From Knowledge Sharing to Firm Performance:

A Predictive Model Comparison

Zhining Wang, China University of Mining and Technology

Pratyush Nidhi Sharma, University of Delaware

Jinwei Cao, University of Delaware

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The authors are grateful for comments on this article by Sunny Rosen (University of Delaware). Send correspondence to Zhining Wang, School of Management, China University of Mining and Technology, Xuzhou, Jiangsu, 221116, China, wangzhining@cumt.edu.cn. Pratyush Nidhi Sharma, 217 Purnell Hall, Newark, DE, 19716, USA, pnsharma@udel.edu. Jinwei Cao, 210 Purnell Hall, Newark, DE, 19716, USA, jcao@udel.edu. This research is supported by the National Science Foundation of China (Grant No. 71302140) and China Postdoctoral Science Foundation (Grant No. 2014T70565).

Abstract

This study investigates how knowledge sharing (KS) contributes to firm performance (FP) through the enhancement of innovation and/or intellectual capital (IC) using data collected from Chinese high-technology firms. The paper proposes three alternative models that suggest different mediating roles of innovation and IC components in the KS→FP nomological network based on existing theory. The paper then compares these models in terms of in-sample explanatory and out-of-sample predictive powers using consistent partial least squares path modeling (PLSc). Results indicate that in the best performing model, innovation and IC simultaneously mediate the relationship between KS and FP in this specific context. The findings offer insights regarding the parallel mediation roles of innovation and IC in the KS→FP process, showcase the predictive utility of PLSc, and can help managers set priorities when leveraging KS to achieve specific performance goals.

Keywords: knowledge sharing; innovation; intellectual capital; firm performance; explanatory and predictive power; holdout sample; causal asymmetry

1. Introduction

Knowledge sharing (KS) is an integral component of knowledge management

that helps transform individual knowledge into organizational knowledge and improve firm performance (FP) (Foss, Husted, and Michailova, 2010). However, the mere implementation of KS may not guarantee improvements in performance (Haas and Hansen 2007). Two parallel streams of work that investigate how KS benefits organizations suggest that innovation and intellectual capital (IC) are critical drivers of FP, and may mediate the effect of KS on performance (Liao, Fei, and Chen, 2007; Wang, Wang, and Liang, 2014; Wang and Wang, 2012).

Although existing research helps researchers to better understand the value of KS in organizations, several broad concerns still remain. First, the roles of innovation and IC in the nomological network between KS and FP remain unclear. Companies may intuitively assume that KS will help them build IC that will subsequently enable them to innovate and achieve better performance. Conversely, as a McKinsey study about innovation in China shows, companies can also innovate quickly due to successful KS before or while building a knowledge and experience base (IC) (McKinsey Global Institute, 2015). This finding begs the question whether a logical order (mediation chain) exists or IC and innovation simultaneously mediate the relationship between KS and FP. Second, although KS influences various aspects of innovation (e.g. Liao et al., 2007), extant research seldom examines how innovation speed and quality, the two central components of innovation, transmit the effects of KS to FP. Finally, few studies focus on the components of IC (i.e. human, structural and relational capital) simultaneously to explore their roles in the KS→FP relationship.

This paper intends to fill these gaps and compares three alternative model specifications to examine how KS may contribute to FP through innovation and IC, by utilizing the knowledge-based view (KBV) and innovation and IC literature. The primary purpose of this research is to determine which one of the three possible KS-based alternative models provides a more complete explanation and best prediction of FP in a real-world context, and to clarify the mediating roles of innovation and IC components in the KS→FP nomological network. The study tests the models on a survey of top executives in Chinese high-technology firms (CHTF). Findings indicate that the model in which innovation and IC play parallel mediation roles between KS and FP not only explains the highest proportion of variance, but also provides the best prediction of FP. In addition, a specific component of IC, relational capital (RC) has the most significant effect on FP, indicating the importance of RC in the CHTF context.

The present work makes the following contributions. First, by providing empirical support for the links among KS, innovation, IC, and FP in one integrated framework, the study bridges the gap between two parallel streams of work, thereby clarifying the KS→FP nomological network and enriching the theoretical understanding of the role and implications of KS in firms. Second, by confirming the influence of explicit and tacit KS on innovation and IC constructs, which in turn lead to FP, this study offers specific insights concerning the role of innovation and IC and adds to the KBV literature. Third, the best performing model has the highest explanatory and predictive power for FP, and can therefore help managers set

priorities when leveraging KS for achieving specific performance goals. Finally, by comparing the three theoretically motivated models for their explanatory and predictive powers this paper exemplifies the predictive model comparison approach using PLSc. While often regarded as a predictive technique, researchers use PLS-based methods extensively for causal-explanatory modeling while ignoring the predictive aspect. This study presents an example of how researchers can motivate their prediction studies using PLSc. The following sections discuss existing research, the three alternative models, predictive model comparison approach, results, and implications in detail.

2. Literature Review

Knowledge sharing (KS): Explicit and tacit KS. KS refers to the process of transmission, communication, interaction, and coordination of knowledge or expertise that helps improve organizational productivity, absorptive and innovation capacity, and sustain competitive advantage (Liao et al., 2007; Wang et al., 2014). Recent research focuses on the distinction between explicit and tacit KS and the impact on firm performance (Wang and Wang, 2012; Wang et al., 2014) by utilizing Polanyi's (1967) typology of knowledge and knowledge creation theory (Nonaka, 1994).

Explicit KS is the process of sharing codified knowledge that can be captured and transmitted within an organization. Such knowledge may appear in documents and reports, procedures and policies, or handbooks (Hislop, 2013). On the other hand, tacit KS refers to the sharing of knowledge that individuals possess but is hard to express in symbolic or written form. Thus, tacit knowledge relates to the experiences

and expertise, uncommon understandings, insights and intuitions, and knowledge of “more than we can tell” (Polanyi, 1967, p. 4; Peet, 2012).

KS can enhance organizational knowledge-based resources/capabilities and lead to the improvement of work outcomes through the exchange and utilization of scattered information, experiences, practices, insights, and uncommon understandings. However, due to a variety of potential barriers, such as people’s inherent hostility, search and transfer costs, and misaligned incentive systems, it is challenging for organizations to successfully implement KS (Haas and Hansen, 2007). Furthermore, mere implementation of KS may not guarantee improved performance. Therefore the question of whether and how KS contributes to firm performance (FP) attracts significant research attention. Recent literature examines the link between KS and FP from various angles (Hsu, 2008; Wang et al., 2014; Wang and Wang, 2012), resulting in two main streams of studies. One stream of research involves the area of intellectual capital (IC), which basically concerns the knowledge of staff, infrastructure, and relationships within a firm (Wang et al., 2014). Another stream of research relates to innovation, such as the creation of new products, services, and processes (Drucker, 2014). Both streams of research indicate that KS can lead to FP through intermediate variables such as innovation and IC (Wang and Wang, 2012; Wang et al., 2014).

Intellectual capital (IC): Human, structural and relational capital. IC refers to the total amount of knowledge that an organization can leverage for conducting business and gaining competitive advantage (Subramaniam and Youndt, 2005). Wang

et al. (2014) study the individual IC components, such as human, structural, and relational capital in detail. This paper defines human capital as the summation of employees' competences, knowledge, skills, innovativeness, attitudes, commitment, wisdom, and experiences, which represents an organization's entire available knowledge stock (Campbell, Coff, and Kryscynski, 2012). On the other hand, structural capital is the valuable knowledge asset embedded in organizational culture, routines, procedures, information systems, hardware, software, databases, company images, patents, copyrights, trademarks, and so on (Aramburu and Saenz, 2011). Finally, relational capital refers to the knowledge and learning capabilities that exist in relationships between an organization and the stakeholders (Bontis, 1998; Yang and Lai 2012).

Researchers find that KS contributes to IC components by enhancing individual knowledge and performance (Hsu, 2008; Quigley, Tesluk, Locke, and Bartol, 2007), improving organizational capabilities (Zahra, Neubaum, and Larraneta, 2007), and strengthening professional relationships (Hu, 2009). Knowledgeable individuals with excellent problem-solving experiences and skills are in turn essential for producing new products, improving managerial and operational efficiency, and boosting quality and productivity (Campbell et al., 2012). Similarly, improvements in organizational capabilities lead to higher quality work with lower costs (Aramburu and Saenz, 2011). Finally, enhanced professional relationships help to optimize the business model by learning from experiences and lessons from the outside (Cousins, Handfield, Lawson, and Petersen, 2006; Wang et al., 2014). Therefore, all the IC components are expected

to have a positive influence on FP.

Innovation speed and quality. Innovation involves adopting or creating new products, services, work processes, or management procedures to gain organizational competitive advantage (Drucker, 2014). Scholars recognize speed and quality as two critical characteristics of successful innovation in complex and rapidly changing business environments (Wang and Wang, 2012). Innovation speed is the pace of progress of an innovation, from the conception and initial development to the ultimate commercialization. A firm's ability to accelerate the generation of new products or processes relative to the competitors reflects innovation speed (Kessler and Chakrabarti, 1996; Allocca and Kessler, 2006). On the other hand, innovation quality refers to the process and end result of innovation (Haner, 2002). A variety of indices may capture innovation quality such as effectiveness, features, reliability, cost, value to the customer, innovation degree, and complexity (Wang and Wang, 2012).

Existing research indicates that KS results in improved innovation capability (Liao et al., 2007) and innovation performance (Taminiau, Smit, and de Lange, 2009). KS leads to innovation speed and quality because it makes the decision-making process more efficient and effective by providing the basis for knowledge coordination and cooperation (Wang and Wang, 2012). Increased innovation speed helps organizations respond quickly to changing market requirements and gain customers due to the first-mover advantage (Kessler and Chakrabarti, 1996; Allocca and Kessler, 2006). Improved innovation quality improves the resource utilization within an organization and enhances quality management, organization

responsiveness, and customer satisfaction, which form the basis of profit on new products or services (Haner, 2002; Wang and Wang, 2012). Therefore, improvements in innovation speed and quality directly impact FP.

Firm performance (FP): Operational and financial performance.

Researchers consider operational and financial performance as the critical components of FP due to the impact of these elements on firm competitiveness and survival (Wang and Wang, 2012; Wang et al., 2014). Operational performance reflects the underlying success factors ranging from quality control to cost management within a firm that lead to competitive advantage in the long-term (Samson and Terziovski, 1999). This paper defines operational performance as the combination of customer satisfaction, quality development, cost management, responsiveness, and productivity. Conversely, financial performance refers to how well a firm uses assets to generate revenues as reflected by the firm's financial statements.

3. Three Alternative Models

Although existing research has reached a consensus that innovation and IC play mediating roles between KS and FP, their roles and the logical order in the KS→FP nomological network remain unclear. Based on the logical relationships between innovation and IC, this paper deduces three alternative models from existing parallel research streams to explain the roles of innovation and IC in the KS→FP nomological network.

Model 1: KS→IC→Innovation→FP. Studies grounded in the knowledge-based view suggest that KS directly leads to improvements in various IC

components (Wang et al., 2014). KS not only changes employees' attitudes (Reychav and Weisberg, 2009) and competencies (Hsu, 2008), but also facilitates transformation of individual knowledge to organizational knowledge, resulting in the advancement of technological capabilities (Zahra et al., 2007) and organizational effectiveness (Yang, 2010), as well as building trust among employees (Luna-Reyes, Black, Cresswell, and Pardo, 2008). Research also shows that IC leads to stronger innovation capabilities (Wu, Chang, and Chen, 2008). Specifically, IC components such as human, organizational, and social capital positively influence incremental and radical innovative capabilities (Subramaniam and Youndt, 2005). Because innovation is an important antecedent of FP and organizational competitive advantage (Chen and Huang, 2009), researchers may assume that KS impacts IC components first, subsequently affecting innovation, and eventually bringing changes to FP. The first model reflects this logic and is shown in figure 1.

Figure 1 here.

Model 2: KS→ Innovation→ IC→ FP. A parallel research stream suggests that KS may directly improve various aspects of innovation (Wang and Wang, 2012). This stream of literature suggests that KS practices and processes lead to innovation capability (Liao et al. 2007), facilitate the generation of new ideas, processes and products, and improve innovation speed and quality (Wang and Wang, 2012). Innovation may in turn affect the stock of intangibles and facilitate the development of IC (Marqués, Simón, and Carañana, 2006). Several studies contend that the process of innovation enhances the knowledge, skill, and experience of employees

(Amadi-Echendu, 2007), improves the organizational structure, mechanisms and capabilities (O'Connor, 2008), and strengthens the embedded relationships (Guevara and Bounfour, 2013). These studies also treat IC as the immediate antecedent of organizational success (Wang et al., 2014). Thus, the second model posits that KS impacts innovation first, subsequently affecting IC, and eventually leading to FP (figure 2).

Figure 2 here.

Model 3: $KS \rightarrow (IC \mid Innovation) \rightarrow FP$. Models 1 and 2 are both based on chain mediation logic (Taylor, MacKinnon, and Tein, 2011), but disagree with regards to the direction of effects between innovation and IC. A third model (figure 3) proposes simultaneous multiple-mediation and places innovation and IC at the same intermediate level in the $KS \rightarrow FP$ nomological network to capture strategies adopted by various types of firms. Rather than positing a logical order between IC and innovation, this model assumes that both processes may coexist in various degrees among diverse high-technology firms, ranging from large to small and new to old. Theoretically, the model allows KS to affect FP through either one or both linkages depending on firm characteristics, and does not require firms to employ both the mechanisms to the same extent at the same time. For example, a recent McKinsey study shows that newer Chinese companies focus more on rapid innovation than IC to achieve higher performance (McKinsey Global Institute, 2015), since acquiring and strengthening IC requires a relatively chronic accumulation of support from other factors (Reich and Kaarst-Brown 2003). Conversely, larger companies with installed

bases may suffer from innovation inertia and allocate larger resource shares to consolidate IC as a way to achieve process efficiencies and higher performance levels (Herbig and Kramer, 1993). Thus, this model includes both IC and innovation at the same level to capture strategies adopted by various types of firms.

Figure 3 here.

4. Predictive model comparison approach

This study compares the three alternative KS models based on both their in-sample explanatory and out-of-sample predictive powers. A common approach to PLS model comparisons relies solely on the explanatory perspective while ignoring the predictive aspect. For example, in technology acceptance research Plouffe, Hulland, and Vandenbosch (2001) compare the technology acceptance (TAM) and perceived characteristics of innovating (PCI) models solely on their explanatory power. Similarly, Venkatesh, Thong, and Xu (2012) compare the unified theory of acceptance and use of technology (UTAUT) to an extended version that includes three additional constructs (UTAUT2) solely based on the explanatory power (R^2). While such comparisons are useful in assessing explained variance in a given sample, they provide no information about the real-world predictive power of models. In fact, model comparisons solely based on explanatory power may lead researchers to over-fit their models, negatively impacting their generalizability to other samples (Sharma and Kim, 2012). Worse, as Shmueli (2010) argues, researchers often confuse explanatory power with predictive power. In reality, predictive power cannot be inferred from explanatory power (Shmueli and Koppius, 2011). In a recent editorial,

Woodside (2013) also stresses on the need for testing for predictive validity of models and not just model fit.

In contrast to theory-driven explanatory modeling, predictive modeling is more data-driven, and focuses on building models that accurately predict new or unseen data using the associations between manifest variables. Thus, while the metric optimized in explanatory modeling is in-sample explained variance (R^2), predictive modeling requires the use of training and holdout sets and out-of-sample accuracy criteria such as root mean square error (RMSE).

Prediction can be a vital tool for comparing competing theories, improving them, and assessing the predictability of empirical phenomena (Shmueli and Koppius, 2011), even if the underlying causal processes are not well understood (Sutton, 1998). Predictive analytics can help resolve the mixed conclusions of existing explanatory models by assessing their real-world predictive powers (Shmueli and Koppius, 2011). This method is especially useful in comparing non-nested models belonging to different theoretical frameworks. The three models posited in this study are all theoretically plausible and derivable from different streams of existing research, thus necessitating a predictive approach.

Although prediction and explanation are different goals, a predictive model that also explains the underlying phenomena well is very useful because it may not only be generalizable and reproducible but also interpretable, thus leading to new theoretical insights. Gregor (2006) proposes a taxonomy of theories that include explanatory (E), predictive (P), and explanatory and predictive (EP) classes. Models

that achieve a balance between prediction and explanation (EP) are more valuable than solely explanatory (E) or predictive (P) models. The main purpose of this study is to select a model that not only explains but also predicts firm performance well, and employs a two-step strategy that first analyzes the models for their in-sample explanatory power and subsequently compares them on their out-of-sample predictive power.

5. Data

Sample. This study utilizes convenience sampling and key informant methods to conduct a survey of CEOs, general, or senior managers of 800 Chinese high-technology firms (CHTF), with each company receiving one questionnaire. CHTF have independent intellectual property rights, talented staff, and heavily invest in research and development. The increasingly competitive global economy in which they function necessitates a deeper understanding and better management of knowledge resources that are critical for survival and success. Thus, CHTF provide a suitable real-world context to explore the predictive and explanatory abilities of the models. A total of 328 out of 356 received responses were complete (valid response rate of 41 percent). T-test comparisons of firm size and age of the earliest and last 82 respondents are statistically insignificant, suggesting that non-response bias is not a concern.

Survey measures and items. To ensure construct reliability and validity, the study draws measurement items from existing scales, and translates them to Chinese (the study uses the back translation method to ensure the validity of the translations).

An expert panel consisting of two professors, six CEOs and senior managers examined the face validity of the items. Data collection began with the final questionnaire after two rounds of pretests and revisions. All questionnaire items use a seven-point Likert-type scale. For more details of the constructs, items, and their sources, see Appendix I.

Control variables. Firm age and size (natural log of number of employees) act as control variables to account for differences among firms and their potential impact on performance (Yasuda, 2005).

Common method bias. Survey-based studies that collect data on predictor and criterion variables from the same respondent may suffer from common method bias (CMB). The measured latent marker variable approach can help detect and control CMB (Chin, Thatcher, Wright, and Steel, 2013). This study uses the construct-level correction approach with four unrelated items to apply the marker variable method. The results show that the path loading and model fit values are consistent with original estimates (Appendix II). This suggests that CMB is not a serious issue.

Causal asymmetry. Causal symmetry in relationships among latent variables means that high (low) values of predictors are both necessary and sufficient for high (low) values of predicted variables to occur (Woodside, 2013). On the other hand, causal asymmetry implies that a more complex combination of antecedents, or causal recipes, may be at work (Ragin, 2008). Failing to account for causal asymmetry may result in incomplete or even incorrect causal understanding of phenomena under study. While this aspect is critical for causal-explanatory studies, data-driven predictive

analytics relies on association rather than causation, and focuses more on assessing the quality of out-of-sample predictions than causal explanations (Shmueli and Koppius, 2011). Finally, an important aspect of asymmetrical relationships is that they imply heteroscedasticity (Clark, Gilligan, and Golder, 2006), and that heteroscedasticity tests can help rule out causal asymmetry (Tsebelis, 1999). The results (Appendix III) show that both Breusch-Pagan and Koenker tests for heteroscedasticity are not significant and do not reject the null hypothesis for the two endogenous variables (FP and OP). This finding suggests that causal asymmetry is less of a concern for this study.

6. Empirical Methodology

Generating accurate out-of-sample predictions in the holdout sample requires consistent path estimates obtained from the training sample. This study uses consistent partial least squares path modeling (PLSc) to obtain consistent path estimates from training data, and compare the explanatory and predictive abilities of the models due to the lack of consistency in PLS path estimates in common factor models (Dijkstra and Henseler, 2015). PLSc not only focuses on maximizing explained variance but also provides consistent path estimates in models involving reflective constructs, thereby improving prediction estimates. This feature can be especially useful to create EP class of theories. Furthermore, variance-based methods such as PLSc have an advantage over covariance-based SEM techniques because they yield determinate predictions (Becker, Rai, and Rigdon, 2013).

Measurement model validity. The study performs a series of tests for

reliability and convergent and discriminant validity for reflective constructs (Hair, Hult, Ringle, and Sarstedt, 2013). All path loadings in table 1 are significant, and are close to or exceed recommended threshold value (0.70). In addition, the average variance extracted (AVE) and composite reliability (CR) of all constructs are close to or exceed recommended threshold values of 0.50 and 0.70, respectively, thereby establishing sufficient convergent validity and reliability.

Table 1 here.

Tables 2 and 3 show the results of discriminant validity test using the Fornell-Larcker criterion and Heterotrait-Monotrait (HTMT) ratio (Henseler, Ringle, and Sarstedt, 2015). All diagonal elements in table 2 are appreciably greater than off-diagonal elements, thereby satisfying the Fornell-Larcker criterion. Additionally, all values in table 3 are smaller than recommended HTMT cut-off value of 0.85, providing ample evidence of discriminant validity of constructs.

Tables 2 and 3 here.

Structural model comparisons. The original sample ($N = 328$) is divided into training ($N = 246$) and holdout ($N = 82$) samples using a 75:25 rule (Steckel and Vanhonacker, 1993). The study first compares the three models for their explanatory powers using in-sample fit measures (R^2 and Adjusted R^2) on the training sample. Table 4 presents PLSc path estimates and in-sample measures for the three models. The differences in R^2 between models 1 and 3, and between models 2 and 3 are sizable. This result suggests that model 3 performs best in explaining variance in FP and OP. Adjusted R^2 shows similar results.

While R^2 based metrics allow for the evaluation of in-sample explanatory power, they cannot be the sole criteria for model selection due to their tendency to increase with model complexity (i.e. over-fitting; Sharma and Kim, 2012; Woodside, 2013). Stone-Geisser Q^2 is an in-sample measure of predictive relevance that guards against over-fitting problems by using leave-one-out cross validation (blindfolding), and is useful to assess generalizability to other samples (Hair Jr. et al., 2013). Model 3 shows highest in-sample predictive relevance for FP and OP. Thus, all three in-sample measures strongly prefer model 3 to the other two.

An interesting finding is that RC has a significant effect on both FP and OP. However, SC and HC have significant positive impact only on OP but not on FP (see Table 4). This result might be unique to Chinese contexts, because researchers have found that *guanxi*, the focus on interpersonal relationships, is a critical factor in doing business in China (Luo, Huang, and Wang, 2012). Another plausible explanation is that high-tech companies must partner more to create research and development alliances as technology development becomes increasingly complex (Hernandez, 2015).

Table 4 here.

Assessing out-of-sample prediction abilities of models requires a holdout set and use of out-of-sample prediction criteria (Shmueli and Koppius, 2011). Here, root mean square error (RMSE) acts as a measure of prediction accuracy, while out-of-sample R^2 measures the amount of variance explained in the holdout sample (Becker et al., 2013). Statistical significance of predictors and model fit are irrelevant

while assessing predictive abilities of models (Shmueli and Koppius, 2011). Instead, training sample weights are used to generate out-of-sample predictions on the holdout sample. Since training and holdout data come from the same population they are identically distributed, and any bias due to survey instrument or self-selection is irrelevant, because the same mechanism operates at time of prediction (Shmueli and Koppius, 2011).

As Table 5 shows, model 3 has lowest RMSE value among the three models, and provides the most accurate prediction for both firm performance measures. In terms of out-of-sample R^2 , model 3 again performs best for FP and OP, suggesting that this model is the best among the three alternative models for both explanation and prediction.

Table 5 here.

7. Discussion

Summary. This study compares three alternative models using data from CHTF to clarify roles of innovation and IC components in the $KS \rightarrow FP$ nomological network. The model comparison uses the consistent partial least squares path modeling (PLSc) method, which provides both in-sample explanatory and out-of-sample predictive powers, in order to generate more reproducible and interpretable results. PLSc provides consistent path estimates in common factor models while PLS does not (Dijkstra and Henseler, 2015). Obtaining robust path estimates from training samples is necessary to generate accurate out-of-sample predictions on the holdout set. The model comparison results show that models 1 and

2 demonstrate lower in-sample explained variance and out-of-sample predictive accuracy than model 3. Model 3 not only explains the highest proportion of variance but also provides best prediction of FP, indicating that innovation and IC play parallel mediation roles between KS and FP. In addition, RC has significant effect on both FP and OP while SC and HC had significant positive impact only on OP but not on FP, indicating the importance of RC in the CHTF context.

Implications. This paper bridges the gap between two parallel streams of work (innovation or IC as mediator) by clarifying links among KS, innovation, IC, and FP in one integrated framework. The best performing model (model 3) suggests that innovation and IC play simultaneous mediation roles between KS and FP, and, although not hypothesized in this paper, may develop synergy or feedback between each other over the long term. This result can help managers in high-tech industries set priorities when leveraging KS to achieve performance goals. The central lesson managers should learn from this research is the fallacy of the assumption that innovation only occurs after building strong IC, or vice versa. Instead, managers should develop strategies to promote innovation and IC concurrently. Therefore, R&D, IT, and HR departments should work together to draw up deliberate plans to efficiently utilize KS to achieve higher performance, irrespective of firm size and age. Moreover, firms can reap performance benefits due to KS, regardless of whether they are leaning more toward innovation, building stronger IC bases, or both.

The results also highlight the importance of RC in the CHTF context. Thus, CHTF must focus on building relational capital to see stronger returns on their KS

efforts. This finding assumes even more importance in light of a recent finding by Wallace (2009) that while 88 percent of executives indicated that the strength of their client, customer, and referral relationships was critical to achieving their goals, only 25 percent of those same executives had formal processes for planning, managing, and growing business relationships. Executives must initiate formal processes that enhance perceptions of credibility, integrity, and authenticity among stakeholders and clients. CHTF must move beyond a transactional mind-set and on to the development of trust-based, mutually beneficial, and long-term associations with customers, suppliers, partners, and employees (Gulati, Huffman & Nielsen 2002). Relational capital impacts both operational and financial performance of firms and should be viewed as a strategic asset.

This analysis also helps to benchmark predictive abilities of existing KS-based models, and validates assertions of the predictive validity of the constructs, specifically in the Chinese context. The out-of-sample R^2 metric is especially helpful in this regard because of the ease of interpretation, and shows that Model 3 has small-medium out-of-sample R^2 (17% for FP and 22% for OP), as per Cohen's (1992) rules of thumb. In contrast, the in-sample R^2 is medium-large (between 34% for FP and 43% for OP). Predictive analytics can be useful in assessing the distance between theory and practice (Shmueli and Koppius, 2011). Thus, while model 3 does a better job of explaining and predicting OP than FP in the CHTF context, the generally low out-of-sample R^2 values suggest that much room for improvement remains in the predictive abilities of these models, which future research should address. The

predictive benchmarks set in this study can be useful and meaningful for researchers as references for this purpose.

Finally, the study not only adds insights to the KBV literature by demonstrating how KS contributes to FP through the simultaneous mediation of IC and innovation, but also showcases the predictive role of PLSc. In particular, this paper presents an example of the predictive model comparison approach that also takes explanatory power into account. A nice feature of path models is that they are transparent and allow interpretation of links among variables. This feature can help the creation of explanation and prediction (EP) class of theories as suggested by Gregor (2006). Theories in the EP class not only make testable propositions and provide causal explanations but also predict which makes them superior to theories that belong only to the explanation (E) or prediction (P) class. In particular, by following a theory-driven two-step model comparison process using PLSc, this paper highlights possible steps involved in creation of EP class of theories.

Limitations. The cross-sectional nature of data does not permit us to make causal inferences empirically; rather directionality among constructs is implied as a form of association based on existing theory. Second, the best-performing model postulates that innovation and IC play parallel mediation roles between KS and FP, but does not advance any reciprocal effects between innovation and IC. Future research should examine this possibility using non-recursive modeling, especially over the long term. Finally, the results and the benchmarks in this study are strictly applicable only to Chinese contexts. Future studies should expand to other contexts to

provide a wholesome picture regarding the effects of innovation and IC in the KS→FP nomological network.

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Table 1
Convergent Validity and Reliability

Construct	Item	Loading	t-Val	AVE	CR
Explicit KS (ES)	es1	0.62	9.97	0.46	0.83
	es2	0.75	11.85		

	es3	0.70	10.41		
	es4	0.67	9.82		
	es5	0.64	9.53		
	es6	0.63	9.45		
Financial Performance (FP)	fp1	0.70	11.88	0.54	0.87
	fp2	0.72	12.11		
	fp3	0.87	16.47		
	fp4	0.70	10.39		
	fp5	0.67	10.23		
	fp6	0.71	11.02		
Human Capital (HC)	hc1	0.72	9.53	0.51	0.84
	hc2	0.60	7.68		
	hc3	0.74	10.94		
	hc4	0.80	10.58		
	hc5	0.69	9.02		
Innovation Quality (IQ)	iq1	0.77	13.56	0.51	0.84
	iq2	0.67	9.92		
	iq3	0.77	15.56		
	iq4	0.69	9.97		
	iq5	0.67	11.36		
Innovation Speed (IS)	is1	0.74	13.02	0.54	0.86
	is2	0.80	15.02		
	is3	0.78	13.44		
	is4	0.65	10.11		
	is5	0.71	13.85		
Operational Performance (OP)	op1	0.76	12.92	0.55	0.86
	op2	0.71	12.62		
	op3	0.74	12.79		
	op4	0.73	12.33		
	op5	0.77	14.73		
Relational Capital (RC)	rc1	0.75	15.20	0.51	0.84
	rc2	0.63	11.31		
	rc3	0.78	15.29		
	rc4	0.75	14.65		
	rc5	0.64	11.13		
Structural Capital (SC)	sc1	0.84	13.82	0.54	0.89
	sc2	0.80	13.88		
	sc3	0.63	8.13		
	sc4	0.81	12.66		
	sc5	0.67	9.89		
	sc6	0.66	9.75		

	sc7	0.70	11.07		
Tacit KS (TS)	ts1	0.80	12.01	0.50	0.87
	ts2	0.66	9.96		
	ts3	0.61	9.02		
	ts4	0.74	11.95		
	ts5	0.66	8.09		
	ts6	0.78	12.28		
	ts7	0.66	10.11		
Firm Age (FA)	fa	1.00	NA	1.00	1.00
Firm Size (FS)	fs	1.00	NA	1.00	1.00

Table 2
Discriminant Validity (Fornell-Larcker Criterion)

	ES	FA	FP	FS	HC	IQ	IS	OP	RC	SC	TS
ES	0.67										
FA	0.01	1.00									
FP	0.45	-0.03	0.73								
FS	-0.03	-0.05	0.04	1.00							
HC	0.38	-0.09	0.35	0.18	0.71						
IQ	0.46	-0.02	0.45	-0.01	0.37	0.71					
IS	0.49	-0.06	0.36	0.05	0.39	0.48	0.74				
OP	0.46	-0.02	0.41	0.02	0.38	0.48	0.46	0.74			
RC	0.46	0.01	0.52	0.02	0.40	0.43	0.48	0.47	0.71		
SC	0.38	0.02	0.36	0.01	0.35	0.50	0.46	0.45	0.45	0.73	
TS	0.42	0.03	0.44	0.05	0.34	0.40	0.43	0.46	0.40	0.36	0.70

Table 3
Discriminant Validity (HTMT Criterion)

	ES	FA	FP	FS	HC	IQ	IS	OP	RC	SC	TS
ES											
FA	0.02										
FP	0.45	0.05									
FS	0.06	0.05	0.06								
HC	0.38	0.09	0.35	0.18							
IQ	0.46	0.04	0.45	0.05	0.37						
IS	0.49	0.06	0.36	0.04	0.39	0.48					
OP	0.46	0.05	0.41	0.06	0.38	0.48	0.46				
RC	0.45	0.06	0.52	0.05	0.40	0.43	0.47	0.47			
SC	0.38	0.07	0.36	0.07	0.35	0.49	0.46	0.45	0.45		
TS	0.42	0.04	0.43	0.06	0.33	0.40	0.42	0.46	0.40	0.35	

Table 4
Path Estimates and Explanatory Power

Structural Path Estimates (PLSc)						
	Model 1		Model 2		Model 3	
Relationship	Path	p-Value	Path	p-Value	Path	p-Value
ES -> HC	0.37	0.00			0.37	0.00
ES -> IQ			0.30	0.00	0.34	0.00
ES -> IS			0.33	0.00	0.38	0.00
ES -> RC	0.33	0.00			0.33	0.00
ES -> SC	0.30	0.00			0.30	0.00
HC -> IQ	0.17	0.01				
HC -> IS	0.16	0.02				
HC -> FP			0.14	0.01	0.09	0.15
HC -> OP			0.20	0.00	0.16	0.01
IQ -> HC			0.25	0.00		
IQ -> RC			0.28	0.00		
IQ -> SC			0.31	0.00		
IQ -> FP	0.34	0.00			0.21	0.01
IQ -> OP	0.32	0.00			0.15	0.02
IS -> HC			0.24	0.00		
IS -> RC			0.29	0.00		
IS -> SC			0.26	0.00		
IS -> FP	0.24	0.00			0.12	0.08
IS -> OP	0.34	0.00			0.18	0.01
RC -> IQ	0.26	0.00				
RC -> IS	0.28	0.00				
SC -> IQ	0.29	0.00				
SC -> IS	0.25	0.00				
RC -> FP			0.33	0.00	0.29	0.00
RC -> OP			0.25	0.00	0.19	0.00
SC -> FP			0.13	0.02	0.03	0.51
SC -> OP			0.26	0.00	0.18	0.01
TS -> HC	0.20	0.00			0.19	0.00
TS -> IQ			0.29	0.00	0.31	0.00
TS -> IS			0.24	0.00	0.26	0.00
TS -> RC	0.30	0.00			0.30	0.00
TS -> SC	0.24	0.00			0.24	0.00
Control Variables						
	Model 1		Model 2		Model 3	
Relationship	Path	p-Value	Path	p-Value	Path	p-Value

FA -> FP	-0.02	0.49	-0.01	0.78	-0.02	0.58
FA -> OP	0.02	0.47	0.03	0.31	0.03	0.33
FS -> FP	0.06	0.21	0.02	0.58	0.04	0.34
FS -> OP	0.05	0.21	0.01	0.79	0.02	0.62
In-Sample Explanatory Power						
	Model 1		Model 2		Model 3	
	FP	OP	FP	OP	FP	OP
R ²	0.26	0.32	0.23	0.30	0.34	0.43
Adjusted R ²	0.25	0.32	0.22	0.29	0.32	0.41
Q ² Redundancy	0.11	0.15	0.13	0.18	0.15	0.21

Table 5
Out-of-Sample Predictive Accuracy and Power

	Model 1		Model 2		Model 3	
	FP	OP	FP	OP	FP	OP
RMSE	2.88	2.65	2.86	2.63	2.80	2.57
Out-of-sample R^2	0.13	0.17	0.14	0.18	0.17	0.22

Figure 1
Model 1: KS → IC → Innovation → FP

Figure 2
Model 2: KS → Innovation → IC → FP

Figure 3
Model 3: KS → (IC | Innovation) → FP

Appendix I: Survey Measures and Items

Construct	Source	Item	Question
Explicit KS (ES)	Wang et al., 2014; Wang & Wang, 2012	es1	People in my organization frequently share existing reports and official documents with members of my organization.
		es2	People in my organization frequently share reports and official documents that they prepare by themselves with members of my organization.
		es3	People in my organization frequently collect reports and official documents from others in their work.
		es4	People in my organization are frequently encouraged by knowledge sharing mechanisms.
		es5	People in my organization are frequently offered a variety of training and development programs.
		es6	People in my organization are facilitated by IT systems invested for knowledge sharing.
Tacit KS (TS)	Wang et al., 2014; Wang & Wang, 2012	ts1	People in my organization frequently share knowledge based on their experience.
		ts2	People in my organization frequently collect knowledge from others based on their experience.
		ts3	People in my organization frequently share knowledge of know-where or know-whom with

			others.
		ts4	People in my organization frequently collect knowledge of know-where or know-whom with others.
		ts5	People in my organization frequently share knowledge based on their expertise.
		ts6	People in my organization frequently collect knowledge from others based on their expertise.
		ts7	People in my organization will share lessons from past failures when they feel necessary.
Innovation Speed (IS)	Wang & Wang, 2012	is1	Our company is quick in coming up with novel ideas than that of key competitors.
		is2	Our company is quick in new product launching than that of key competitors.
		is3	Our company is quick in new product development than that of key competitors.
		is4	Our company is quick in new processes than that of key competitors.
		is5	Our company is quick in problem solving than that of key competitors.
Innovation Quality (IQ)	Wang & Wang, 2012	iq1	Our company does better in coming up with novel ideas than that of key competitors.
		iq2	Our company does better in new product launching than that of key competitors.
		iq3	Our company does better in new product development than that of key competitors.
		iq4	Our company does better in processes improving than that of key competitors.
		iq5	Our company does better in management improving than that of key competitors.
Human Capital	Bontis, 1998;	hc1	Employees hold suitable work experience for accomplishing their job successfully in our

(HC)	Chen, Shih, & Yang, 2009; Hsu & Fang, 2009; Youndt et al., 2004		company.
		hc2	Employees of our company have excellent professional skills in their particular jobs and functions.
		hc3	The company provides well-designed training programs.
		hc4	The employees of our company often develop new ideas and knowledge.
		hc5	Employees are creative in our company. .
Structural Capital (SC)	Bontis, 1998; Hsu & Fang, 2009; Wu, Chang, & Chen, 2008	sc1	The overall operations procedure of our company is very efficient.
		sc2	Our company responds to changes very quickly.
		sc3	Our company has an easily accessible information system.
		sc4	Systems and procedures of our company support innovation.
		sc5	Our company's culture and atmosphere are flexible and comfortable.
		sc6	Our company emphasizes new market development investment.
		sc7	There is support among different departments in our company.
Relational Capital (RC)	Bontis, 1998; Hsu & Fang, 2009; Longo & Mura, 2011	rc1	Our company discovers and solves problems through intimate communication and effective collaboration.
		rc2	Our company maintains appropriate interactions with its stakeholders.
		rc3	Our company maintains long-term relationships with customers.

		rc4	Our company has many excellent suppliers.
		rc5	Our company has stable and good relationships with the strategic partners.
Operational Performance (OP)	Wang, Liang, Zhong, Xue, & Xiao, 2012; Wang et al., 2014; Wang & Wang, 2012	op1	Customer satisfaction of our company is better than that of key competitors.
		op2	Quality development of our company is better than that of key competitors.
		op3	Cost management of our company is better than that of key competitors.
		op4	Responsiveness of our company is better than that of key competitors.
		op5	Productivity of our company is better than that of key competitors.
Financial Performance (FP)	Wang, Liang, Zhong, Xue, & Xiao, 2012; Wang et al., 2014; Wang & Wang, 2012	fp1	Return on investment of our company is better than that of key competitors.
		fp2	Return on assets of our company is better than that of key competitors.
		fp3	Return on sales of our company is better than that of key competitors.
		fp4	Average profitability of our company is better than that of key competitors.
		fp5	Profit growth of our company is better than that of key competitors.
		fp6	Sales growth of our company is better than that of key competitors.

Appendix II: Measured Latent Marker Variable Approach for CMB

	With Marker		Without Marker	
Relationship	Path	p-Value	Path	p-Value
ES -> HC	.36	0.00	0.37	0.00
ES -> IQ	.34	0.00	0.34	0.00
ES -> IS	.38	0.00	0.38	0.00
ES -> RC	.33	0.00	0.33	0.00
ES -> SC	.30	0.00	0.30	0.00
HC -> FP	.09	0.12	0.09	0.15
HC -> OP	.16	.01	0.16	0.01
IQ -> FP	.20	.01	0.21	0.01
IQ -> OP	.15	.00	0.15	0.02
IS -> FP	.12	.07	0.12	0.08
IS -> OP	.18	.01	0.18	0.01
RC -> FP	.29	0.00	0.29	0.00
RC -> OP	.20	0.00	0.19	0.00
SC -> FP	.03	0.55	0.03	0.51
SC -> OP	.18	0.01	0.18	0.01
TS -> HC	.20	0.00	0.19	0.00
TS -> IQ	.31	0.00	0.31	0.00
TS -> IS	.26	0.00	0.26	0.00
TS -> RC	.30	0.00	0.30	0.00
TS -> SC	.24	0.00	0.24	0.00
Model Fit				
	FP	OP	FP	OP
R ²	0.33	0.42	0.34	0.43

Appendix III: Tests for Heteroscedasticity (Causal Asymmetry)

Dependent Variable	Test	$\chi^2_{(7)}$	<i>p-value</i>
OP	Breusch-Pagan	11.34	.12
	Koenker	12.70	.08
FP	Breusch-Pagan	4.38	.73
	Koenker	3.56	.83