.054	.004 to .077	-.022 to .129	31
Nonfinancial measure	3	639	.102	67.74	.136	.065 to .138	.049 to .223	38

Structural holes[b]	13	2,207	.134	26.63	.179	.096 to .171	-.066 to .404	224
Growth measures	9	1,940	.115	51.63	.153	.075 to .154	-.015 to .321	130
Profit measures	3	698	.035	61.29	.041	.007 to .062	-.027 to .108	12
Nonfinancial measures	3	584	.283	42.85	.377	.251 to .315	.309 to .445	141
Network diversity[b]	18	4,598	.239	13.98	.318	.172 to .315	-.029 to .465	562
Growth measures	7	914	.078	63.36	.103	.022 to .133	-.016 to .222	65
Profit measures	6	1,079	.109	60.71	.146	.085 to .132	.034 to .258	83
Nonfinancial measures	4	1,959	.277	32.69	.369	.188 to .365	.253 to .485	155

Note: K=number of samples; N=overall number of observations; Rw=sample size weighted mean correlation; Corrected *r*=reliability corrected and sample size weighted effect size; Fail-safe *N*=the number of unknown or unpublished studies of the same relationship with a true effect size of 0 that it would take to widen the reported 95% confidence interval enough to include zero. [a] Overall relationship indicates the average effect size of all network dimensions combined.

[b] Samples used to calculate the overall effect size of each social capital variable include studies using composite performance measures. The latter are excluded when calculating effect sizes for individual growth, profit, and nonfinancial measures because composite measures contain performance indicators from more than one of the three categories.

In the second section of Table 5, I report the disaggregated correlations between individual social capital dimensions and small firm performance. The results consistently report positive effect sizes of each social capital measure: network size (r_c = .167), strong ties (r_c = .162), weak ties (r_c = .085), structural holes (r_c = .179), and network diversity (r_c=.318). For each effect size the confidence interval did not include zero, thus confirming that it was statistically significant. To test whether the effect sizes were statistically different from each other, I calculated a Z-score for each pair of effects. This analysis revealed that the effect size of network diversity was significantly larger than the effect sizes of the other social capital variables (Z-scores ranged from 2.43 to 4.80). Furthermore, the effect size of weak ties was significantly smaller than the effect sizes of network size (Z = -2.28) and structural holes (Z = -2.01).

Homogeneity analyses of each effect size indicated that, similar to my findings for the overall effect of social capital, the sampling error variances for the individual social capital dimensions were all well below 75% (Table 5). This finding, together with the observation that each credibility interval included zero and was larger than the .11 threshold suggested by Geyskens et al. (2009), indicated that moderators were likely to influence the relationship between each individual social capital dimension and small firm performance.

3.4.2. Theoretical moderator analysis

3.4.2.1. New vs. old small firms

My first set of hypotheses argued that firm age serves as a temporal contingency in the link between social capital and performance. Hypothesis 1a predicted that strong ties will be more positively related to the performance of new firms, whereas Hypothesis 1b proposed that weak ties will have a stronger positive relationship with the performance of old firms. As shown in Table 6, firm age did moderate the link between strong ties and performance but in the opposite direction than was hypothesized. The positive effect size of strong ties was larger for old firms (r_c =.204) than new firms (r_c =.128). This difference was statistically significant ($Z = 2.50$, $p<.05$), as indicated by the increase in sampling error variance for both subgroups compared to the overall effect. Thus, Hypothesis 1a was not supported. Results in Table 6 also show that effect sizes of weak ties were somewhat larger for new firms (r_c =.134) than old firms (r_c =.029). Although the difference between the two effects was marginally significant ($Z = 1.90$, $p<.10$), Hypothesis 1b was not supported. The credibility interval for old firms still contained zero, however, indicating the presence of other moderators.

Next, Hypothesis 1c predicted that structural holes will have a stronger positive relationship with performance among old firms than new firms. As shown in Table 6, however, Hypothesis 1c was not supported. In contrast to my prediction, effect sizes of structural holes were larger for new firms (r_c =.269) than old firms (r_c =.065). This difference was statistically significant ($Z = 2.43$, $p<.05$). The sampling error variance increased substantially for the old firms' subgroup while its credibility interval did not include zero, indicating homogeneity. Yet, effects of structural holes remained heterogeneous for the new firms' subgroup, suggesting the presence of additional moderators.

Finally, Hypothesis 1d predicted that network diversity will be more valuable for new firms than old firms. In support of the hypothesis, Table 6 reveals that network diversity had a greater positive effect size among new firms (r_c =.377) than among old firms (r_c =.196). This difference was statistically significant ($Z = 2.52$, $p<.05$). As indicated by the increased percentage of variance explained by sampling error, homogeneity of each subgroup was higher compared to the overall effect. The credibility interval for the old firms' subgroup still included zero, however, suggesting the presence of other moderators.

Table 6:

Results of bivariate theoretical moderator analysis

Social capital variable	k	N	Rw	Sampling error (% variance)	Corrected *r* (c*r)*	95% Confidence interval	95% Credibility interval	Z-score	Fail-safe *N*
H1a-d: New vs. old small firms									
Network size new firms	13	2,996	.076	76.78	.102	.047 to .104	.032 to .173	2.53*	120
Network size old firms	15	2,929	.168	16.98	.224	.123 to .212	-.066 to .514		330
Strong ties new firms	17	3,186	.095	57.60	.128	.061 to .128	.006 to .250	2.50*	202
Strong ties old firms	18	2,945	.143	35.38	.204	.131 to .154	.077 to .331		357
Weak ties new firms	5	897	.101	48.15	.134	.051 to .150	.007 to .261	1.90†	63
Weak ties old firms	6	985	.022	55.44	.029	.002 to .041	-.058 to .116		11
Structural holes new firms	7	1,163	.201	18.48	.269	.138 to .263	-.021 to .684	2.43*	189
Structural holes old firms	6	1,044	.049	65.62	.065	.011 to .086	.045 to .333		33
Network diversity new firms	9	3,322	.283	31.90	.377	.223 to .342	.141 to .613	2.52*	357
Network diversity old firms	9	1,276	.147	27.23	.196	.101 to .192	-.054 to .446		171

Social capital variable	k	N	Rw	Sampling error (% variance)	Corrected *r* (c*r)*	95% Confidence interval	95% Credibility interval	Z-score	Fail-safe *N*
H2a-d: High-technology vs. low-technology industries									
Network size high-tech	6	1,021	.172	18.59	.230	.132 to .211	-.083 to .314	2.35*	136
Network size low-tech	9	2,031	.087	47.82	.116	.056 to .117	.107 to .353		96
Strong ties high-tech	8	1,002	.104	37.56	.139	.027 to .180	-.078 to .356	0.49	132
Strong ties low-tech	10	1,932	.067	68.75	.089	.016 to .117	-.002 to .176		79
Weak ties high-tech	6	1,194	.091	47.23	.120	.069 to .112	-.025 to .265	0.41	67
Weak ties low-tech	4	688	.062	59.37	.083	.028 to .095	.013 to .153		29
Structural holes high-tech	4	781	.249	11.81	.332	.175 to .222	-.027 to .691	1.98*	137
Structural holes low-tech	6	1,207	.084	47.11	.113	.018 to .149	.054 to .279		62
Network diversity high-tech	5	1,923	.396	27.54	.528	.287 to .504	.229 to .827	2.94**	306
Network diversity low-tech	6	2,053	.131	33.73	.174	.103 to .158	.029 to .319		100

Social capital variable	k	N	Rw	Sampling error (% variance)	Corrected *r* (c*r)*	95% Confidence interval	95% Credibility interval	Z-score	Fail-safe *N*
H3a-d: Established vs. emerging economies									
Network size established	14	2,752	.098	65.95	.131	.066 to .129	.053 to .209	1.27	171
Network size emerging	14	3,173	.156	11.88	.208	.102 to .209	-.161 to .578		284
Strong ties established	16	2,559	.089	39.51	.119	.051 to .126	.007 to .231	1.89†	156
Strong ties emerging	19	3,572	.138	33.68	.189	.129 to .146	-.001 to .379		347
Weak ties established	4	889	.096	60.01	.123	.089 to .102	.040 to .206	1.99*	46
Weak ties emerging	7	993	.044	58.06	.059	.031 to .056	-.011 to .129		34
Structural holes established	7	843	.173	19.51	.231	.099 to .246	-.088 to .550	1.02	136
Structural holes emerging	6	1,364	.117	13.68	.156	.097 to .136	-.003 to .315		104
Network diversity established	9	2,277	.290	20.23	.387	.237 to .342	.064 to .710	1.97*	369
Network diversity emerging	9	3,321	.189	30.83	.252	.151 to .226	-.007 to .517		195

Note: k=number of samples; N=overall number of observations; Rw=sample size weighted mean correlation; Corrected *r*=reliability corrected and sample size weighted effect size; Z-score=statistic based on test for significance of difference in effect sizes; † p<.10, * p<.05, ** p<.01, two-tailed test; Fail-safe *N*=the number of unpublished studies of the same relationship with a true effect size of 0 that it would take to widen the reported 95% confidence interval enough to include zero.

Table 7:

Results of bivariate methodological moderator analysis

Variable	k	N	Rw	Sampling error (% variance)	Corrected *r* (c*r*)	95% Confidence interval	95% Credibility interval	Z-score	Fail-safe *N*
Publication bias									
Published studies	51	11,842	.173	9.03	.230	.153 to .192	-.031 to .491	0.78	1,128
Unpublished studies	10	1,421	.148	33.42	.197	.087 to .209	.133 to .261		211
Research design									
Cross-sectional	56	12,060	.172	27.63	.229	.101 to .242	.023 to .435	1.53	1,261
Longitudinal	5	1,203	.123	35.34	.151	.067 to .178	-.018 to .320		71
Performance measure									
Subjective scale	34	6,591	.231	16.12	.331	.181 to .280	.013 to .648	3.75**	1,158
Objective quantified	27	6,672	.099	33.02	.132	.071 to .126	-.059 to .323		332

Social capital variable	k	N	Rw	Sampling error (% variance)	Corrected *r* (c*r*)	95% Confidence interval	95% Credibility interval	Z-score	Fail-safe *N*
Performance dimension[a]									
Growth	29	5,547	.092	33.80	.123	.049 to .135	-.067 to .313	0.40[b]	324
Profit	17	3,252	.106	28.46	.141	.051 to .161	-.059 to .341	-4.16**[c]	235
Non-financial	14	3,530	.251	15.62	.332	.181 to .321	.063 to .601	4.52**[d]	478
Performance data source									
Self-reported	51	11,322	.167	9.58	.222	.103 to .230	-.168 to .612	0.97	1,110
Archival	10	1,941	.141	34.09	.188	.041 to .240	-.005 to .370		181
Social capital measure									
Tie-based	22	4,677	.154	52.94	.205	.121 to .186	.081 to .329	0.40	439
Scale	39	8,586	.172	13.75	.223	.109 to .234	-.091 to .537		853
Tie content									
General advice	33	8,239	.139	28.57	.186	.111 to .166	.001 to .371	3.14**	591
Specific	28	5,024	.208	42.15	.277	.177 to .238	.113 to .440		779

Note: K=number of samples; N=overall number of observations; Rw=sample size weighted mean correlation; Corrected *r*=reliability corrected and sample size weighted effect size; Z-score=statistic based on test for significance of difference in effect sizes; † p<.10, * p<.05, ** p<.01, two-tailed test; Fail-safe *N*=the number of unpublished studies of the same relationship with a true effect size of 0 that it would take to widen the reported 95% confidence interval enough to include zero. [a] Studies that use composite measures of performance are excluded when calculating effect sizes for growth, profit, and nonfinancial measures. Composite measures contain performance indicators from more than one of the three categories, thus preventing us from assigning these studies to a single category.
[b]Growth versus profit, [c]profit versus nonfinancial, [d]nonfinancial versus growth

Table 8:

Results of meta-regression predicting effect size of social capital on small firm performance

	Model 1		Model 2		Model 3		Model 4		Model 5	
Variables	B	p-value	B	p-value	B	p-value	B	p-value	B	p-value
New firm	0.012	0.401	0.029	0.397	0.021	0.351	0.026	0.302		
High-tech industry	0.079	0.001	0.083	0.000	0.087	0.000	0.082	0.000		
Emerging economy	-0.047	0.101	-0.032	0.081	-0.037	0.091	-0.041	0.088		
Strong ties	0.009	0.324								
Strong ties * new firm	-0.067	0.001								
Strong ties * high-tech industry	0.017	0.307								
Strong ties * emerging economy	0.091	0.046								
Weak ties			-0.076	0.031						
Weak ties * new firm			0.089	0.000						
Weak ties * high-tech industry			0.026	0.209						
Weak ties * emerging economy			-0.015	0.071						
Structural holes					0.018	0.266				
Structural holes * new firm					0.112	0.000				
Structural holes * high-tech industry					0.131	0.034				
Structural holes * emerging economy					0.037	0.301				
Network diversity							0.077	0.021		
Network diversity * new firm							0.094	0.000		

Network diversity * high-tech							0.202	0.000		
Network diversity * emerging economy							-0.081	0.041		
Published study									0.023	0.219
Longitudinal study									0.007	0.421
Subjective performance measure									0.084	0.000
Nonfinancial performance measure									0.107	0.000
Self-reported performance measure									0.011	0.322
Tie-based social capital measure									0.019	0.511
General tie content									-0.047	0.001
R^2	0.495		0.447		0.497		0.605		0.489	
F-value	5.77		4.92		5.94		7.29		5.11	
Significance level	0.001		0.001		0.001		0.001		0.001	

Note: dependent variable is the overall effect size of social capital on small firm performance

3.4.2.2. High-technology vs. low-technology industries

My next set of predictions revolved around the moderating role of industry context. Hypothesis 2a proposed that strong ties will have a stronger positive relationship with performance in low-technology industries, whereas Hypothesis 2b predicted that weak ties will be more positively related to performance in high-technology industries. Both hypotheses were not supported. As shown in Table 6, effect sizes of strong ties were somewhat larger for high-technology industries (r_c =.139) than low-technology industries (r_c =.089). Furthermore, weak ties had slightly greater effect sizes in high-technology industries (r_c =.120) than in low-technology industries (r_c =.083). In both cases, differences in effect sizes were not statistically significant. Although the percentage of variance due to sampling error variance increased in some instances, the credibility intervals for each subgroup contained zero. Thus, other moderators are likely to exist.

Next, Hypothesis 2c predicted that structural holes in entrepreneurs' personal networks will have a stronger positive relationship with performance among small firms in high-technology industries. In support of this hypothesis, Table 6 shows that the positive effect size of structural holes was larger in high-technology industries (r_c =.332) than in low-technology industries (r_c =.113). The moderating effect was statistically significant ($Z = 1.98$, $p<.05$), while the average sampling error in the two subgroups accounted for an increased percentage of variance compared to the overall effect. The credibility interval for the effect of structural holes in high-technology industries still included zero, however, suggesting the presence of other moderators in this subgroup.

Hypothesis 2d predicted that network diversity will have a stronger positive relationship with performance among small firms in high-technology industries. In support of the hypothesis, Table 6 shows that the positive effect size of network diversity was indeed larger in high-technology industries (r_c =.528) than in low-technology industries (r_c =.174). This difference in effect size was statistically significant ($Z = 2.94$, $p<.01$). Although the credibility intervals for each subgroup excluded zero the variance explained by sampling error was still well below 75%, suggesting that other moderators may exist.

3.4.2.3. Emerging vs. established economies

My final set of hypotheses postulated that the social capital—performance link varies between emerging and established economies. According to Hypothesis 3a, strong ties will be more strongly related to performance in emerging economies. Table 6 reveals that the effect size of strong ties was larger in emerging economies (r_c =.189 vs. r_c =.119). The difference was only marginally significant (Z = 1.89, p<.10), thus providing moderate support for Hypothesis 3a. Although the average variance explained by sampling error was higher than for the overall effect, the effect size for emerging economies remained heterogeneous since the credibility interval still included zero. As for weak ties, Table 6 shows that effect sizes were larger in established economies (r_c =.123) than in emerging economies (r_c =.059). In support of Hypothesis 3b, this difference was statistically significant (Z = 1.99, p<.05). The percentage of variance due to sampling error increased substantially compared to the overall effect but effects of weak ties in emerging economies remained heterogeneous, as indicated by the large credibility interval containing zero. Other moderators may thus be in operation within this subgroup.

Hypothesis 3c postulated that structural holes in entrepreneurs' personal networks will have a stronger positive relationship with performance in established economies. Although the effect size of structural holes was indeed larger for small firms in established economies (r_c =.231) than in emerging economies (r_c =.156), the difference was not statistically significant (Z = 1.02, n.s.). Hypothesis 3c was thus not supported. Effects of structural holes among firms in emerging economies also remained heterogeneous, as indicated by the large credibility interval containing zero. Further moderators may therefore exist.

Finally, Hypothesis 3d predicted that network diversity will be more positively related to performance in the context of established economies. In support of the hypothesis, Table 6 shows that the effect size of network diversity was significantly larger in established economies (r_c =.387) than in emerging economies (r_c =.252). Effects in both subgroups appeared more homogenous than the overall effect, but the low percent of variance due to sampling error suggests the presence of other moderators.

3.4.3. Methodological moderators

The results pertaining to my examination of methodological moderators in the overall relationship between social capital and small firm performance are presented in Table 7. With regard to research design, the relationship between social capital and performance appears to be stronger in cross-sectional studies (r_c =.229) than in studies using a time-lag between the collection of network and performance data (r_c =.151). However, the difference in effect sizes was not statistically significant (Z = 1.53), possibly due to low statistical power resulting from the small number of longitudinal studies.

As for measurement of small firm performance, Table 7 shows that effect sizes were larger for studies employing subjective scales (r_c =.331) than for studies using quantitative performance measures (r_c =.132). This difference was statistically significant (Z = 3.75, p<.01). Effect sizes were also larger when studies considered nonfinancial performance outcomes (r_c =.332) than when studies focused on growth (r_c =.123) or profit outcomes (r_c =.141). These differences in effect sizes were statistically significant (p<.01). In terms of data sources used, however, results indicate that studies employing archival performance data produced only slightly smaller effect sizes (r_c =.188) than studies relying on self-reported performance data (r_c =.222). This difference was not statistically significant (Z = 0.97, n.s.).

In examining the possible moderating influence of social capital measurement, I found no significant differences in effect sizes between studies that employ tie-based measures and studies using networking scales (r_c =.205 and r_c =.223, respectively; Z = 0.40, n.s.). By contrast, Table 7 does reveal that differences in the type of network examined in primary studies may influence research findings. Effect sizes were smaller for studies examining the general advice networks of entrepreneurs (r_c =.186) than the effect sizes generated by studies focusing on entrepreneurs' network relations with specific entities such as ties with managers at other firms or government officials (r_c =.277). This difference was statistically significant (Z = 3.14, p<.01).

3.4.4. Meta-regression results

I checked the robustness of my bivariate analyses by conducting meta-regressions. As shown in Table 8 I modeled, for each social capital variable, its main effect and interaction terms with the three moderators as predictors of the relationship between social capital and small firm performance. Support for my hypotheses was assessed by examining the significance of the interaction terms, which indicated whether the effect size of each social capital variable differed across the moderator subgroups.

As shown by the significant interaction effects in Model 1 of Table 8, effect sizes of strong ties were smaller for new firms than old firms but larger in emerging economies than established economies. Conversely, Model 2 reveals that weak ties had larger effect sizes for new firms than old firms but smaller effect sizes in emerging economies than established economies. Effect sizes of strong ties and weak ties were not, however, moderated by industry context. These findings thus mirror the results from my bivariate analyses, which supported Hypotheses 3a and 3b but failed to support Hypotheses 1a, 1b, 2a, and 2b. Next, Model 3 shows that the effect size of structural holes was larger for new firms than old firms. Likewise, structural holes had a larger effect size in high-tech than low-tech industries. Yet the effect size of structural holes did not differ across emerging and established economies, as reflected by the lack of a significant interaction effect. Consistent with the bivariate results, these findings support Hypothesis 2c and fail to support Hypothesis 1c and 3c. Finally, the main effect of network diversity reported in Model 4 reveals that its effect size was larger compared to the overall effect. Consistent with my bivariate analyses, the significant interaction terms also show that the effect size of network diversity was larger for new firms and high-tech industries but smaller for emerging economies.

3.5. Discussion

Studies examining the role of social networks in the entrepreneurial process have exploded over the last two decades, yet little agreement exists about what network configurations are most beneficial for entrepreneurial firms (Maurer and Ebers, 2006). In this study, I sought to consolidate empirical network studies in entrepreneurship research by presenting a meta-analytic review of extant findings on the relationship between entrepreneurs' personal networks and new venture performance. My analysis of 61 independent samples revealed a positive overall relationship between social capital and small firm performance (r_c=.211). This finding is important because it suggests that although entrepreneurs must invest substantial resources to cultivate their networks, social capital does create value for small firms. While some have noted that empirical evidence on the performance benefits of entrepreneurial networks appears unconvincing (Watson, 2007), the effect sizes observed in my study are comparable to those for entrepreneurial personality traits (Zhao et al., 2010) and substantially greater than the association between human capital and performance (Unger et al., 2011).

In comparing the relative influence of different dimensions of social capital, I found that weak ties, structural holes and network diversity were all positively related to performance. On the one hand, these results contribute to recent debates about the value of bridging and bonding forms of social capital (Adler and Kwon, 2002) by revealing that, on average, the former seems relatively more valuable in the small firm context. Despite the coordination advantages of cohesive networks (Obstfeld, 2005), it appears that the novelty benefits associated with bridging social capital are more critical for entrepreneurs (Burt, 1992). On the other hand, my findings suggest that not all bridging properties of entrepreneurs' personal networks have the same performance implications. I found that effect sizes of weak ties were significantly smaller than those of structural holes, while network diversity had the strongest positive relationship with small firm performance. This result suggests that the current focus on relational and structural network properties in extant literature must be complemented with research that directly considers the quality of resources held by entrepreneurs' network contacts and the mechanisms through which they can be accessed and leveraged. Furthermore, rather than pitting bonding and bridging dimensions of entrepreneurial networks in a "horse race" to see which are more important for performance, my results suggest that future research should consider the effects of more complex network configurations that combine both forms of social capital (cf. Oh, Chunch & Labianca, 2004). Although this theory is emerging (Martinez and Aldrich, 2011), most empirical studies to date have focused on the main effects of certain network properties. I found, however, that each social capital dimension may interact differently with different moderators, indicating that researchers will benefit from testing more integrative models that include multiple network and contingency variables.

3.5.1. Implications of theoretical moderators

In support of recent contentions that the network requirements of small firms might change over time (Martinez and Aldrich, 2011), my meta-analysis revealed that structural holes in entrepreneurs' personal networks are more valuable for new firms than old firms. Interestingly, this result contradicts Hite and Hesterly (2001) and Maurer and Ebers (2006) who argue that the limited legitimacy of new firms increases their reliance on cohesive networks for resource acquisition. Their argument thus emphasizes that structural holes increase the "altercentric uncertainty" faced by prospective resource providers concerning the quality of the new firm (Podolny, 2001). Yet structural holes, by offering superior information benefits, may actually lower entrepreneurs' "egocentric uncertainty" about which market opportunities to pursue. One explanation for the unexpected finding, then, is that for new firms the benefits of egocentric uncertainty reduction through structural holes outweigh the costs of concurrent increases in altercentric uncertainty. Accordingly, I invite future research to disentangle these mechanisms and study how entrepreneurs can optimize their social capital to reduce both types of uncertainty.

The results also indicated that strong ties are more beneficial for older firms. This finding contrasts with Greve and Salaff (2003), Jack (2005), and Lechner et al. (2006) who argue that strong ties are particularly valuable in the emergence phase. It appears that strong ties can be a liability for new firms as they demand substantial investments and may limit entrepreneurs' autonomy to cultivate new ties (Steier and Greenwood, 2000). In this regard, recent research has shown that entrepreneurs initially tend to frantically search for resources by forming many weak ties, only some of which are later transformed into strong ties (Hallen and Eisenhardt, 2012). Yet unlike Larson and Starr's (1993) prediction that entrepreneurs will increasingly focus on a few essential ties, my results suggest that weak ties and network diversity continue to benefit older firms whereas network size even becomes more valuable over time. Future research, therefore, may study how entrepreneurs can manage the potential trade-off between strengthening existing network connections and forming new ties to unfamiliar contacts. According to Vissa (2012), entrepreneurs' networking actions that deepen or broaden their social capital are quite distinct, suggesting that the temporal sequencing of these actions warrants more research attention.

My findings also revealed differences in social capital performance effects across industries. This is an important result since past research has mostly employed single industry samples or treated industry as a control variable. I found that structural holes and network diversity had a stronger positive relationship with small firm performance in high-technology industries. This suggests that the bridging dimensions of social capital are especially valuable for promoting the adaptability of small firms in uncertain environments where knowledge is widely dispersed and rapidly evolving (Rowley et al., 2000). A key implication is that future research will benefit from documenting the actual process by which networking influences entrepreneurs' alertness to environmental changes and their ability to respond to these changes. If social capital indeed serves to align small firms with their industry context, then future studies must also examine why some entrepreneurs are able to reconfigure their personal networks to fit changing industry conditions while others experience "network inertia" (Kim et al., 2006).

The lack of significant inter-industry differences in the performance implications of weak and strong ties also merits further discussion. A possible explanation is that, in high-technology industries, the search scope benefits of weak ties might be offset by the difficulty to exchange complex technological knowledge through distant connections (Hansen, 1999). Similarly, in low technology industries, the knowledge transfer benefits of strong ties might be attenuated because knowledge in these industries tends to be better understood and thus flows equally well through weak ties. A logical inference is that the distinction between high and low-technology industries might be too crude to accurately capture cross-industry differences in the knowledge environments of small firms. Accordingly, an important direction for future research will be to identify which dimensions of social capital are most valuable under the unique knowledge conditions of different industries. Characteristics such as knowledge tacitness and complexity, locus of knowledge creation, and the degree of appropriability may also cause industries to develop very distinct network structures (Rosenkopf and Schilling, 2007). Future research could therefore study how strong and weak ties might differentially enable entrepreneurs to navigate different types of industry networks and identify the implications for small firm performance.

My meta-analysis also exposed that the social capital—performance relationship depends on whether small firms operate in emerging or established economies. I found that whereas weak ties and network diversity had a stronger positive association with performance in established economies, strong ties were more beneficial in emerging economies. Given the limited comparative research done so far (Batjargal, 2010), these results are insightful because they illuminate how entrepreneurs in different institutional environments might need to configure their personal networks differently to achieve high performance. Contrary to my expectations, however, I found no significant differences in the magnitude of the relationship between structural holes and performance. One explanation for this result is the possibility that there is substantial institutional, economic, political, and cultural heterogeneity across individual emerging economies (Hoskisson et al., 2000). The unique developmental trajectories taken by different emerging markets thus points to a need to consider how such diversity affects the value of different networking strategies. In fact, some have suggested that as formal institutions increasingly surface, entrepreneurs in emerging economies might rely less of social capital to grow their firms (Peng and Luo, 2000). Clearly this contention warrants empirical scrutiny. At the same time, future research may examine what forms of social capital enhance entrepreneurs' responsiveness to the rapid institutional transformations currently unfolding in various established markets that struggle to maintain their historic advantages over emerging economies.

3.5.2. Implications of methodological moderators

My analysis of methodological moderators produced several key insights. I found that effect sizes were somewhat stronger in cross-sectional studies, although the difference was not statistically significant. This result is promising from a research efficiency perspective but also raises new questions about the temporal stability of the relationship between social capital and performance. Some have argued that social capital performance benefits might grow over time because it takes time for entrepreneurs to cultivate trust with, and access resources from, their network contacts (Larson and Starr, 1993). Others, however, have noted that social capital might only yield temporary advantage since entrepreneurs' network ties can decay over time and be replicated by competitors (Baum, McEvily & Rowley, 2012). The former view suggests that effect sizes will be larger for longitudinal studies, whereas the latter view implies the opposite. Since my results did not provide definitive support for either perspective, and were based on a small number of longitudinal studies, I invite future research to examine how entrepreneurs might preserve and enhance the value of different forms of social capital over time.

Regarding measurement of small firm performance, I found that self-reported and archival measures produced similar effect sizes. This is good news from a data collection standpoint, as self-reported performance data are often easier to obtain in the context of small firms. Yet findings also revealed that subjective scales yielded somewhat stronger correlations than self-reported quantitative measures of performance. One implication is that future research may benefit from using multiple measures, combining scale items with quantitative indicators. Another implication is that studies could explore why there might be any divergence in research findings across subjective and objective performance measures. One intriguing possibility is that the efficacy of subjective measures, by often framing performance relative to the firm's key competitors, highly depends on entrepreneurs' biases in making such comparisons. More research is needed to understand how entrepreneurs' network relationships might influence their differential identification with, and access to information about, particular competitors.

My analysis also indicated that the social capital—performance link was stronger for measures of nonfinancial performance than for growth or profit measures. The result suggests that if studies only consider small firms' financial performance and disregard their operational effectiveness, they may risk understating the true value of entrepreneurs' social capital. A direct implication is that future research will benefit from adopting more refined measures of performance that tap into the varied elements of the entrepreneurial process such as opportunity recognition, resource assembly, and legitimacy attainment (Elfring and Hulsink, 2003). In so doing, studies can clarify how different forms of social capital might facilitate certain business processes but constrain others, and how these influences combine to ultimately affect small firms' financial performance (cf. Slotte-Kock and Coviello, 2010).

In examining the influence of social capital measurement, I found that tie-based measures and scale items yielded similar effect sizes. The result is surprising because tie-based measures, by eliciting entrepreneurs' specific network contacts and their relationships, may yield finer-grained indicators of social capital than scale items asking respondents to assess some global characteristic of their personal networks. The seeming equivalence of scale items is good news from a research efficiency standpoint, suggesting that researchers carefully consider whether the high respondent burden associated with tie-based measures is justified by their research question. More broadly, however, my findings raise the issue of how the reliability and validity of existing social capital measures can be improved. Indeed, respondents often underreport weak ties, overestimate their centrality in a network, and perceive nonexistent relationships among their network contacts (Marsden, 2005). To improve data quality, future studies may collect network data using multiple techniques such as archival sources, diaries, electronic traces, direct observation, and experiments. Theoretically, the idea that entrepreneurs may have biased network perceptions also points to intriguing research questions. Future research may begin to uncover the various schemas entrepreneurs use to navigate different types of networks, study the origins and development of these perceptions, and examine how perceptual biases in forming and leveraging networks influence opportunity discovery and resource mobilization by entrepreneurs.

I also found that effect sizes were smaller when primary studies considered the general advice networks of entrepreneurs than when they examined ties to distinct entities such managers at large firms or government officials. It thus appears that different types of network ties have distinct performance implications, suggesting that future research may benefit from further developing fine-grained measures of network content. So far, many researchers have adopted an instrumental view of social capital, viewing network relations as conduits through which entrepreneurs strategically obtain information and resources. Yet network ties also contain expressive contents of positive or negative effect. Positive affective ties may provide entrepreneurs with a sense of belonging, convey their social identities to external stakeholders, and transmit normative expectations from the environment (Ibarra, Kilduff & Tsai, 2005). Negative affective ties entail interpersonal dislike which may threaten entrepreneurs' identities, disrupt their access to external resources, and bias decision-making by focusing attention on counter-role models (Labianca and Brass, 2006). Given the limited work in this area, I encourage future researchers to develop new measures of entrepreneurs' positive and negative affective relations, examine how they may change over time as entrepreneurs construct and alter their identities, and study their distinct consequences for small firm performance.

3.5.3. Limitations and future research directions

This meta-analysis has several limitations. First, my findings are limited to surviving firms because most primary studies overlooked failed firms. Examining survivor bias is critical because the social capital of entrepreneurs may influence both their willingness and ability to exit their ventures. For instance, structural holes may lower entrepreneurs' performance thresholds (Gimeno, Folta, Copper & Woo, 1997) by increasing their autonomy and exposure to alternative business opportunities (Burt, 1992). Future research is encouraged to study how social capital influences the likelihood of business closure and the specific mechanisms involved.

Second, many primary studies included in this meta-analysis have employed cross-sectional data such that the possibility of reverse causality cannot be ruled out. Future studies should employ longitudinal data to disentangle the causal effects. In so doing, scholars may draw on recent methodological advances such as latent growth modeling (Bliese and Ployhart, 2002) and actor-based network models (Snijders, Bunt & Steglich, 2010) to examine how changes in entrepreneurs' personal networks direct, and are shaped by, the evolution of their firms. In addition to addressing causality concerns, this type of research could explore new questions. For instance, what trajectories of network change create most value? How does churn in entrepreneurs' personal networks (i.e. the adding and dropping of network contacts, ties, and structural holes) affect small firm performance? When is network stability more desirable and under what conditions are dynamic personal networks advantageous?

Third, to unearth the mechanisms underlying the reported effect sizes, more research is needed that captures potential mediating variables at different levels of analysis. I have conceptualized social capital at the individual level but considered performance at the firm level. Although this approach is consistent with past work (Maurer and Ebers, 2006), it raises questions about the processes through which social capital translates into firm level outcomes. Future research may therefore directly consider how social capital influences entrepreneurs' motivations, goals, emotions, and decision-making (De Carolis et al., 2009). In so doing, researchers could disentangle the individual level returns to social capital from its firm level impact. Studies may also examine how the network ties of employees, founders, and the firm as a whole combine to influence firm outcomes. This would enable researchers to evaluate the relative importance of, and potential complementaries between, social capital at different levels.

Fourth, by contrasting bridging and bonding views of social capital, I have disregarded potential complementarities between the two perspectives. Recent research indeed suggests that optimal network configurations often combine bonding and bridging elements (Gulati et al., 2011). Likewise, I have examined each contextual contingency independently while they are in fact nested (Welter, 2011). Since social capital beneficial in one context can be detrimental in another, it might be difficult for entrepreneurs who traverse such contexts to optimize their social capital. To examine this, future studies may adopt a configurational perspective (Stam and Elfring, 2008) by studying how configurations of multiple network and contingency variables influence small firm performance. This research could also explore how entrepreneurs who operate in multiple contexts resolve the tension emerging from context-specific network requirements. For instance, do entrepreneurs who expand into other markets benefit more from redeploying their accumulated social capital or from building distinctively different networks in each context? What factors facilitate or constrain such "network ambidexterity"?

Fifth, my results indicated the likely presence of other moderators. One idea that deserves more attention is the possibility that the knowledge, skills, and personality traits of entrepreneurs might condition the value of social capital. There is, for instance, evidence that entrepreneurs with diverse career experiences (Stam, 2010) and self-monitoring personalities (Oh and Kilduff, 2008) develop richer networks. Likewise, more research is needed that examines heterogeneity in firms' abilities to absorb and leverage social capital resources. For example, whether small firms extract value from particular networks may depend on the extent to which they follow a niche or generalist strategy (Echols and Tsai, 2005). Future research may therefore study how the resources, capabilities, and competitive positioning of small firms affect returns to social capital.

3.6. Conclusion

By synthesizing cumulative findings and uncovering new moderators, this meta-analysis contributes toward better understanding of the contingent value of social capital for small firms and reveals how sampling, research design, and measurement may influence research findings. For entrepreneurs, my results clearly indicate the importance of cultivating personal networks rich in bridging social capital but also reveal that distinct networking strategies are needed at different points in time and in different industries and countries. For researchers, my study certainly supports the increasingly prominent role that social capital theory assumes in the entrepreneurship field but raises new questions about its temporal and contextual boundary conditions. I truly hope that these insights invite scholars in the field to further disentangle the varied roles networks may assume in the entrepreneurial process.