INSIDER KNOWLEDGE AND OUTSIDER KNOWLEDGE: EFFECTS ON NEW VENTURE FORECASTING ACCURACY

MICHAEL L. DEVAUGHN[1]
University of St. Thomas
Opus College of Business
U.S.A.

MYLEEN M. LEARY
Montana State University
College of Business
U.S.A.

PRITAM DEY
University of Minnesota
Carlson School of Management
U.S.A.

Abstract

Forecasting is an inherently difficult process. This task is especially complicated in the context of new ventures where the typical firm has no operating history on which to draw and the firm's founders may have limited experience working together collectively as group. In this study, we argue that improving forecasting outcomes in new ventures may depend on the firm's access to different types and sources of knowledge. We investigate these arguments in the context of new ventures in the U.S. banking industry and find that both inside knowledge, embedded in founding team experience, and outside knowledge, generated by external consultants, improve forecasting accuracy.

Key Words: Founding teams; Consultants; Experience; U.S. banking industry

[1] Michael L. DeVaughn Opus College of Business, University of St. Thomas 1000 LaSalle Ave. S. Mail TMH 343 Minneapolis, MN 55403 U.S.A. Ph: 1.651.962.4297 Fax: 1.651.962.4710 eMail: deva2917@stthomas.edu

1. INTRODUCTION

Forecasting is an inherently uncertain process. Pundits often draw the analogy that forecasting is like driving a car and trying to navigate the road ahead by looking back in the car's rear view mirror. This task is especially difficult in the new venture context where typically the firm itself has no operating history on which to draw and the firm's founders may have limited experience working together collectively as group. Though more art than science, forecasting accuracy is likely to improve as knowledge and experience is accumulated over time. We investigate these arguments in the context of new ventures in the U.S. banking industry.

Past studies have highlighted the importance of the entrepreneurial founding team in providing access to different types resources (e.g., human, financial and knowledge) for the new venture. Recently, however, scholars have begun to pay much closer attention to the relative knowledge and information advantages conferred by background characteristics of founding teams. For example, Beckman, Burton & O'Reilly (2007) move from a traditional approach of looking solely at the amount of experience present on a team to a more nuanced view of examining such attributes as background affiliation and founding team entrances and exits in explaining new venture outcomes. Our paper builds on this view. We look at how founding team access to inside knowledge (different types of founding team experiences), and outside knowledge (external consulting advice) combine to inform an important start-up activity—forecasting financial performance.

2. THEORY DEVELOPMENT AND HYPOTHESES

2.1 Inside Knowledge

Existing research has established the importance of knowledge held by insiders to the success of the new venture (Schoonhoven et al., 1990; Heirman & Clarysse, 2007). Generally speaking, insiders tend to include members of the new venture's founding team. Such insiders are deemed to possess valuable knowledge and experience that facilitates achieving a wide variety of performance outcomes (Shane & Stuart, 2002; Hsu, 2004). New ventures often thrive because founding team members are often able to deploy this knowledge in unique ways that create value for the firm. For example, team members with prior founding experience represent a source of domain-specific routines that the firm can tap into to address issues critical associated with the start-up of the new venture, such as developing financial forecasts.

While we maintain that overall founding team experience is important, we suggest that it may be more instructive to specify the various types of founding team experience that might impact forecasting outcomes (Argote, McEvily & Reagans, 2003). We focus on four specific types of founding team experiences might be relevant: (1) prior shared experience, (2) prior founding team experience, (3) heterogeneous occupational experience represented by the team, and (4) total industry experience represented by the team. We develop hypotheses for each of these below.

2.2 Prior Shared Experience

Recent research has demonstrated a link between prior shared experience among founding team members and firm outcomes (Eisenhardt & Schoonhoven, 1990; Roure & Keeley, 1990; Kor, 2003; Reuf, Aldrich & Carter, 2003; Beckman, 2006; Delmar & Shane, 2006; Zheng, DeVaughn & Zellmer-Bruhn, 2007). These outcomes range from the influence on the goals and aspirations of the new firm (Delmar & Shane, 2006), to the type of strategy that the prospective new firm chooses to pursue at start-up (Beckman, 2006), to the impact on speed of new product or service launches (Schoonhoven et al., 1990; Heirman & Clarysse, 2007). Collectively, this research implies that founders with prior shared experience, because of their common affiliation, are likely to share common ideas about firm operating logics and firm values. Moreover, prior shared experience also facilitates efficient interpersonal processes and interaction routines among founding team members (Zheng, DeVaughn & Zellmer-Bruhn, 2007). Taken together, this suggests that founders with prior shared at a previous firm in the same industry are likely to have both a common, uncontested view of the firm's forecasting activities and prior forecasting experience. Therefore, we expect prior shared experience to increase forecasting accuracy.

H1: Greater prior shared experience on the new venture founding team increases forecasting accuracy

2.3 Prior Founding Experience

Research in entrepreneurship has demonstrated that prior founding experience can be valuable in the context of new ventures. Such work has argued that prior founding experience represents a source of domain specific knowledge that an entrepreneur can tap into during the start-up stage of his or her new venture. Shane & Stuart (2002) and Hsu (2004), for example, maintain that prior founding experience is useful for a whole host of start-up tasks, many of which can impact whether or not a new venture successfully gets off the ground. Shane & Stuart (2002) point out that prior founding experience can help entrepreneurs raise start-up capital, speed a new venture's transition to a liquidity event (such as an initial public offering) and avoid outright failure of the new firm. Similarly, Hsu (2004) argues that entrepreneurs with prior founding experience show an ability to access their first round of financing more quickly and amass higher levels of capital for their current venture than those founders that do not.

With respect to forecasting, we expect prior founding experience to be valuable as well; founding teams with repeat founders should have previous experience developing financial forecasts in this specific start-up context. Such founding teams should have access to a larger pool of relevant, start-up specific knowledge from which they can draw. This should, in turn, lead to better forecasting outcomes. Therefore:

H2: Greater prior founding experience on the new venture founding team increases forecasting accuracy.

2.4 Heterogeneous Occupational Experience

There is an active stream of research that suggests diversity, conceived as variety or heterogeneity within a team, can improve team outcomes (Harrison & Klein, 2007). The central premise of this work is the idea that a team can be viewed as an information-processing instrument for the organization (Hinsz, Tindale & Vollrath, 1997) and that teams that maintain a 'requisite variety' of heterogeneity (Ashby, 1956) are better able to parlay greater information richness into positive outcomes. Simply stated, firms whose members represent heterogeneous information pools, via their knowledge, functional background, experience or external social ties are likely to outperform firms comprised of more homogeneous members (Argote & Ingram, 2000). In our context, heterogeneity, in terms of occupational background and experience, means that a new firm may have access to a wider range of practices, routines and norms, based on the collective distinct experiences of the team. We argue that the benefits of heterogeneity may extend to important practices such as forecasting, where firms may be able to capitalize on this heterogeneity to improve its forecasting accuracy. Thus:

> H3: Greater heterogeneous occupational experience on the new venture founding team increases forecasting accuracy.

2.5 Total Industry Experience

Previous knowledge gained from organizations in the same industry can represent a key strategic asset if it can be effectively transferred to a new venture (Shane, 2000; Klepper, 2001). While such prior industry experience can be valuable, it assumes that such experience is relevant to the new venture. Several studies have supported the notion that past relevant experience is linked to successful new venture outcomes (Cooper & Bruno, 1977; Vesper, 1980; Van de Ven, Hudson & Schroeder, 1984; MacMillan, Zemann & Narasimha, 1987; Stuart & Abetti, 1987). Prior industry experience is beneficial because it provides founders with the opportunity to accumulate knowledge about tasks and roles and master routines and practices that might be germane in their new venture setting (Reagans, Argote and Brooks, 2005).

At the level of the founding team, prior industry experience is important because it means that members of the team are likely to share knowledge and information with each other and thus increase the pool of knowledge that is available to the entire team. Moreover, this cache of knowledge can represent information that is distinct from the knowledge that a single team member contributes directly (Reagans, Argote & Brooks, 2005). Having access to such knowledge may allow founding teams to better anticipate start-up difficulties and improve its forecasting accuracy. Thus, we maintain:

> H4: Greater total industry experience on the new venture founding team increases forecasting accuracy.

2.6 Outside Knowledge

In the arguments above, we focus on knowledge resources generated by internal firm sources, founding team members. However, we know that new firms often rely on an external network of formal and informal advisors (e.g., consultants, friends and family, outside investors, etc.) that reside beyond of the boundary of the firm (Chrisman & McMullan, 2000; Chrisman, McMullan & Hall, 2005). These outsiders can add value by providing new firms with specialized knowledge and advice in particular areas of need where the firm lacks specific expertise (Mole, 2002). With such an arrangement, new firms can focus their own limited resources on opportunities and tasks that are more aligned with the existing capabilities of the firm, thereby improving the efficacy of the start-up process.

2.7 Outside Consulting Assistance

As 'knowledge entrepreneurs' (Schaffer, 1988; Schaffer & Thompson, 1992), consultants are in a position to offer knowledge and skills that can help managers overcome challenges that they may be unequipped to deal with. In some industries, consultants are hired to facilitate the successful launch of a new firm. In the case of new banks, we find that consultants play a particularly vital role in the start-up process; they help fledgling new firms navigate the non-routine, complex regulatory environment that characterizes start-up in the banking industry (DeVaughn & Leary, 2007). Consultants are useful in such contexts because they have accumulated valuable, relevant and privileged knowledge via repeated assignments with similar clients in the same sector of the industry (Fichman, Clark, Handley & Sturdy, 2008) and such knowledge is likely to be unique compared to the firm's internally generated knowledge. Thus, by bringing to bear outside knowledge that leverages its deep, repeat experiences in helping similar firms develop forecasts, outside consultants can help the firm improve its forecasting accuracy. Therefore we claim:

H5: The use of an outside consultant by the new venture founding team increases forecasting accuracy.

3. RESEARCH METHOD

3.1 Research Context

The research context of new ventures in the U.S. banking industry is an appropriate one for this study. First, banking has proven to be fertile ground for examining start-up firms (Bamford, Dean & McDougall, 2000; Bamford, Dean & Douglas, 2004; DeVaughn & Leary, 2007). Moreover, with some 1,900 new banks launched nationally and 129 launched state-wide in Florida during the time span covered by this study, this context is especially fitting. Second, in banking, forecasting is an especially critical task. Success in the banking industry can hinge on a firm's ability to make accurate forecasts, particularly loan growth and deposit growth.

Finally, as a regulated industry, banking is subject to substantial oversight by regulators. With new banks, regulators seek accurate forecasts with little deviation. This is because regulators view fledgling new banks as financially fragile during their initial years of operation (DeYoung, 2000). Regulators believe that banks that report results that exceed forecasts run the risk of failure from loss of control (due to fast and unsustainable growth) and that banks that do not meet forecasts run the risk of failure via lack of market acceptance. Thus, accurate forecasting is a strategic operating imperative in the banking industry in the eyes of both shareholders, who seek maximum returns, and regulators, who seek stable growth.

3.2 Sample

Our sample includes the population of new state chartered commercial banks in Florida during the 11-year period between 1996 and 2006, the most active period for new bank charter requests. A total of 129 new banks were launched during the period. Twelve observations were ultimately dropped from the sample because of missing information on one or more variables for a final sample size of 117. This sample was used to test our hypotheses.

3.3 Data

Information on new bank founding team members was collected from biographical entries on new bank charter applications submitted to the Florida Office of Financial Regulation, a state-level bank regulatory agency responsible for chartering new banks in Florida. This information was also checked and cross-referenced with data compiled using local, regional and national bank trade publications. Data on bank forecasts were also collected from entries on new bank charter applications submitted to the Florida Office of Financial Regulation. As part of the application process, each new bank must submit an initial business plan that includes projections covering its first three years of bank operations. Demographic and structural information on the banks in the study was collected from the FDIC's *Institution Database*, a repository that lists data on all banks that maintain federal deposit insurance. Information on the macroeconomic conditions in the geographic markets of the prospective new banks was collected from the U.S. Department of Commerce's Bureau of Economic Analysis. Finally, Thomson's *North American Financial Institutions Directory* was also used as a final check to identify bank founding team members and to cross-validate other demographic entries taken from the previously mentioned sources.

3.4 Measures

3.5 Dependent Variable

The dependent variable in our study is forecasting accuracy (*forecast error*). We measure forecasting accuracy by computing the absolute percentage error between the predicted and actual values of a specific forecast. (Lower forecast error values indicate higher forecasting accuracy.) The absolute percentage error is computed as follows:

$$|\text{(Predicted value – Actual value)}| / \text{Actual} \times 100$$

To measure forecasting accuracy for more than one forecast across a specific time horizon, we calculate the mean percent error—the average of the absolute percentage error). In this study, we look at each new bank's first two full calendar year forecasts for three categories: loans, deposits and net income. Thus, we use the mean percent error, computed over two 1-year forecasting periods, to report a single measure of the average forecast error for each new bank's loans, deposits and net income projections.

Though there are several methods of calculating forecast error, the measure that we select, absolute percentage error, is appropriate given the nature of our forecast. The absolute percentage error approach does not differentiate between positive and negative forecast error. The underlying assumption of this method is that the likelihood of a negative error (underpredicting the actual value) and a positive error (overpredicting the actual value) is the same and random. In the banking industry, this assumption holds. In fact, regulators penalize new banks for both positive and negative forecasting errors. Bank regulators tend to view negative forecast error as a signal that the new bank is not meeting acceptance in the marketplace and positive forecast error as a signal that the new bank may be growing too quickly. Regulators believe that both scenarios are equally risky and threaten the viability of the fledgling new bank. Thus, new banks have little incentive to purposely overperform or underperform relative to their forecasts.

3.6 Independent Variables

3.7 Inside Knowledge

We employ four variables to measure different aspects of the knowledge and experience held by members of the new bank's founding team. First, we account for prior shared experience, *PSE*, on the founding team by noting the number of team members who have previously worked together at a prior banking institution before the launch of the new bank. Second, we measure the relative occupational heterogeneity of the founding team using a Blau (1977) index score. Higher index scores indicate that the team is more diverse with respect to the occupational backgrounds and experiences of its members. This variable is labeled *Blau*. We measure a third aspect of founding team experience, prior new bank start-up experience, by taking a count of the number of founding team members who have been involved in previous bank start-up efforts. We label this variable *former founder*. Finally, we account for a fourth aspect of founding team experience, total (banking) industry experience of the team, *industry experience*, by summing the total years of banking industry experience represented by each member of the team.

3.8 Outside Knowledge

We measure the impact of outside consulting assistance on forecasting accuracy by noting whether or not a new bank engaged a consultant to assist in the start-up process. Many prospective new banks hire consultants to assist in developing their initial business plans. This information is detailed in the bank's charter application that is filed with bank regulators. We use an indicator variable, *consultant*, scored 0 or 1, to denote consultant use.

3.9 Control Variables

We control for certain structural characteristics of the firm that might impact forecasting accuracy. Such characteristics have the effect of increasing the complexity of the firm and thus complicating forecasting. We include a variable to account for the organizational form of the firm (i.e., whether or not the new firm is part of a bank holding company), *BHC*. Choosing a bank holding company structure triggers a set of additional regulatory and reporting requirements for new banks. One such requirement is the preparation of two sets of financial forecasts (rather than a single set). Bank holding company banks must develop forecasts for both the bank holding company and the underlying bank. In addition, these forecasts are often linked in important, but complex ways, complicating the forecasting process. We use an indicator variable, scored 0 or 1, to note whether or not the new bank is part of a bank holding company at start-up.

A second structural characteristic that might impact forecasting accuracy is the size of a new bank's branch network. A bank whose initial plans include just a single bank branch may have a less difficult time forecasting than a bank whose plans include multiple bank branches during the start-up period. Accounting for customer growth plans, expenses and profits should be easier when the firm only has to consider variables associated with a single location. We use the variable *branches* to indicate the number of branch locations that each new bank opens during the forecasting period.

The financial structure of the new bank is the final structural characteristic for which we control. We use the amount of start-up equity capital that each new bank raised prior to the launch of the bank as a measure of its financial structure. Close observers of the banking industry argue that new banks with high levels of equity capital may be under pressure from investors to rapidly deploy this capital in order to increase returns. Such an impetus may lead to erratic and less predictable managerial decisions and behavior, compromising the firm's forecasting accuracy. We include the variable *initial capital* to account for the amount of start-up capital raised by each new bank.

We also control for specific environmental characteristics that might impact the bank's forecasting accuracy. First, we control for the general macroeconomic environment of the new bank. We look at changes in both the employment and population growth in the county in which the new bank is launched. The relative volatility of these economic factors may impact the new bank's ability to accurately forecast the demand for its products and services. We denote these variables in our model as *employment* and *population*. They are measured by looking at the percentage change (from the previous year) in employment and population in the year in which the new bank files its bank charter application with regulators.

In addition, we also control for competitive conditions in the market in which the new bank is launched. The number of existing competitors in the new bank's geographic trade area might also impact the bank's forecasting accuracy. It may be more difficult to prepare an accurate forecast if the bank has to account for many rather than just a few competitors. We account for competitive conditions by noting the density or number of existing financial institutions, *institutions*, in the same county as the new bank prior to its launch.

We include three additional control variables in our model. The first is a control for top management involvement in the forecasting process. Prior research has argued that top management involvement (i.e., CEO or other top operating official) in the development of a firm's forecast may either increase or decrease the accuracy of that forecast (Wacker & Sprague, 1995). The rationale for improving the firm's forecasting accuracy stems from top management's ability to increase the firm's commitment to achieving the forecast (Wacker & Sprague, 1995). On the other hand, top management involvement in the forecasting process may also decrease forecasting accuracy as top officials may develop a forecast that reflects 'hopes and wishes' rather than realistic targets (Plossl, 1973). We include the control variable *CEO* in our model to indicate whether or not the CEO was involved in developing the bank's forecast. We also include a control variable for the size of the founding team, *team size*. The size of the founding team can be viewed as a proxy for the resources available to the new bank. Finally, we include a dummy variable, *unique*, to account for two bank observations in our data that represent unusual values across a number of key variables and clear outliers based on regression residual analysis.

3.10 Analysis

We use an ordinary least squares (OLS) model specification to test our hypotheses. We enter our independent research variables into the model in a hierarchical manner to better evaluate the explanatory power of each set of variables. Finally, we run three independent regression models, one for each forecast type (i.e., loan growth, deposit growth and net income).

4. RESULTS

4.1 Bivariate Results

The descriptive statistics and correlations from our study are presented in Table 1. From this data we observe that the average new bank launched with almost $11 million in initial start-up capital, opened 3 bank branches during the start-up period and more often than not (in 56 percent of the cases) received consulting assistance at start-up. Moreover, the correlation matrix shows that forecasting error (in the areas of loan and deposit growth) appears to be most strongly associated with the number of bank branches opened during the start-up period, the amount of initial start-up equity capital raised by the bank and whether or not the bank's CEO was involved in the forecasting process.

4.2 Regression Results

We specify a series of regression models to test our hypotheses (shown in Table 2 and Table 3). Table 2 shows the hierarchical regression results for the loan growth forecast and Table 3 shows the full model regression results for the deposit growth and net income forecasts. and the net income forecast. With respect to the control variables in our full model for loan growth, Table 2, *population*, *branches* and *unique* reach levels of statistical significance and are positively related to forecast error. For example, an increase in the number of bank branches opened during the new bank's start-up period is associated with an increase in forecasting error for loan growth.

Concerning our hypothesized variables, we find that of the founding team experience related variables, only *industry experience*, the sum total years of industry experience represented by the founding team is statistically significant ($p < .05$). The negative coefficient of this variable indicates that greater industry experience does indeed reduce forecasting error for loan growth, supporting our hypothesis (H4). In addition, our hypothesis regarding outside consulting assistance (H5) is also supported. We find that *consultant* is statistically significant ($p < .05$) and also negatively related to forecasting error. That is, the use of consultants by new banks at start-up reduces forecast error (improves forecast accuracy) for loan growth.

In Table 3, we specify our model for both deposit growth and net income forecasts. For deposit growth, we find a pattern of results that are similar to the loan growth forecast model above, save a few exceptions. First, in the full model for deposit growth, the control variable for the size of the founding team, *team size*, is negative and marginally significant ($p < .10$). Second, we find that none of the founding team experience variables are statistically significant. Finally, similar to the loan growth forecast model, we find that outside consulting assistance, *consultant*, is also negative and statistically significant ($p < .05$), indicating that the use of outside consultants by new banks at start-up also improves deposit growth forecasts as well.

Our results for the net income forecast model are markedly different; none of our research variables of interest are statistically significant. We find no support for our founding team experience variables or outside consulting assistance. Thus, neither inside nor outside experience appears to affect forecasting accuracy for net income.

5. DISCUSSION AND CONCLUSION

In this study, we set out to investigate the relative contribution of insider knowledge (characterized by various types of founding team experience) and outsider knowledge (provided by consultants) to achieving a specific entrepreneurial outcome: developing accurate forecasts. While we made the case that various types of founding team experience might be important for developing accurate forecasts, we also argued that the outside knowledge provided by specialized industry consultants might also be important since such consultants have access to relevant and privileged knowledge, which might improve the firm's forecasting accuracy. Finally, we looked at the impact of having access to these two types of knowledge on the firm's forecasting accuracy in three specific areas: loan growth, deposit growth and net income.

With respect to insider knowledge, our results were mixed. We reported no effect for previous bank founding experience, prior shared work experience or heterogeneous occupational experience among founding team members across three different types of forecasts. However, we did find that the total banking industry experience represented by the founding team did indeed improve forecasting accuracy, but only in the area of loans. On the other hand, our findings for outsider knowledge, were less ambivalent. New banks that used consultants during the start-up process benefited with more accurate forecasts for both their loan growth as well as their deposit growth forecasts (net income forecasts were unaffected).

Despite the equivocal nature of these overall results, we believe our findings are nevertheless both informative as well as consistent with the most current thinking on research directions in the organizational learning literature (Argote, 1999; Argote & Ophir, 2002). For example, Argote has pointed out that many organizational learning studies typically take an all-encompassing view of experience sometimes obfuscating important insights. A more fine-grained and nuanced view—one that considers the type of experience or the characteristics of experience—may be necessary to better understand the boundary conditions relationships between experience and outcomes. In this study, we heed Argote's advice and specify how and why different types of experience might be helpful to firms in developing accurate forecasts. As a result, we find that different types of forecasts are informed by different types of experience; a finding that emerged because we were able to 'decompose' experience into more fine-grained elements.

Moreover, our results are also informative. In retrospect, the fact that industry experience is helpful in producing accurate forecasts for loans, but not for deposits or net income, is not so surprising. Making loans is *the* fundamental banking activity. That one could improve in forecasting in this area with more experience over time is a reasonable assumption since managers have complete control over this activity. By contrast, forecasting deposits is a bit more complex. First, bank deposits are inherently more volatile than loans. Large deposits, those greater than $100,000, are particularly interest-rate sensitive, and are considered highly unstable by bank regulators. They are deemed ‘volatile liabilities’ and are *not* counted among a bank’s ‘core’ deposits. Therefore, trying to project deposit balances can be difficult. Second, banks can engage in many different types of activities in order to attract deposits (e.g., soliciting ‘brokered’ deposits through other institutions). This too complicates forecasting deposit growth.

With regard to outsider knowledge, our results are consistent with both theory and logic. As we argued in our hypotheses, engaging a consultant to assist in the start-up process allows the new bank to leverage a consultant’s accumulated experience with other similar clients in similar contexts. Because of their repeated experiences, consultants should be able apply specific, relevant knowledge which serves to improve the forecasting process. Our findings appear to support this notion.

The unexpected results of this study relate to net income forecasts. While useful for predicting loan growth and deposit growth forecasting accuracy, our model was not quite as helpful in predicting net income forecasting accuracy. In fact, the overall model seemed to be poor fit, accounting for only about 6 percent of the overall variance explained. It is clear that net income forecasting is being driven by a different set of factors than those presented here. Again, in retrospect, this is not entirely surprising. Forecasting net income is intrinsically complex; many variables affect net income (e.g., pricing, interest rates, expenses, etc.) each of which must also be accurately forecast in order to derive net income. Thus, forecasting net income can be seen as a kind of ‘compound’ forecast, which by its very nature is more difficult and complex.

Taken together, these results indicate that both inside and outside knowledge are valuable resources for the fledgling new firm in developing its initial financial forecasts. Though we find that outsider knowledge supplied by consultants appear to be more helpful across a wider variety of forecasts than insider knowledge, nevertheless both types of knowledge are important. Moreover, we should be cautious in discounting the importance of insider knowledge. While only total industry experience proved useful in predicting forecasting outcomes, recent research has found that prior shared experience is important in predicting other types of outcomes, such as new venture launch times (DeVaughn, 2008). Thus, we argue that inside knowledge remains important to the firm.

Finally, our study examined only three types of forecasts made by the firm. However, we know that there are other important forecasts that are required at start-up as well. For example, new banks must also provide a forecast for loan loss reserves, the amount of money that a bank must set aside for loans expected to go into default. This too is a key forecast where accuracy counts since loan loss reserves are subtracted from a bank’s income and thus can impair its profits. Therefore, we suggest that future studies consider other types of forecasts that are required of new firms at start-up.

Our results inform both theory and practice. With respect to organizational learning theory, this research takes a ‘fine-grained’ approach to assess the impact of experience, as advocated by Argote, McEvily & Reagans (2003). In our study, we distinguish between different types of experience and find that certain types and sources of experience matters more than others, depending on the specific forecast of interest. Thus, we too add that future studies should take great care in specifying the type of experience it intends to investigate and be more cautious about broadly generalizing to other types of experience. With respect to practice, this research underscores the importance of identifying and matching the right types of knowledge resources to the right types of forecasting activities in order to achieve the firm’s desired goals.

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TABLE 1

Descriptive Statisitcs and Correlations

ID	Obs	Variable	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	117	Forecast Error Loans	0.97	1.87	0.04	12.33																
2	117	Forecast Error Deposits	0.67	0.99	0.01	7.05	0.79															
3	117	Forecast Error Net Income	6.89	19.27	0.03	135.36	0.10	0.17														
4	117	Employment	2.69	2.53	-4.1	16.6	-0.07	-0.15	-0.14													
5	117	Population	2.18	1.12	0.1	6.9	0.13	0.08	-0.03	0.32												
6	117	Existing Fin Institutions	27.70	15.85	5	79	0.15	0.20	-0.08	-0.10	-0.16											
7	117	Bank Holding Company	0.06	0.24	0	1	-0.02	0.01	0.12	0.03	0.04	-0.01										
8	117	Branches	3.00	2.6	1	20	0.51	0.68	0.08	-0.10	0.01	0.15	0.03									
9	117	Initial Capital (mil)	10.96	11.09	3.95	100.6	0.23	0.32	-0.01	-0.08	0.08	0.30	-0.07	0.54								
10	117	CEO	0.96	0.20	0	1	-0.21	-0.23	0.04	0.07	0.13	-0.21	0.05	-0.02	0.01							
11	117	Unique Banks	0.02	0.13	0	1	0.70	0.82	0.04	-0.17	-0.10	0.31	-0.03	0.64	0.38	-0.30						
12	117	Team Size	10.04	2.80	5	20	-0.11	-0.15	0.07	-0.08	0.06	-0.27	0.09	-0.07	-0.04	0.15	-0.07					
13	117	Blau Heterogeneity	0.75	0.07	0.46	0.87	-0.03	-0.03	0.00	0.10	0.14	-0.14	0.00	-0.08	-0.05	0.04	-0.09	0.19				
14	117	PSE	0.78	0.42	0	1	0.00	0.18	0.11	-0.08	0.11	0.03	0.05	0.25	0.16	0.19	0.07	0.02	0.15			
15	117	Former Founders	1.10	1.39	0	6	0.02	0.06	-0.05	0.18	0.32	0.01	0.06	0.07	0.12	0.05	0.09	0.04	-0.04	0.25		
16	117	Log Industry Experience	4.23	0.55	1.61	5.31	-0.15	-0.02	0.01	-0.09	0.05	-0.09	0.09	0.20	0.20	0.29	0.04	0.39	0.07	0.31	0.26	
17	117	Consultant	0.56	0.50	0	1	-0.15	-0.10	-0.05	0.00	0.08	-0.08	0.08	0.07	0.17	0.15	-0.01	-0.02	-0.12	-0.11	0.08	0.14

Correlations > 0.24 significant @ p >.01
Correlations > 0.18 significant @ p >.05

TABLE 2

Loan Growth Forecast Error Regression

	Model 1	Model 2	Model 3
Employment	-0.02	-0.03	-0.03
	(0.05)	(0.05)	(0.05)
Population	0.35***	0.38***	0.38***
	(0.12)	(0.12)	(0.12)
Institutions	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)
BHC	-0.07	0.04	0.15
	(0.51)	(0.50)	(0.49)
Branches	0.10	0.13*	0.13*
	(0.07)	(0.07)	(0.07)
Initial Capital	-0.01	-0.01	-0.01
	(0.00)	(0.00)	(0.00)
CEO	-0.28	0.21	0.39
	(0.65)	(0.66)	(0.65)
Unique Bank	9.60***	9.55***	9.50***
	(1.34)	(1.32)	(1.30)
Team Size	-0.05	-0.01	-0.01
	(0.05)	(0.05)	(0.05)
Blau		0.59	0.23
		(1.71)	(1.68)
PSE		-0.18	-0.33
		(0.32)	(0.32)
Former Founder		-0.06	-0.05
		(1.00)	(1.00)
Industry Experience		-0.65**	-0.57**
		(0.27)	(0.26)
Consultant			-0.58**
			(0.25)
Observations	117	117	117
Constant	0.84	2.22	2.54
Adj. R^2	0.52	0.54	0.56

* = p < .10
** = p < .05
*** = p < .01

TABLE 3

Deposit Growth Forecast Error Regression Model

Employment	-0.03
	(0.02)
Population	0.16***
	(0.05)
Institutions	-0.01
	(0.01)
BHC	0.17
	(0.20)
Branches	0.10***
	(0.03)
Initial Capital	-0.01
	(0.00)
CEO	-0.06
	(0.26)
Unique Bank	5.25***
	(0.51)
Team Size	-0.03*
	(0.02)
Blau	0.27
	(0.67)
PSE	0.17
	(0.13)
Former Founder	-0.04
	(0.04)
Industry Experience	-0.12
	(0.10)
Consultant	-0.20**
	(0.10)
Observations	117
Constant	0.85
Adj. R^2	0.75

Net Income Forecast Error Regression Model

Employment	-1.00
	(0.80)
Population	0.02
	(1.87)
Institutions	-0.12
	(0.14)
BHC	9.47
	(7.89)
Branches	0.58
	(1.09)
Initial Capital	-0.01
	(0.00)
CEO	3.31
	(10.42)
Unique Bank	2.47
	(20.73)
Team Size	0.45
	(0.77)
Blau	-5.54
	(26.88)
PSE	5.05
	(5.14)
Former Founder	-0.58
	(1.53)
Industry Experience	-2.99
	(4.19)
Consultant	-1.80
	(3.97)
Observations	117
Constant	17.75
Adj. R^2	0.06

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