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Do Non-Large Networks Engage in Portfolio Restructuring? 
A Signal Detection of Peak Period Capability Pressure

Semiu Babatunde Adeyemi  
The Institute of Chartered Accountants of Nigeria (ICAN)

Oladipupo Muhratna Tijani  
Al-Hikmah University

This study considers the local offices of medium-sized audit firms as a unit of analysis. Adapting measures validated in earlier studies, this paper develops a model and evaluates the model that directly describes all variables that affect portfolio structuring in an auditor-client environment during peak periods. Using a sample of 237 local office observations between 2007 and 2011 among medium-sized audit firms in Nigeria, evidence of a positive association between capability pressure and the likelihood of portfolio restructuring is reported. The results lend credibility to the implications of capability pressure characterized by the year-end effects of assurance providers. This position is consistent with earlier studies on portfolio management decisions of external auditors.

“Fit no stereotypes. Don’t chase the latest fads of clients. The situation dictates which approach best accomplishes the team’s mission.” [Authors’ emphasis added] (Colin Powell – former United States Secretary of State). This quotation describes a managerial allocation of resources and the display of flexibility in managerial decision making. Auditors often experience capacity pressure as a result of the peak period syndrome. The best way to overcome this barrier in order to prevent underreported time and premature signoffs depends on the situation (for instance, capacity constraint) and expected results. A technique that works best under a particular peak period pressure may not necessarily work in all cases because of differences in the respective situations.
Auditors must identify what technique will, in a particular accounting period, under particular circumstances and at a particular time, best achieve the containment of audit risk and improve audit quality.

A large number of companies in Nigeria list the end of their reporting period as December. This choice for a company’s calendar year may differ from the country’s actual fiscal year. In some jurisdictions, particularly those that permit tax consolidation, companies that are part of a group must use nearly the same fiscal year (up to three months difference are permitted in some countries such as the U.S. and Japan), with consolidating entries to adjust for inter-company transactions with different fiscal years. Nevertheless, the fiscal year is identical to the calendar year for most publicly traded companies in the U.S., the majority of large corporations in the U.K., and elsewhere (with notable exceptions like Australia, New Zealand, and Japan). Most choices of fiscal year end dates are the product of local laws, regulations, customs, business and trade practices. Similar to what is experienced in developing jurisdictions, the recurrent use of months like December creates the peak period effect. This frequently leads to capability pressure, a phenomenon attributed to the relative concentration of companies with identical fiscal year-end in an auditor client’s portfolio (Lopez & Pitman, 2013).

This capability pressure could result in dysfunctional auditor behavior, including premature sign-off and underreported time (Lovelock, 1984; Parasuraman, Zeithhamel, & Benry, 1985; Margheim & Pany, 1986; Kelly & Margheim, 1990; Sridharan, 1998; Houston, 1999; Landsman, Nelson, & Roundtree, 2009). A number of prior behavioral research and anecdotal evidence have demonstrated that for many service firms, deterioration in quality has often been a by-product of capacity constraints consequential to peak period demands, even though others suggest the contrary (Agoglia et al., 2010). Experiential studies that focus on the effects of workload compression on portfolio management decisions of auditors have been limited, except for a few (Shu, 2000; Lopez & Pitman, 2013) which concentrated on the Big-N firms. Furthermore, recent years have increased complexity and risk is standard fare on an independent auditor’s plate as changing business and risk environments are continually shaped by technology and digitization, globalization, increased local and international regulations and enforcement, as well as expectations for greater transparency (KPMG, 2013). As the business landscape becomes more fast paced, there is movement towards leveraging advanced business analysis techniques to refine the focus on risk and derive deeper insights for new evidence about the current role of capability pressure on portfolio management decisions of auditors.

Given that the Non-Big-N firms are an increasingly important but poorly understood sector of the audit market even in developing jurisdictions, feature specificity in prior studies was considered for the Big-N firms and a model was developed and empirically assessed using a sample of 237 local office-year observations between 2007 and 2011 among medium-sized audit firms in Nigeria. The proxy for auditor capability pressure was the ratio of professional fees from client portfolios with a fiscal year end date of December to total fees. Auditor-client misalignment was also used as a control variable (Shu, 2000). As in Lopez and Pitman (2013), three dimensions of audit risk were measured: earnings manipulation risk, financial performance risk, and litigation risk. This study did not delineate between first-tier, second-tier, and other mid-size audit
firms within the population and the sample only included local offices in Lagos, the commercial nerve center in Nigeria. Hence, there may be induced substantial variation in the subjects' behavior within replications of market treatments which could limit the interpretation of the study's results. The study found evidence of a positive association between auditor capability pressure and the likelihood of portfolio restructuring of a local office during peak period. The result lends credibility to the hypothesis that the likelihood of peak period client portfolio reorganization is increasing with the concentration of companies with a December year-end date in the auditor's portfolio. The outcome of the study's logistic regression shows the existence of a positive link between auditor-client misalignment and the likelihood of peak period portfolio restructuring. The results for the auditor proxies are generally consistent with extant literature, which supports the view that an auditor portfolio and client turnover are largely determined by the presence of risk in their portfolios. This paper's conclusions substantially contribute to audit firm portfolio management literature by placing smaller firms in a developing economic setting under empirical evaluation. This study is useful in the portfolio restructuring strategies of mid-sized audit firms as the unit of analysis in relation to capability pressure during peak periods. It also provides evidence on the differential effects of audit market vicissitudes on Big-N versus Non-Big-N firms. It strengthens past studies involving audit risk dimensions and clients' portfolio management for assurance providers. As a supply side determinant of client portfolio management, it is a unique line of proof explorable by audit market niches.

Prior Studies and Background

This section will discuss evidence from past studies on auditors' workload compression during the busy season and implications for a client's portfolio management. A relevant hypotheses in each subsection will also be developed.

Size and Importance of Non-Large Networks

Concentration in the market for audit services exists in the literature. The existence of a two-tiered audit market has also been documented. The implicit assumption is that smaller audit firms are incapable of providing equivalent levels of audit services to large public company clients (Ferguson, Francis, & Stokes, 2003). While the four large networks have subsidiaries in the country, there are over 916 registered accountancy firms in Nigeria (Nairametrics, 2012). However, there are other large and medium-sized firms with market share for over 17,284,671 micro-small and medium enterprise (MSMEs) (National Bureau of Statistics, 2010) clients. This sector of the audit market contributes to MSMEs tremendous role in reengineering the socio-economic landscape of the country. The market for auditing in Nigeria is self-regulated and there is no mandatory restriction to the “audit only” model, hence medium and small audit firms are not prohibited from offering non-audit services. Subsequently, these professional partnership firms contribute to MSME's social and political role in local employment creation, balanced resource utilization, income generation, utilization of local technology and raw materials, and in helping to promote change in a gradual and peaceful manner through the provision of non-audit services. These range of services
include but are not limited to consulting in areas of financial information systems, design and implementation, and tax-related services. This segment of external auditing in Nigeria constitutes more than 90% of the entire population (13 large/medium-sized and 903 small firms) (Nairametrics, 2012). Hence there is a need to understand the phenomenon of client portfolio structuring in this sector.

Audit Firm Portfolio Risk Management

Audit firms are increasingly recognizing that effective portfolio management assists with decisions that set them apart from their competitors in terms of organizational success. A significant portion have in their tactical strategies, vibrant portfolio management culture and frequently implement appropriate tools and practices. Effective client portfolio management supports audit firms’ intent, direction, and progress towards achieving strategic objectives (Gramling et al., 1998; Bell et al., 2002). When making portfolio management decisions, auditors preferentially price their assurance services while being cognizant of risk differences amongst their clients. Anecdotal evidence has related the overall audit engagement risk primarily to that associated with litigation costs even though there is another dimension of audit risks. Thus, auditors consider this assessment as a vital component of client portfolio management (Huss, Jacobs, & Patterson, 1993; Johnstone, 2000). When managing clients’ portfolios, auditors should note, but also not solely focus on, litigation risk (Asare, Hackenbrack, & Knechel, 1994; Asare & Knechel, 1995; Huss & Jacobs, 1991). When managing their portfolio, various strategies are adopted to control for risk, which may include, but are not limited to, close monitoring of personnel related policies, heightened financial reporting related risks, management integrity, internal controls and the performance of additional audit procedures (Boone, Khurana, & Raman, 2008; Manry, Mock, & Turner, 2008).

Research on clients’ portfolio management is important given that incorrect decisions create potential liabilities that may affect audit quality and ultimately auditor’s financial viability and reputation (Colbert, Leuhlfing, & Alderman, 1996), yet a limited amount of accounting studies do provide insights into the client portfolio management decisions of assurance providers from the supply side. In response to this limitation of data, in a two-party experimental setting, Gramling et al. (1998) demonstrated the impact of legal liability regimes and differential client risk on audit client acceptance, pricing, and audit effort decisions. This laboratory-market-based study provides researchers with direct evidence of the impact of perceived litigation risks of audit fees and efforts when selecting audit clients. This method has been developed and utilized in earlier studies (Schatzberg, 1990; Schatzberg & Sevcik, 1994; Dopuch, King, & Schatzberg, 1994). Using proprietary data on audit effort, billing rates and risk assessments in the portfolio of continuing clients of a major accounting firm, Johnstone and Bedard (2005) studied shifts in audit planning and pricing decisions within a three year period. They assert that consistent with accelerating litigation, environmental, regulatory scrutiny, and planned audit efforts, average client billing rates tend to increase. The result of the study also suggests that engagement teams demonstrate particular concern for clients with heightened risks related to financial reporting, management integrity, and internal controls. This implies that it is unlikely that increased fees resulting from opportunistic
pricing have positive implications for audit quality.

Driven by increasingly large awards, settlements and insurance costs, the second half of the 1980's was plagued by a considerable increase in litigation pressure on large audit firms (Arthur Anderson et al., 1992), leading to widespread concerns that major audit firms were “not going to be doing business with companies that [were] at risk…and the general well-being of the public [was] not going to be served because the better talent [was] not going to be out on the most difficult situations” (Chicago Tribune, 1987, C8). Subsequent mergers among large audit firms were suggested as a response to the increase in litigation liability pressure (Lys, 1993) having an adverse impact on the supply side of the audit market. In a twenty-two year partitioned period of study, Choi, Doogar, and Ganguly (2004) investigated whether the financial riskiness of large audit firms varied with changing audit liability litigation environment. The study, which was delineated into four distinct phases across different client types (e.g., incoming clients, continuing clients), and auditor types (Big-N, Non-Big N) observed that during the time when the Big 6 market shares grew appreciably, the proportion of litigations-industry clients grew at about the same rate as the proportion of such clients in the population. This also supported the view that the riskiness of the Big-N client portfolios reacted to changes in the audit litigation liability environment.

Local Bias and Auditor Client Portfolio

Empirical and anecdotal examinations recommend that research on auditing phenomena be conducted at city-level markets (Francis & Krishnan, 1999). Using city markets as a unit of analysis, Francis and Krishnan (1999) found that the national accounting firm market leader is not the city-specific market leader the majority of the time. Variation in market leadership at the city-level suggests that the reputations of individual accounting firms vary from city to city. Perhaps many of the final audit outcomes are local office auditor dependent (Krishnan, 2002; Choi, 2007; Choi et al., 2004; Charles, Su, & Wu, 2010; Timmermans, 2013; Asthana, 2013).

While some consider the effect of geographic proximity on audit quality insignificant (Timmermans, 2013), others affirm that the size of local audit offices are major determinants of both audit quality and fees (Choi et al., 2004) as local auditors offer higher quality jobs (Choi, 2007). More conservatively, Asthana (2013) asserted that geographic diversification has a detrimental effect on audit quality, probably due to strain on resources of audit office. Every so often, the local offices of the Big-N firms operate as decentralized, semi-autonomous structures (Bell et al., 2002). Timmerman (2013) found that geographic proximity did not affect the quality of audit. The position of this study is affirmed due to the smaller distances in the Netherlands auditor-clients neighborhood. Perhaps the Dutch audit market is one in which there is no distinction between local and non-local auditors, hence it may be concluded that the result be generalized with caution. Using over 19,000 observations for over 3,000 clients over a ten year period, Asthana (2013) detected that geographic diversification had adverse effects on audit quality while Gaver and Patterson (2007) discovered that the comparative prominence of a client to a local office attenuated auditor oversight over reporting decisions. Most importantly, the
role of local partners in client acceptance, retention, and dismissal decisions of a firm cannot be overemphasized (Lopez & Pitman, 2013). Since audit firms that are more financially integrated are associated with riskier client portfolios (Hay, Baskerville, & Qiu, 2007), the first hypothesis is offered:

\[ H_1: \text{Local auditor office structures positively influence the portfolio management decisions of local partners.} \]

**Capability Pressure and Portfolio Management**

The public accounting workplace has long been acknowledged as a high stress environment (Gaertner & Ruhe, 1981; Weick, 1983). The relationship between stress and job related outcomes have similarly been well-recognized in behavioral and psychological studies on an individual and organizational performance basis (Sager, 1990; Spector, Dwyer, & Jex, 1988; Williams et al., 2001; Chen, Silverthorne, & Hung, 2006; Virtanen et al., 2009), in particular, absenteeism (Spector et al., 1988). Several accounting literatures also provide the link between job stress and a profession which includes underperformance, job dissatisfaction, job burnout, turnover (Choo, 1997; Fischer, 2001; Fogarty et al., 2000; Larson, 1991; Libby, 1983; Rebele & Micheals, 1990; Senatra, 1980; Smith, Davy, & Everly, 1995, 2007; Sweeney & Summers, 2002), and the inherent risks that could cause damage to public trust in the audit firm in particular and the accountancy profession in general (DeZoort & Lord, 1997). The pressure on time and meeting the budget may lead to a substandard quality of the audit and ultimately lead to premature sign-off, a superficial review of documents, and acceptance of insufficient client verbal evidence (Alderman & Dietrick, 1982; Kelley & Marghean, 1990).

Dalton, Hill, and Ramsay (1997) found that auditors worked more than 60 hours a week during busy season. These workloads did not often decrease during off-peak periods either as would have been expected (Sweeney & Summers, 2002; Ward & Albright, 2009). Noor (2011) stressed the positive relation with job stress. The busy season is a phase characterized by system performance constraints (Mukherjee & Chatterjee, 2006), and hence may influence portfolio restructuring decisions to reduce local office risk and expand the client set arrangement. Therefore,

\[ H_2: \text{Capability pressure will positively influence auditor peak period clients' portfolio restructuring.} \]

**Firm Capacity and Auditor Client Misalignment**

Bills (2012) described auditor-client misalignment as a situation in which low quality auditors serve high quality clients which are to be served by higher quality auditors and vice versa. This auditor-clientele adjustment is often driven by changes in economic conditions and market competition (Johnson & Lyns, 1990; Shu, 2000). Large but risky companies switching auditors are able to engage other Big-N firms (Reynolds & Francis, 2000) as auditor resignations are influenced by misalignment. Further, clients are able to utilize their opportunity sets as auditors react to manage their portfolio (Lopez & Pitman, 2013). In the post Enron period, Landsman, Minutti-Meza, and Zhang (2009) recounted evidence of increased sensitivity to auditor-client
misalignment. With both parties having limitless opportunities for switching business relationships, the likelihood of increased probability for an auditor’s receptiveness to change during their busy season client portfolios exists. Therefore,

\[ H_3: \text{Auditor-client misalignment will have the positive effect of changes to peak period portfolio changes.} \]

**Auditor Risk Factors and Portfolio Restructuring**

Although there are a number of risk considerations in audit engagements, behavioral evidence suggests three major risks relating to auditor-client realignments (Cassell et al., 2010): earnings manipulation risk (EMR), financial performance risk (FPR), and litigation risk (LR). Evidence suggesting auditors screening of high-earnings risk management clients appears to be rather scanty. Financial reporting manipulations such as unusual levels of accruals are associated with litigation against auditors (Lyns & Watts, 1994; Heninger, 2010). Where an auditor is concerned about a client’s inappropriate earnings management, the initial reaction is to avoid (in the case of a new assignment) or withdraw (in the case of existing client) his services (Asare et al., 1994; Knechel, 2001). Johnstone (2000) asserted that auditors adapt to risk differential effects by screening out high-risk clients, even though they are indifferent to such risks when it comes to audit planning and pricing. Auditors often experience a greater demand on audit resources for clients with income increasing accruals (Abbott, Parkers, & Peters, 2010). DeFond and Subramanyam (1998) emphasized that discretionary accruals were significantly income-decreasing in the year prior to a change, and generally insignificant in the post auditor shifting years. Thus,

\[ H_4: \text{Clients-sets earnings management risk will have a positive effect on peak period portfolio changes.} \]

In a study investigating the effects of fraud and going-concern risk on an auditors’ assessment of the risk of material misstatements and resulting audit procedures, Allen et al. (2007) analyzed the association between these risks and an auditors’ assessment. They found that both fraud risk and going-concern risks were significantly related to the risk of material misstatement. This suggests that a client’s financial condition can affect the audit risk evaluation of assurance professionals (Kreutzfeldt & Wallace, 1986; Palmrose, 1987). It also remains a key factor in portfolio structuring (Choi et al., 2004).

\[ H_5: \text{Increases in the level of clients’ financial risk positively affect peak period portfolio restructuring.} \]

One of the leading challenges in the audit profession is litigation risk (Lowe & Peckers, 2000). The contemporaneous increase in litigation and internal control risk amplifies the benefits associated with objectivity and defensibility, thus resulting in an interactive effect on decision aid reliance for the audit function. Auditors would often respond to litigation risk by increasing audit fees, planned hours, and evidence requirements (Simunic, 1980; Barron, Pratt, & Stice, 1994; Houston, 1999) particularly...
in areas of subjective judgments such as accruals and accounting estimates (Lys & Watts, 1994). Auditors are particularly attuned to potential overstatements of financial performance when the risk of litigation risk is heightened (Barron, Pratt, & Stice, 2001; Hirst, 1994), hence operating environment litigation risks may affect audit reporting decisions (Lopez & Pitman, 2013).

\[ H_6: \text{Intensification of litigation risk will affect peak period client portfolio restructuring.} \]

Research Method

Independent Variable

In order to measure the impact of workload compression, clients’ misalignment and auditor risk on portfolio restructuring, the current study developed a model based on local offices of mid-sized audit firms. The decision to restructure the portfolio by audit firms was modeled as a function of all other variables of interest. The existence of incoming and outgoing clients during busy season representing portfolio restructuring was predicated with PPP_RST. The absence of portfolio constituent changes during this period equalled 0 and 1. Using a logistic regression model, local offices were defined without portfolio reshuffling during the busy season as a baseline condition as adapted from previous studies. Data cross-sections were defined according to auditors’ sign-off date. This was used in place of the financial statement year in order to eliminate potential timing issues resulting from the gap between the audit completion date and a client’s fiscal year-end. This will also afford the opportunity to eliminate the joint audit influence.

Dependent Variables

The independent variables of interest included December workload compression, auditor-client misalignment, earnings manipulation risk (EMR), financial performance risk (FPR), and litigation risk (LR) (all three were captured under audit risk). Controls for average client size, local office size, international affiliation, and the fixed effects of time were also included. Further, portfolio size (PRT_SIZE) was operationalized as the mean of the logs of audit fees from the list of clients captured from each local office, while the log of total audit fees from each local office was used for the size of local audit office (LCT_SIZE). As indicated in an earlier section, the concentration of companies in busy season in the auditors’ portfolio was referred to as December capability pressure (DEC_CP). This was the proxy for the proportion of aggregate audit fees from peak period clients’ total fees generated by the audit client in a particular year.

Auditor-client misalignment in the portfolio of local audit offices was classified with predicted probabilities above a predetermined cutoff point as misaligned. The paper developed an estimate of the probability that a company be paired with a medium-sized audit firm. In developing a proxy for misalignment, the ratio of audit fees from auditor-client pairs classified as misaligned to total audit fees obtained by a local office in an audit calendar year was adopted. Where higher values were obtained for this variable, it can be concluded that there was a greater concentration of misaligned clients within the portfolio. The existence of this feature suggested an expectation of auditor switching. The study adapted variable operationalization as adopted in Lopez
and Pitman (2013) and other literature as cited. The weight (audit fees) of absolute value of performance-adjusted discretionary accruals of all portfolio clients in each local office was used as a proxy for earnings manipulation risk (EMR). Since discretionary accruals quantified the magnitude of management reporting discretions, higher values (EMR) indicated higher levels of the presence of earnings management activity among the clients of a local office.

Financial performance risk (FPR) reflected the overall level of financial performance risk among companies in the auditor's portfolio. The weighted variable was calculated using audit fees. The proxy was the weighted average of the Altman Z-score of all companies in the portfolio of the local firms (Altman, 1968). In this case, higher values were associated with lower likelihood of financial risk or bankruptcy. Subsequently, the Altman score was multiplied by -1 prior to estimating the variance as higher values indicated higher overall levels of financial performance risk. The ratio of audit fees from clients whose industries were characterized by litigation, to total audit fees produced by a local office during the audit year was the proxy for litigation risk (LR). For the purpose of this study, it was projected that financial services, information and telecommunications technology, oil and gas, and service utilities had higher potential litigation risks or auditors. Consequently, higher overall levels of litigation risk in auditor client portfolio were indicated by higher LR values, which were expected to influence auditor switching decisions. For office size, the proxy was the log of total audit fees from each local office, while for client size, it was the mean of the logs of audit fees from all portfolio clients. FIRM_1, FIRM_2, FIRM_3, and FIRM_4 were proxies for the local offices of the firms included in the study sample.

Survey Design

Data for this study were collected through primary sources accessed from four local offices of selected medium-sized audit firms. These firms with local office locations supported this paper's research with enough information relevant to estimate the different components of the regression model. The paper limited the sample to Lagos offices and to maximize the number of company-year observations in the estimation, each regression model variable was separately operationalized. Beginning with an original sample of 836 local office-year observations between 2007 and 2011 from the firms which were considered accessible from privileged information, 599 observations were eliminated due to incomplete data. The final sample therefore consisted of 237 local-office year observations, representing 4 local offices of the firms being surveyed. The untabulated sample construction revealed that of this figure, local offices with expanding clients' portfolio restructuring represented 104 observations, while contracting clients' portfolio restructuring represented 133 observations. Lopez and Pitman (2013) described expanding client portfolio as a positive difference between audit fees emanating from incoming and outgoing December year-end clients, and contracting client portfolios.

Results of Analysis

Procedures

A preliminary analysis was performed by means of survey tabulation. The
objective was to gather results according to the topic of interest. Therefore, it allowed for making a comparative analysis and also to contrast the tendencies of different variables. A multivariate analysis was also conducted that focused on exploring the degree of dependency between the binary dependent variable that was the peak period client portfolio restructuring and the independent variables of interest. In order to achieve this, two steps were carried out. First, a factorial analysis was used to evaluate the influence of individual variables and their interactions in order to identify a reduced number of factors which could readily explain them. Second, a logistic regression was applied to analyze the influence of those factors on the dependent variable, making use of the stepwise procedure as a significant predictor in each of the regressions performed.

Descriptive Statistics

Subsequent to the partitioning of the sample into offices with and without portfolio restructuring during the busy season, the study arrived at 237 and 172 observations respectively. The results presented in Table 1 revealed that offices with active portfolio restructuring during the peak periods had a higher concentration of clients with December year-ends (0.893 vs. 0.864; p-value = 0.098). Further, there was also a higher concentration of financial risk in the portfolio of such offices with active restructuring as compared to those offices without changes (-1.462 vs. -1.788; p-value < 0.001). With regards to office size, the study found offices with active portfolio changes during the peak period significantly larger than others without client restructuring (18.802 vs. 16.421; p-value < 0.001). Other detail revealed that Firm_2 had the largest proportion of local offices with changes (LOCL_FM2 = 0.318), while Firm_3 was discovered to be the most sensitive without portfolio restructuring (LOCL_FM3 = 0.386).

Table 1: Descriptive Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Local offices with peak-period portfolio restructuring</th>
<th>Local offices without peak-period portfolio restructuring</th>
<th>Combined Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>(n = 237)</td>
<td>(n = 599)</td>
<td>(n = 836)</td>
<td></td>
</tr>
<tr>
<td>DEC_CP</td>
<td>0.893</td>
<td>0.864</td>
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<td>13.453</td>
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<td>13.319</td>
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<td>17.456</td>
<td>18.326</td>
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<tr>
<td></td>
<td>18.643</td>
<td>17.679</td>
<td>18.442</td>
</tr>
<tr>
<td></td>
<td>1.321</td>
<td>0.342</td>
<td></td>
</tr>
<tr>
<td></td>
<td>17.456</td>
<td>&lt;0.001</td>
<td></td>
</tr>
<tr>
<td>LOCL_FIRM1</td>
<td>0.214</td>
<td>0.307</td>
<td>0.234</td>
</tr>
<tr>
<td></td>
<td>0.000</td>
<td>0.216</td>
<td>18.319</td>
</tr>
<tr>
<td></td>
<td>0.402</td>
<td>0.410</td>
<td>0.442</td>
</tr>
<tr>
<td></td>
<td>0.307</td>
<td>0.328</td>
<td></td>
</tr>
<tr>
<td>LOCL_FIRM2</td>
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<td>0.214</td>
<td>0.243</td>
</tr>
<tr>
<td></td>
<td>0.000</td>
<td>0.214</td>
<td>18.319</td>
</tr>
<tr>
<td></td>
<td>0.452</td>
<td>0.342</td>
<td>0.434</td>
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<tr>
<td></td>
<td>0.214</td>
<td>0.006</td>
<td></td>
</tr>
<tr>
<td>LOCL_FIRM3</td>
<td>0.251</td>
<td>0.386</td>
<td>0.274</td>
</tr>
<tr>
<td></td>
<td>0.000</td>
<td>0.325</td>
<td>18.319</td>
</tr>
<tr>
<td></td>
<td>0.342</td>
<td>0.184</td>
<td>0.418</td>
</tr>
<tr>
<td></td>
<td>0.386</td>
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<td></td>
</tr>
<tr>
<td>LOCL_FIRM4</td>
<td>0.223</td>
<td>0.242</td>
<td>0.241</td>
</tr>
<tr>
<td></td>
<td>0.000</td>
<td>0.244</td>
<td>18.319</td>
</tr>
<tr>
<td></td>
<td>0.502</td>
<td>0.421</td>
<td>0.403</td>
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<tr>
<td></td>
<td>0.242</td>
<td>0.539</td>
<td></td>
</tr>
</tbody>
</table>
In Table 2, the paper presented the result of the Pearson correlation coefficients. Inter-firm affiliation indicators were found to be high and statistically significant. The correlations between the three proxies of auditor risk and CLIENT MISALIGNED were positive and significant. These were revealed in the values indicated between 30.8% and 32.6%. It can be concluded from this that there was a positive relationship between auditor-client misalignment and auditor exposure to riskier clients. This indicated that Hypotheses 4, 5, and 6 are supported.

### Table 2: Correlations

<table>
<thead>
<tr>
<th>DEC_CP</th>
<th>MIS_ALIGNED</th>
<th>EMR</th>
<th>FPR</th>
<th>LRC</th>
<th>PRT_SIZE</th>
<th>LCT_SIZE</th>
<th>LOCL_FIRM1</th>
<th>LOCL_FIRM2</th>
<th>LOCL_FIRM3</th>
<th>LOCL_FIRM4</th>
</tr>
</thead>
<tbody>
<tr>
<td>DEC_CP</td>
<td>1.00</td>
<td>-0.024</td>
<td>0.040</td>
<td>0.064</td>
<td>-0.032</td>
<td>0.167</td>
<td>0.079</td>
<td>-0.024</td>
<td>-0.136</td>
<td>0.079</td>
</tr>
<tr>
<td>MIS_ALIGNED</td>
<td>-0.024</td>
<td>1.000</td>
<td>0.221</td>
<td>0.223</td>
<td>0.355</td>
<td>-0.167</td>
<td>-0.104</td>
<td>-0.047</td>
<td>0.028</td>
<td>0.095</td>
</tr>
<tr>
<td>EMR</td>
<td>0.040</td>
<td>0.221</td>
<td>1.000</td>
<td>0.124</td>
<td>0.201</td>
<td>-0.057</td>
<td>0.032</td>
<td>-0.067</td>
<td>0.043</td>
<td>-0.086</td>
</tr>
<tr>
<td>FPR</td>
<td>0.064</td>
<td>0.223</td>
<td>0.124</td>
<td>1.000</td>
<td>0.000</td>
<td>0.029</td>
<td>0.014</td>
<td>0.150</td>
<td>0.794</td>
<td>0.219</td>
</tr>
<tr>
<td>LRC</td>
<td>-0.032</td>
<td>0.223</td>
<td>0.201</td>
<td>0.000</td>
<td>1.000</td>
<td>0.032</td>
<td>0.011</td>
<td>0.001</td>
<td>0.062</td>
<td>0.047</td>
</tr>
<tr>
<td>PRT_SIZE</td>
<td>1.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>1.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>LCT_SIZE</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>1.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>LOCL_FIRM1</td>
<td>-0.024</td>
<td>-0.043</td>
<td>-0.045</td>
<td>-0.045</td>
<td>-0.045</td>
<td>-0.045</td>
<td>1.000</td>
<td>-0.012</td>
<td>-0.087</td>
<td>0.185</td>
</tr>
<tr>
<td>LOCL_FIRM2</td>
<td>0.040</td>
<td>0.124</td>
<td>0.201</td>
<td>-0.167</td>
<td>-0.045</td>
<td>0.032</td>
<td>-0.067</td>
<td>0.032</td>
<td>0.011</td>
<td>0.001</td>
</tr>
<tr>
<td>LOCL_FIRM3</td>
<td>0.064</td>
<td>0.040</td>
<td>0.029</td>
<td>-0.014</td>
<td>-0.045</td>
<td>0.167</td>
<td>-0.067</td>
<td>0.032</td>
<td>-0.067</td>
<td>0.043</td>
</tr>
<tr>
<td>LOCL_FIRM4</td>
<td>0.000</td>
<td>0.124</td>
<td>0.201</td>
<td>-0.167</td>
<td>-0.045</td>
<td>0.032</td>
<td>-0.067</td>
<td>0.032</td>
<td>-0.067</td>
<td>0.043</td>
</tr>
</tbody>
</table>

**Logistics Regression**

In the final stage of the study, a logistics regression was performed to establish which of the factors had the greatest incidence on peak period portfolio restructuring amongst evaluated firms. In terms of the independent variables, the resulting values of the factorial analysis were gathered for each of the observations in the survey, according to the record of the statistical software (SPSS) during the study. A stepwise procedure was used to ensure the best selection of variables. Table 3 depicted the results of the probability of portfolio restructuring for each local office during the peak periods. Using the observations from the original sample (n = 836) in the estimation, the results indicated that the estimated regression coefficient for DEC_CP achieved a positive and significant status. This suggested that an increase in capability pressure led to the auditor-clients' portfolio restructuring during peak periods, supporting Hypothesis 2. The current study posited that this relationship may be the result of deficiency in quality monitoring of clients' interactions and marketing policies. Essentially, clients would switch between auditors where they perceived similar audit service quality could be obtained from other firms at reduced costs. The study also relayed this connection to the regulatory pronouncement of the Central Bank of Nigeria. According to the Bank's Prudential Guidelines for Deposit Money Banks, external auditor tenure shall be for
a maximum period of ten years from the date of the first appointment after which the firm shall not be reappointed in the bank until after another ten years. However, it was expected that the impact of this requirement on peak period portfolio restructuring would be insignificant, given that a larger proportion of banks in Nigeria are audited by the largest networks, which was not the focus of this study. However, the impact of accelerated filing requirement might be considerable. Hence the study augmented alternate clarifications to this finding in the robustness test.

**Table 3: Logistics Regression of the Probability of Portfolio Restructuring During the Peak Period in a Local Office**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Predicted</th>
<th>Coefficient</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sign</td>
<td>Estimate</td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>+</td>
<td>-4.167</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>DEC_CP</td>
<td>+</td>
<td>0.894</td>
<td>0.004</td>
</tr>
<tr>
<td>MISALIGNED</td>
<td>+</td>
<td>0.682</td>
<td>0.079</td>
</tr>
<tr>
<td>EMR</td>
<td>+</td>
<td>2.304</td>
<td>0.089</td>
</tr>
<tr>
<td>FPR</td>
<td>+</td>
<td>0.168</td>
<td>0.007</td>
</tr>
<tr>
<td>LR</td>
<td>+</td>
<td>-0.021</td>
<td>0.896</td>
</tr>
<tr>
<td>PRT_SIZE</td>
<td>+</td>
<td>-1.212</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>LCT_SIZE</td>
<td>+</td>
<td>1.324</td>
<td>&lt;0001</td>
</tr>
<tr>
<td>LOCL_FIRM1</td>
<td>+</td>
<td>0.132</td>
<td>0.218</td>
</tr>
<tr>
<td>LOCL_FIRM2</td>
<td>+</td>
<td>0.208</td>
<td>0.173</td>
</tr>
<tr>
<td>LOCL_FIRM3</td>
<td>+</td>
<td>0.244</td>
<td>0.132</td>
</tr>
<tr>
<td>LOCL_FIRM4</td>
<td>+</td>
<td>0.103</td>
<td></td>
</tr>
<tr>
<td>YEAR</td>
<td>+</td>
<td>(included)</td>
<td></td>
</tr>
</tbody>
</table>

\( n = 237 \)

Pseudo \( r^2 = 43.67\% \)

\( \text{Chi}^2 = 231.74 (<.001) \)

*P-values are based on robust standard errors obtained from the asymptotic covariance matrix.*
Table 4: Logistic Regression of a Net Decrease in the Size of the Peak Period Client Portfolio of a Local Office – Reduced Sample

<table>
<thead>
<tr>
<th>Variable</th>
<th>Predicted</th>
<th>Coefficient</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>+</td>
<td>-5.121</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>DEC_CP</td>
<td>+</td>
<td>0.983</td>
<td>0.004</td>
</tr>
<tr>
<td>MISALIGNED</td>
<td>+</td>
<td>0.783</td>
<td>0.004</td>
</tr>
<tr>
<td>EMR</td>
<td>+</td>
<td>2.204</td>
<td>0.438</td>
</tr>
<tr>
<td>FPR</td>
<td>+</td>
<td>0.142</td>
<td>0.017</td>
</tr>
<tr>
<td>LR</td>
<td>+</td>
<td>-1.243</td>
<td>0.241</td>
</tr>
<tr>
<td>PRT_SIZE</td>
<td>+</td>
<td>-1.218</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>LCT_SIZE</td>
<td>+</td>
<td>1.324</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>LOCL_FIRM1</td>
<td>+</td>
<td>0.138</td>
<td>0.398</td>
</tr>
<tr>
<td>LOCL_FIRM2</td>
<td>+</td>
<td>0.241</td>
<td>0.217</td>
</tr>
<tr>
<td>LOCL_FIRM3</td>
<td>+</td>
<td>0.238</td>
<td>0.148</td>
</tr>
<tr>
<td>LOCL_FIRM4</td>
<td>+</td>
<td>0.145</td>
<td></td>
</tr>
<tr>
<td>YEAR</td>
<td>+</td>
<td>(included)</td>
<td></td>
</tr>
</tbody>
</table>

n = 176
Pseudo r² = 46.37%
Chi² = 197.31 (<.001)

P-values are based on robust standard errors obtained from the asymptotic covariance matrix. One-tailed p-values when signs are reported.

The likelihood of portfolio restructuring was higher when there was a higher level of auditor-client misalignment, earnings management risk, and financial risk. This was indicated in the estimated coefficients for these variables. The result of the logistics regression showed positive and significant estimated coefficients for MISALIGNED, EMR, and FPR, supporting Hypothesis 3. A similar result was obtained for litigation risk (LR). This was a substantial deviation from the findings of Lopez and Pitman (2013) that asserted that the estimated coefficient for LR was not significant amongst local offices of the Big-N-Firms in relation to the likelihood of changes to the busy season client portfolio. For the control variables, none of the firm affiliation indicators were statistically significant. However, the likelihood of portfolio restructuring among the firms during peak periods was significantly higher among offices with larger clients (CLS_SIZE), and office size (OFF_SIZE), supporting Hypothesis 1.

Reduced Sample Regression

For the purpose of understanding the distinctive bearing of capability pressure on portfolio management decisions of auditors beyond immediate variables such as service quality and marketing policies as identified earlier, a monopolistic effect on local offices of contracting peak period client portfolio restructuring (PORTF_RST_
DEC) was explored. Hence, the study eliminated the sample from expanding peak period client portfolio restructuring. Subsequently, PORTF_RST_DEC was defined as the dependent variable in the reduced sample regression. A value of 1 was implied for the negative difference between audit fees for the incoming December year-end clients. Outgoing December year-end clients was negative and 0 if otherwise. As a baseline condition, audit offices without portfolio restructuring during the peak periods were used as baseline condition. The result of the reduced sample regression was presented in Table 4, from which two fundamental variances were discovered. First, the control for expanding peak period client portfolio restructuring in the reduced sample regression revealed greater estimated regression coefficient for MISALIGNED. Also, that of EMR was no longer significant. This suggested that for contracting peak period portfolio restructuring in local firms, auditor-client misalignment became a weightier dynamic for portfolio management and the existence of variances in risk priorities amongst surveyed firms.

Robustness Test

The effect of identifiable extraneous variables was captured with a robustness test. The study developed two alternative variations of the PORT_RST variable: the log of net changes in audit fees from restructured clients in the portfolio, and the log of net changes in the restructured portfolio. To ensure that the significance and interpretation of the regression results remained unchanged, insignificant clients' portfolio restructuring set at less than 10% was also eliminated. To account for client-motivated restructuring, an alternative to the original regression model was established using an alternate PORT_RST wherein 1 indicated a situation of portfolio restructuring resulting from client-motivated dismissals, and 0 if caused by other factors. The regression remained significant and in the expected direction. The study also recognized the possibility of significant changes in continuing clients' operations such as technology, merger/amalgamation, acquisitions and takeovers, and divestiture which could affect the workload compression of the auditor. This is an instance where the auditor made no portfolio restructuring. As such, the paper addressed this concern using the estimation of an OLS version of the regression model and percentage of portfolio restructuring as the dependent variable. The result of the robustness test conducted along this line remained positive and significant. The study reflected the probability of the influence of local offices with a peak period other than December creating a bias for the result. Therefore, the outcome added an indicator to the main regression model identifying local offices without December as the peak period and eliminated them from the sample in order to investigate whether the results were robust for this condition. The study found that none of the tests altered the interpretation of the estimated coefficients for the independent variables. After adjusting for January year-end companies in auditor portfolios, an additional robustness check was conducted and found that the result interpretations remain unchanged. However, the use of a reduced sample under the robustness test indicated that some of the estimated coefficients for the audit risk factors increased.

Conclusions

Large global accounting networks emerged in response to the demands of
multinational companies which required their auditors to have similar global reach and consistent audit expertise around the world. Over the years, these networks have invested substantially in harnessing the necessary tools and skills to meet the market demands for high quality audits. Subsequently, the large networks competed intensely with industry expertise, innovation, quality, and cost resulting in their dominance in most economies. A larger proportion of extant audit literature focused on markets that included and were dominated by Big-N audit firms providing audit services to the largest, most complex organizations, with significant neglect of the Non-Big-N audit firms. This study represented and attempted to provide a particularly interesting and rich empirical investigation in which the emergence of other groups of audit firms in an increasingly competitive market were examined. The study’s model considered the local offices of medium-sized audit firms as the unit of analysis. Adapting measures validated in earlier studies, a model was developed that directly described all variables affecting portfolio structuring in an auditor-client environment during the peak periods. Using a sample of 237 local office-year observations between 2007 and 2011 among medium-sized audit firms in Nigeria, evidence of a positive association between capability pressure and the likelihood of portfolio restructuring in the local office of medium-size audit firms was found. The results lend credibility to the implication of capability pressure characterized by the December year-end effect of assurance providers. This position was consistent with earlier studies on portfolio management decisions of the external auditors (Lopez & Pitman, 2013) which studied the Big-N-firms using similar variables.

The effects of other extraneous variables were eliminated and a robustness test conducted which substantiated the interpretation of the estimated coefficients for the independent variables identified in the study. Evidence was found of a direct positive relationship between auditor-client misalignment and the possibility of portfolio restructuring. Furthermore, the probability of the influence of local offices with peak periods consisting of clients with year-end other than December created a bias for the result. Therefore an indicator was added to the main regression model identifying offices without December as their peak period and eliminated them from the sample in order to investigate whether the results were robust for this condition. The study found that none of the tests altered the interpretation of the estimated coefficients for the independent variables.

This study did not delineate between second-tier and other mid-sized audit firms within the population. The sample only included local offices in Lagos, the commercial nerve center in Nigeria. Hence, there may be induced substantial variation in the subjects’ behavior within replications of market treatments which could limit the interpretation of the results. Additional research is encouraged that investigates the effect of workload compression on audit fees, as well as on audit quality in developing economies. In particular, empirical research on the impact of adjustment on the tenure of external auditors on deposit money banks in Nigeria on auditor switches will be significant at this stage, given the volatility of the financial services industry in Nigeria. Future research that considers sector and industry peculiarity, industry concentration of audit firms, and the effects of reliance on corporate reporting may benefit from the model developed herein.
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The Role of IT Investments in Fostering Firm Innovations: An Empirical Study

Erastus Karanja
North Carolina Central University

Ganesh D. Bhatt
Morgan State University

Information Systems scholars and practitioners continue to devote more resources in trying to unravel how Information Technology (IT) investments create business value. Although there is an emerging consensus on the positive role of IT investments in creating business value, there is still a need for research studies that empirically examine the mechanisms or intermediate processes through which these IT investments lead to business value. This study examines the relationship between IT investments and firm innovation - one of the understudied mechanisms or intermediate processes in the IT business value paradigm. An investigation of this link identifies an important underlying mechanism that may explain how IT investments indirectly create business value. Using IT investments and innovation (patents) data, the researchers test hypotheses grounded in the Knowledge-Based View (KBV) theory of the firm. After controlling for firm and industry factors, the empirical results provide support for the effect of IT investments on firm innovation.

In the past four decades, Information Systems (IS) scholars and business practitioners have carried out a number of studies aimed at unraveling how Information Technology (IT) investments create business value. These studies have made significant contributions in the understanding of the relationship between IT investments and firm and industry level competencies (Banker et al., 2011; Tallon, 2010; Im, Grover, & Teng, 2013). However, there is still a need for research studies that investigate the mechanisms through which IT investments create economic rents in the firm. This research is motivated by the call for research studies that investigate the effects of business processes and, specifically, innovation through which IT investments create
economic rents in the firms (Devaraj & Kohli, 2003; Melville, Kraemer, & Gurbaxani, 2004; Piccoli & Ives, 2005). Thus, the aim of this study is to empirically investigate the effects of IT resources on firm innovation, while taking the firm as the unit of analysis.

An investigation of the impact of IT investments on firm innovation is important because of the managerial implications that such results entail. For instance, various researchers have examined how IT interacts with other firm resources to spur performance differentials (Bhatt & Grover, 2005; Mithas et al., 2012; Tallon, 2010) and how IT returns are mediated by organizational processes such as customer satisfaction (Mithas, Krishnan, & Fornell, 2005). The objectives of this study are closer to the aforementioned; although the scope goes beyond by incorporating firm innovation as the underlying mechanism through which firms earn above normal economic rents. Second, authors have called for “theoretical frameworks that explain how and why these [IT] investments” create business value (Sambamurthy, Bharadwaj, & Grover, 2003, p. 238).

This study addresses the above call by developing a theoretical framework that ties IT investments to firm innovation and specifically aligns the attributes of the knowledge based view theory of the firm to IT investments and innovation mechanisms. Strategically, innovation ranks among the top and most dominant initiatives associated with the rising levels of firms’ IT investments (Ahuja, 2000; Teece, 2009). Many business managers have indicated that innovation is the engine of growth and the dominant driver of business value (Baya, Gruman, & Mathaisel, 2011). Innovation is the process through which new products, processes, business models, organizational frameworks, or services are thought out, developed, and brought to the market with the aim of generating economic rents, while satisfying customer needs (Katkalo, Pitelis, & Teece, 2010). For example, product innovations can lead to competitive advantages or expansion into new and emerging markets. Process innovations, through improvement in production efficiency, can create cost-effective production and marketing methods and services. Innovation has also been defined as the adoption of an idea, process, or behavior that is new to the adopting firm (Damanpour, 1996).

In spite of the importance of innovation in creating business rents, the extant research studies have not explicitly outlined which variables and business processes foster innovation leading to an inexplicable and confusing body of knowledge. Thus, the goal of this research is to answer the following question:

**What is the relationship between IT investments and firm innovation while controlling for specific firm factors such as growth, leverage, marketing and advertising intensity, and size, and industry-specific factors such as market share, diversification, role of IT in the industry, and environmental uncertainty?**

To answer the aforementioned question, this study adopts IT investments data from InformationWeek 500 and patents data, as a measure of innovation output, from the National Bureau of Economic Research (NBER). The values for the firm and industry control variables are generated from the Compustat dataset. In total, the panel dataset consisted of 483 global firms over a 7 year period (1991-1997). The research model is shown below in Figure 1.
The IT investments and innovation model being tested in this research are not claimed to be exhaustive. It should be viewed as a parsimonious subset of a larger model since the complexity of organizations suggests that no single study could test all the relevant variables and their relationships. A parsimonious model was deliberately suggested that consisted of some of the key variables that may explain the relationship between IT investments and firm innovations.

Theoretical Background and Hypotheses

This study draws from the Knowledge Based View (KBV) theory of the firm to set up a theoretical framework. The main aim is to investigate the effects of IT investments on firm innovation while controlling for several salient firm and industry level factors.

Knowledge Based View Theory of the Firm

Knowledge Based View theory of the firm addresses how firms attain sustainable competitive advantages by using knowledge to build capabilities from resources. According to the KBV theory, organizational capability entails the ability of a firm to search, explore, acquire, assimilate, and apply knowledge about organizational resources, capabilities, and market opportunities (Grant, 1996; Kraaijenbrink, Spender, & Groen, 2010). Organizational capabilities are embodied in organizational technologies, business processes, product improvements, executive decision making, as well as organizational adaptations and renewal. Certainly, the more information and knowledge a firm can acquire from external and internal sources and competently distribute it within the firm, the more efficient a firm becomes in renewing and reconfiguring its resources and capabilities.

In line with the KBV theory of the firm, a number of studies have paid considerable attention to the concept of organizational dynamic capabilities (Helfat & Winter, 2011; Sambamurthy et al., 2003; Trkman, 2010). This line of inquiry has been motivated by the desire to address the increasingly important question of how organizations gain and sustain competitive advantages in complex and dynamic environments (Teece,
Pisano, & Shuen, 1997). The mere existence of specific resources and capabilities is not sufficient to gain and sustain competitive advantage because changing environmental stimuli often demand new and innovative organizational responses.

As such, in order to gain and sustain a competitive advantage, an organization needs to reconfigure and recombine its resources and capabilities to meet the demands of a dynamic, uncertain, and fluid competitive environment. This particular process of reconfiguration and recombination has led to the concept of dynamic capabilities (Teece, 2009). According to Teece et al. (1997), dynamic capabilities refer to the processes through which organizations reconfigure and recombine their resources to gain the performance advantages. Dynamic capabilities are considered critical because they allow an organization to reconfigure and recombine its existing knowledge in such a way as to be able to respond to the challenges of complex dynamic environments (Katkalo et al., 2010) and can be captured through firm innovations.

**IT Investments and Innovation**

In many organizations, most of the business processes are either associated or fully embedded in sophisticated IT infrastructures. Thus, the strategic role of IT in the firm has led to an upsurge in IT investments (Mithas et al., 2012; Tallon, 2010). In the IT intensive firms, IT expenditures are almost 8% of total sales (Kobelsky et al., 2008) and almost 40% of the firm’s total capital expenditures (Karanja & Patel, 2012; Ranganathan & Brown, 2006). Firms invest in IT because of the inherent ability of IT to provide important tools for knowledge management through the gathering, manipulating, and sharing of information and knowledge (Alavi & Leidner, 2001). These activities allow a firm to better understand the changes in the current environment and to reconfigure existing resources and capabilities for innovation and competitive performance in response to the changes in the internal and external competitive environments (Lopez-Nicolas & Merono-Cerdan, 2011).

In addition, IT resources enable a firm in augmenting its knowledge management capabilities (Joshi et al., 2010). IT resources not only facilitate the process of creating new knowledge through employees and stakeholders interactions, but also enable the process of knowledge reconfiguration and renewal. In addition, the sharing of knowledge within the firm creates synergies as IT can open several avenues to recombine and reconfigure knowledge from different perspectives that lead to innovation (Barbaroux, 2012; Joshi et al., 2010).

According to Zahra and George (2002), dynamic firm capabilities are closely related to the absorptive capacity of firms. Absorptive capacity, according to Cohen and Levinthal (1990), refers to the ability of a firm to acquire, assimilate, transform, and exploit knowledge. Acquisition and assimilation of knowledge are associated with the potential for absorptive capacity, while transformation and exploitation of knowledge represent realized absorptive capacity (Zahra & George, 2002). Since IT can be an important tool in supporting and enhancing a firm’s knowledge acquisition capability by enhancing the speed, quantity, and quality of knowledge, it is likely that firms can get strategic benefits as a result of faster identification of useful knowledge that is important for the operations of the firm. For example, query-engines, expert systems, decision support systems, and many customized tools can capture and process
information rapidly and accurately (Alavi & Leidner, 2001; Joshi et al., 2010).

Conversely, IT resources can also support a firm’s capability in assimilating useful knowledge as part of the organizational memory. The assimilation capability allows a firm to compare information and thus make more informed decisions. The informed decision making is conducive to a firm’s ability to generate new ideas, products, and services and eventually bring them to market to satisfy customers’ needs and concurrently generate economic rents. Finally, IT resources can facilitate the exploitation of existing knowledge as well as the exploration of new knowledge. IT-enabled absorptive capacity involves knowledge exploitation by synthesizing and refining existing knowledge (Joshi et al., 2010). Conversely, knowledge exploration involves the transformation of knowledge through the merging of different databases, categorization and classification of knowledge frames, as well as by creating visual maps. Thus, IT resources can be an important tool for knowledge exploration and exploitation that eventually yields products, services, or business process innovations.

IT investments also contribute to the dynamic capabilities of the firm by providing resources that enable the recombination and reconfiguration of different knowledge domains. For instance, in the biotechnology industry, cooperation among different firms’ networks is associated with new medical products and processes (Shan, Walker, & Kogut, 1994). Thus, the innovative ability and the resulting innovative output of a firm are dependent on the size of the direct and indirect ties that exist between the firm and its partners (Ahuja, 2000). Thus, it is argued that investments in IT resources provide platforms that enable and facilitate the interactions and collaborations among different stakeholders both within and outside the firm boundaries. The resultant inter-group and intra-group interactions and collaborations within and between organizations entail exchanging views, information, and ideas that help in generating knowledge, codification of useful knowledge, and informing processes (Prasanna, Hitt, & Brynjolfsson, 2012). Therefore,

\[ H_0: \text{While controlling for salient firm and industry factors, IT Investments are positively related to higher levels of innovation in the firm} \]

Sample and Variables Used

In the following section, the constructs that are used in this study to test the model depicted in Figure 1 are defined.

**IT Investments**

There are multiple studies that have sought to extricate the complex relationship between IT investments, productivity, and firm performance (Melville et al., 2004; Prasanna & Hitt, 2012). A significant number of these studies have used different definitions and conceptualizations of the IT investments variable. The definition and the conceptualization of IT investments has varied based on whether the research data are obtained from a survey (Preston, Chen, & Leidner, 2008; Sobol & Klein, 2009), interviews with firm executives (Enns, Huff, & Golden, 2003; Leidner, Beatty,
& Mackay, 2003), or are gleaned from archival sources (Bharadwaj, 2000; Banker et al., 2011). Broadly defined, IT investments include all the expenditures made by the firm toward computers and telecommunications resources such as hardware, software, and related human resources and services (Dedrick, Gurbaxani, & Kraemer, 2003). Table 1 provides a short synopsis of some of the prior IS key research studies that have used the IT investments variable as well as the findings of these studies.

Table 1: Key Constructs Used in a Subset of Prior IT Investment Studies

<table>
<thead>
<tr>
<th>Author(s)</th>
<th>Constructs</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mithas et al., 2012</td>
<td>IT investments, profitability, operating expenses, sales, R&amp;D expenses</td>
<td>IT investments positively impact firm sales and profitability through IT enabled revenue growth</td>
</tr>
<tr>
<td>Banker et al., 2011</td>
<td>IT investments, CIO reporting structure, tenure</td>
<td>CIO reporting structure is based on firm’s strategic positioning and they are associated with superior firm performance</td>
</tr>
<tr>
<td>Tallon, 2010</td>
<td>IT investments, customer intimacy, and operational excellence</td>
<td>Small firms strategically use IT for customer intimacy while large firms use IT mainly in operational strategies</td>
</tr>
<tr>
<td>Ravichandran, Liu, &amp; Hasan, 2009</td>
<td>IT investments, diversification, performance</td>
<td>IT moderates the relationship between diversification and performance</td>
</tr>
<tr>
<td>Shin, 2006</td>
<td>IT intensity (IS budgets scaled by selling and general administrative expenses)</td>
<td>Interaction term of IT and strategic direction is positively associated with gross margin and IT is negatively associated with firm performance</td>
</tr>
<tr>
<td>Zhuang, 2005</td>
<td>E-business innovation (early adoption and creative use of electronic commerce technologies)</td>
<td>Significant differences exist between the performance of e-business innovative firms versus the performance averages for their respective industries</td>
</tr>
<tr>
<td>Devaraj &amp; Kohli, 2003</td>
<td>Costs associated with DSS (IT labor, capital, and support)</td>
<td>Support for the IT-Performance relationship after certain time lags</td>
</tr>
<tr>
<td>Brynjolfsson, Hitt, &amp; Yang, 2002</td>
<td>IT spending (installed IT base, Total CPUs, # of PCs)</td>
<td>Financial markets put a higher value on firms with more installed computer capital (combination of computers and organizational structures creates more value)</td>
</tr>
<tr>
<td>Zhu &amp; Kraemer, 2002</td>
<td>E-business use (the extent to which e-business is being used to conduct value chain activities)</td>
<td>Important antecedents of e-business use are technology competence, firm size, financial commitment, competitive pressure, and regulatory support</td>
</tr>
<tr>
<td>Bharadwaj, Bharadwaj, &amp; Konsynski, 1999</td>
<td>IT spending (staff expenditures, hardware, software, and data communications)</td>
<td>For all five years, IT investments had a significantly positive association with Tobin’s q value.</td>
</tr>
<tr>
<td>Francalanci &amp; Galal, 1998</td>
<td>IT expense (ratio of firm-level IT expenses to total premium income)</td>
<td>Increases in IT expenses are associated with productivity benefits when accompanied by changes in worker composition</td>
</tr>
<tr>
<td>Loveman, 1994</td>
<td>IT spending (investments in Hi-Tech capital resources like office, computing and accounting machinery)</td>
<td>IT capital had little, if any, marginal impact on output or labor productivity</td>
</tr>
<tr>
<td>Weill, 1992</td>
<td>IT Investment perceptually categorized by management objective (strategic, informational, and transactional)</td>
<td>Heavy use of transactional IT investment is significantly and consistently associated with strong firm performance over the six years studied. Heavy use of strategic IT is neutral in the long term and is associated only with relatively poor performing firms in the short term</td>
</tr>
<tr>
<td>Strassmann, 1990</td>
<td>IT spending (IT investment budgets, value of installed equipment, IT staff budget, # of PCs and terminals)</td>
<td>Relationship between expenses for computers and business profitability is not consistent</td>
</tr>
<tr>
<td>Cron &amp; Sobol, 1983</td>
<td>Organizational Strategy and computerization</td>
<td>Computerization is related to overall performance</td>
</tr>
</tbody>
</table>
This study adopted the definition of IT investments that was used in the InformationWeek 500 industry magazine (Lou, 1997), in which IT investments included all those expenditures relating to a firm’s IT infrastructures such as PCs, servers, mainframes, communication equipment, software, and other related hardware that are utilized in setting up local and wide area networks, as well as expenditures incurred toward hiring and training IT employees and providing related services. IT investments data from InformationWeek 500 firms has been used extensively in IS research in exploring the various dimensions of IT and firm variables (Banker et al., 2011; Ravichandran, Liu, & Hasan, 2009). Table 2 shows a sample industry breakdown of IT investments into 6 major categories, namely salaries and benefits, hardware, software, IT services, research and development, and others.

As Table 2 illustrates, the allocations of IT investments across the industries and specific firms in each industry do not vary greatly. The values listed are in percentages.

<table>
<thead>
<tr>
<th>Industry Groupings</th>
<th>Salaries &amp; Benefits</th>
<th>Hardware</th>
<th>Software (purchases, development &amp; maintenance)</th>
<th>IT services</th>
<th>R&amp;D</th>
<th>Everything else (includes system administration &amp; maintenance)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Information Technology</td>
<td>29</td>
<td>19</td>
<td>19</td>
<td>13</td>
<td>3</td>
<td>17</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>38</td>
<td>14</td>
<td>17</td>
<td>14</td>
<td>5</td>
<td>12</td>
</tr>
<tr>
<td>Banking/Financial Services</td>
<td>32</td>
<td>20</td>
<td>20</td>
<td>12</td>
<td>5</td>
<td>11</td>
</tr>
<tr>
<td>Automotive</td>
<td>28</td>
<td>18</td>
<td>23</td>
<td>21</td>
<td>3</td>
<td>7</td>
</tr>
<tr>
<td>Biotech/Pharmaceuticals</td>
<td>30</td>
<td>11</td>
<td>20</td>
<td>29</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>Chemicals</td>
<td>31</td>
<td>16</td>
<td>27</td>
<td>16</td>
<td>1</td>
<td>9</td>
</tr>
<tr>
<td>Construction/Engineering</td>
<td>37</td>
<td>20</td>
<td>18</td>
<td>11</td>
<td>4</td>
<td>10</td>
</tr>
<tr>
<td>Consulting/Business Firms</td>
<td>33</td>
<td>17</td>
<td>19</td>
<td>13</td>
<td>5</td>
<td>13</td>
</tr>
<tr>
<td>Consumer Goods</td>
<td>35</td>
<td>10</td>
<td>22</td>
<td>15</td>
<td>3</td>
<td>15</td>
</tr>
<tr>
<td>Insurance</td>
<td>44</td>
<td>14</td>
<td>15</td>
<td>14</td>
<td>3</td>
<td>10</td>
</tr>
<tr>
<td>Hospitality and Travel</td>
<td>34</td>
<td>16</td>
<td>16</td>
<td>17</td>
<td>3</td>
<td>14</td>
</tr>
<tr>
<td>Healthcare and Medical</td>
<td>34</td>
<td>17</td>
<td>20</td>
<td>9</td>
<td>4</td>
<td>16</td>
</tr>
<tr>
<td>Energy Utilities</td>
<td>32</td>
<td>15</td>
<td>23</td>
<td>14</td>
<td>2</td>
<td>14</td>
</tr>
<tr>
<td>Electronics</td>
<td>32</td>
<td>19</td>
<td>17</td>
<td>18</td>
<td>6</td>
<td>8</td>
</tr>
<tr>
<td>Distribution</td>
<td>36</td>
<td>13</td>
<td>16</td>
<td>17</td>
<td>4</td>
<td>14</td>
</tr>
<tr>
<td>Logistics/Transportation</td>
<td>30</td>
<td>15</td>
<td>22</td>
<td>17</td>
<td>3</td>
<td>13</td>
</tr>
<tr>
<td>Media and Entertainment</td>
<td>31</td>
<td>18</td>
<td>27</td>
<td>12</td>
<td>2</td>
<td>10</td>
</tr>
<tr>
<td>Metals/Natural Resources</td>
<td>38</td>
<td>14</td>
<td>17</td>
<td>12</td>
<td>1</td>
<td>18</td>
</tr>
<tr>
<td>Retail-General Merchandising</td>
<td>19</td>
<td>17</td>
<td>25</td>
<td>5</td>
<td>3</td>
<td>31</td>
</tr>
<tr>
<td>Retail-Specialty Merchandising</td>
<td>29</td>
<td>17</td>
<td>21</td>
<td>11</td>
<td>6</td>
<td>16</td>
</tr>
<tr>
<td>Telecommunications</td>
<td>33</td>
<td>14</td>
<td>18</td>
<td>18</td>
<td>4</td>
<td>13</td>
</tr>
</tbody>
</table>

The highest percentage of IT investments is allotted to IT employees' salaries and benefits followed by software, hardware, and IT services in descending order. The specific budgets allocated to Research and Development (R&D) is a mere 3% while systems maintenance and administration services take on an average close to 13% of the total IT investment budgets.
Firm Innovation

Innovation is an important firm strategy and innovative firms have been found to earn above normal profits (Lopez-Nicolas & Merono-Cerdan, 2011). For instance, in the 2009 annual study of the Global 1000 innovators, Booz & Company reported that even with the recession, most of the companies had maintained their innovation projects and that these firms were indeed boosting their innovation investment so as to be competitive in the upturn. According to Robert Lardon, Corporate Vice President for strategy and investor relations at Harman International Industries Inc. (Public, NYSE:HAR), “innovation is what drives our competitive position in all three of our markets - automotive, professional, and consumer and we cannot back off” (Jaruzelski & Deholf, 2009, p. 3). Elsewhere, in the 13th annual ranking of the best 50 firms by Business Week Magazine, BusinessWeek50, Foust (2009, p. 40) indicated that “innovation remains a powerful engine of success” for these firms.

Researchers have generally conceptualized innovation through the amount of money spent by firms in their R&D activities, the number of patents granted to the firm or applied for by the firm, the number of patent citations, new product announcements or introductions, etc. Raw patent counts have been extensively used to represent firm innovations, as they are considered to be a good indicator of the inventive performance of firms, reflecting new technologies, new processes, new services, and new products (Acs & Audretsch, 1989; Ahuja & Katila, 2004; Griliches, 1998; Maarten, Geert, & Jan, 2009; Shan et al., 1994).

For this study, a broad definition of innovation was adopted that included new and improved products, technological artifacts, processes, and services that were either physical in nature or were encapsulated in intangible forms such as key ideas (i.e., software) that have the potential to meet a user's needs and economic rents for the innovating firms and are represented by patents (Joshi et al., 2010). There is a plethora of research studies that have adopted patents as a measure of innovation (Griliches, 1998; Jaffee & Trajtenberg, 2002). A patent confers upon the inventor the sole right to make, use, and sell an invention for a specified period of time, usually 20 years. A patent details information about the specific innovation, the inventors, and the affiliations of the inventors. Thus, a patent clearly illustrates technological and scientific linkages that traverse generations of inventions as well as the knowledge flow across individuals, organizations, geographical regions, and countries (Jaffee & Trajtenberg, 2002).

Patent-based innovations are knowledge driven in that they involve applications and the generation of scientific, technical, and experiential knowledge. Patents are also unique in that they allow the investors/inventors to appropriate a larger portion of the profits accruing from innovations. Patents are the strongest form of legal protections against imitations by other firms (Teece, 1998).

In this research, the above researchers’ conceptualization and measures of innovation were adopted resulting in the use of applied patents and granted patents (Freeman & Soete, 1997; Griliches, 1998). The innovation output of a firm is represented by a factor score that is generated (through factor analysis) after normalizing (log base 10) the raw count values of applied patents and granted patents. The factor score was created to eliminate the limitations of using one variable in the measurement of innovation output, namely the raw count values of either applied for or granted
patents. Applied patents refer to those patents that firms have invested in but have not yet been approved by the United States Patent and Trademark Office (USPTO) while the granted patents refer to the patents which have been approved by the USPTO (Jaffe & Trajtenberg, 2002). Although this factor score only dealt with those innovations that had been patented (output), it was found that the factor score was highly correlated (0.87) with R&D investments, which were considered an input into the innovation process, thus providing a good indication of a firm’s innovative behavior.

Firm and Industry Control Variables

The ability of a firm to innovate is likely to be affected by the firm strategy, firm resources capacity, organizational motivation, organizational goals, as well as the interaction of the firm and the external environment. Also, investments in IT resources are not exogenous but are influenced by the internal firm factors as well as the external market and environmental forces (Xue, Ray, & Sambamurthy, 2012). For instance, the strategy of the organization can be reflected in the way the firm allocates its resources namely the amounts allocated to the R&D initiatives, IT investments, or expansion into new markets through mergers and acquisitions. Also, the debt level of the organization and its growth potential are a reflection of the organizational goals and strategies and have the potential to impact firm innovation.

With regard to the firm environmental factors, the market position of the firm in relation to the competitors, the risk inherent in the environment and the product diversification strategy employed by the firm also affect innovations. Since there are several factors that are likely to influence the relationship between IT investments and innovation, the study incorporates a number of firm and industrial control factors. The firm level control variables are Marketing and Advertising (M&A) intensity, firm size, debt ratio/leverage, and firm growth. The environmental control variables include environmental uncertainty, related and unrelated diversification, market concentration ratio, and the role of IT in the firm industry. These variables have been shown to have an impact on how firms allocate their IT investments (Banker et al., 2011; Kobelsky et al., 2008).

M&A intensity is an indicator of the firm’s marketing capability and represents the efforts geared towards marketing and informing the market about the firm’s new and innovative products, services, or processes. Firm size is controlled because of the varied arguments about the role that organizational size plays in fostering innovation. Debt ratio, also known as leverage, is the amount that the firm owes the creditors in the course of financing the obligations to the customers and stakeholders. Firms carrying a higher debt obligation are perceived to be risky and the risk factor affects the relationship between firm IT investments and commitment to innovation. Firm growth is controlled because growth is associated with increases in resources that lead to higher market share and ultimately higher profit margins that can be ploughed back into innovation focused endeavors.

Environmental uncertainty exemplifies the degree of perceived volatility and rate of change of the environment external to the firm (Matthews & Scott, 1995; Milliken, 1987). Higher levels of uncertainty require that a firm undertake initiatives that are geared towards offsetting the uncertainty. Diversification measures the extent of a
firm’s operations in different industries within the same two digit Standard Industry Classification (SIC) codes (Chari, Devaraj, & David, 2008). Also, related diversification entails the exploitation of economies of scale through the sharing of both physical and human resources across related lines of business. Firms pursuing related diversification strategy will also be more effective in responding to the customer-based opportunities that spur more innovations.

Unrelated diversification measures the extent of a firm’s operations in different two-digits SIC codes. Unrelated diversification is aimed at efficient allocation of capital and other resources in an internal market rather than in the inefficient public market exchanges (Dewan, Michael, & Min, 1998). Industry concentration ratio is an indicator of the relative size of the firm in relation to the industry with higher values being associated with market domination and monopolistic business structures. For instance, monopolists have been shown to innovate more rapidly in order to retain their market share and high profits in markets characterized by low or nonexistent barriers to entry. The industry in which a firm operates can be classified as either hi-tech or low-tech (Francis & Schipper, 1999). Hi-tech firms are thus expected to be savvier at using IT to plan, implement, control, and assess the performance of innovation strategies. Table 3 provides a summary of the research constructs used for the study, their operationalization, and sources of data.

<table>
<thead>
<tr>
<th>Construct</th>
<th>Definition</th>
<th>Data Source</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>IT investments</td>
<td>Annual firm IT investments scaled by sales</td>
<td>IW500</td>
<td>Kobelsky et al., 2008; Banker et al. 2011</td>
</tr>
<tr>
<td>Firm innovation</td>
<td>A factor score generated from applied and granted patents</td>
<td>NBER</td>
<td>Jaffe &amp; Trajtenberg, 2002</td>
</tr>
<tr>
<td>Marketing &amp; advertising intensity</td>
<td>Ratio of marketing and advertising costs scaled by sales</td>
<td>Compustat</td>
<td>Bharadwaj et al., 1999; Chari et al. 2008</td>
</tr>
<tr>
<td>Firm size</td>
<td>Size of the firm measured through market capitalization</td>
<td>Compustat</td>
<td>Fama &amp; French 1993</td>
</tr>
<tr>
<td>Debt ratio/Leverage</td>
<td>Measure of what firm owes external stakeholders</td>
<td>Compustat</td>
<td>Kobelsky et al., 2008; Lang, Ofek, &amp; Stulz, 1996</td>
</tr>
<tr>
<td>Firm growth</td>
<td>Realized growth of the firm based on sales</td>
<td>Compustat</td>
<td>Kobelsky et al., 2008</td>
</tr>
<tr>
<td>Environmental uncertainty</td>
<td>A measure of variability in the environment</td>
<td>Compustat</td>
<td>Kim, 2001; Kobelsky et al., 2008</td>
</tr>
<tr>
<td>Diversification (Related/Unrelated)</td>
<td>Extent to which a firm engages in more than one business venture or line of business</td>
<td>Compustat</td>
<td>Dewan, et al., 1998; Jacquemin &amp; Berry, 1979; Palepu, 1985</td>
</tr>
<tr>
<td>Concentration ratio</td>
<td>A measure of firm power and industry competition based on the 4-digit SIC Codes</td>
<td>Compustat</td>
<td>Bharadwaj et al., 1999; Chari et al., 2008</td>
</tr>
<tr>
<td>Hi-Tech/Low-Tech</td>
<td>A value designating firms in high and low technology industries</td>
<td>Based on SIC Codes</td>
<td>Banker et al. 2011; Francis &amp; Schipper, 1999; Kobelsky et al., 2008</td>
</tr>
</tbody>
</table>

Hi-tech firms have more sophisticated IT resources, which should offer these firms superior capabilities in gathering, analyzing, assimilating, and disseminating information and knowledge within and across firm boundaries leading to more innovative ideas, processes, and products.
Data Analysis and Results

The estimation of the research model used data from three sources: IT investments from *InformationWeek 500*, patents from the National Bureau of Economics Research (NBER), and control variables from Compustat as shown in Table 3. The data set was generated by merging IT investments, innovation, and control variables, which consisted of 69 global firms for a total of 483 observations for IT investments from 1991 to 1997 for innovation from 1991 to 1999, and for control variables from 1991 to 1997. Thus, it is a balanced panel data set.

Data Research Context

Following prior research (Banker et al., 2011; Ravichandran et al., 2009), IT investments data was gleaned from *InformationWeek 500* industry magazine from 1991-1997. The selected firms were those that had accounting/finance data in the Compustat database. The required accounting/finance data enabled the computation of the values for the control variables. Using the Compustat database, each firm was matched with its corresponding SIC code, and a unique identifier known as a Global Company Key (GVKEY, a unique six-digit key assigned to each company in the Compustat database) was generated. This GVKEY was used to match the firms in the NBER Patent Data Project to generate firms that had both IT investments data and patents data. The final sample data set was generated by merging these three disparate data sets and consisted of 69 global firms for a total of 483 observations for IT investments and control variables from 1991 to 1997, and innovations data from 1991 to 1999. Thus, the final sample is a balanced panel data set.

Data Cleaning

Following the recommendations of Hair et al. (2002) and Belsley, Kuh, and Welsch (1980), a number of tests were conducted that aimed at cleaning the data as well as examining the violations of assumptions of multivariate regression analysis. To start with, a number of data transformation techniques were applied and the values were ‘winsorised’ at 5% and 95% levels to eliminate the influence of outliers, which have been shown to be associated with Type I and Type II errors besides skewing the reliability of the estimates (Osborne, 2001). The outliers were eliminated after a careful examination of Cook’s D distance statistics, ‘studentized’ residuals, and DFFITS as suggested by Neter, Wasserman, and Kutner (1990). Secondly, in testing the violations of normality, an examination of the distribution of the variables was done and the results ascertained that the variables were, on average, normally distributed (skewness range: -0.85 to 0.73; kurtosis range -0.49 to 0.65). Also, the Kolomogorov-Smirnov test for normality, which indicated no deviations from normality, and the White’s test (White, 1980) for heteroscedasticity that supported the constant variance assumptions were done.

Thirdly, in testing the presence or absence of multicollinearity, an examination of the Variance Inflation Factors (VIFs) and tolerance values was done and both VIFs and tolerance values were found to be well below the threshold value of 10 (highest value was 1.28) and above the 0.10 (lowest value was 0.72) values, respectively.
(Neter et al., 1990). Finally, the correlation coefficients of the variables used in the regression analysis were evaluated and found to be low enough to signify lack of multicollinearity (rs<0.70), thus justifying simultaneous inclusion in the regression analysis equation models.

**Summary Statistics**

Table 4 provides the descriptive statistics for the study variables for the 483 firms in the sample with IT investments, innovation, and control variables over the 1991 to 1997 period.

<table>
<thead>
<tr>
<th>Research Variables</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Innovation</td>
<td>0.693</td>
<td>8.183</td>
<td>3.843</td>
<td>1.588</td>
</tr>
<tr>
<td>IT investments</td>
<td>0.001</td>
<td>0.075</td>
<td>0.024</td>
<td>0.013</td>
</tr>
<tr>
<td>M&amp;A intensity</td>
<td>0.000</td>
<td>0.100</td>
<td>0.011</td>
<td>0.021</td>
</tr>
<tr>
<td>Debt ratio</td>
<td>0.000</td>
<td>0.857</td>
<td>0.194</td>
<td>0.124</td>
</tr>
<tr>
<td>Firm growth</td>
<td>0.001</td>
<td>3.280</td>
<td>0.098</td>
<td>0.171</td>
</tr>
<tr>
<td>Environmental uncertainty</td>
<td>0.001</td>
<td>0.150</td>
<td>0.032</td>
<td>0.028</td>
</tr>
<tr>
<td>Related diversification</td>
<td>0.000</td>
<td>1.309</td>
<td>0.267</td>
<td>0.310</td>
</tr>
<tr>
<td>Unrelated diversification</td>
<td>0.000</td>
<td>1.824</td>
<td>0.498</td>
<td>0.452</td>
</tr>
<tr>
<td>Industry concentration</td>
<td>0.299</td>
<td>1.000</td>
<td>0.795</td>
<td>0.190</td>
</tr>
<tr>
<td>Hi-tech/Low-tech</td>
<td>0.000</td>
<td>1.000</td>
<td>0.450</td>
<td>0.498</td>
</tr>
</tbody>
</table>

These values are in line with similar studies that used analogous measures and data variables (Bharadwaj, Bharadwaj, & Konsynski, 1999; Chari et al., 2008; Kobelsky et al., 2008). The firms in this sample were weighted toward large firms with mean market capitalization of $9.18 billion (1991-1997), and this value was shown in Table 4 as the log value with base 10 for the firm size variable. The values were comparable to the firms in the Standard and Poor's database of 500 firms. On average, the firms in the sample spent about 2.4% of their sales revenue on IT in the years 1991-1997.
Table 5 presents the correlation coefficients among the variables adopted for this study. The Spearman correlations were above the diagonal while the Pearson correlations were below the diagonal. As predicted, IT investment levels were positively and significantly related to innovation, while innovation was positively and significantly related to marketing and advertising intensity, firm size, firm growth, uncertainty, and related diversification.

Table 5: Correlations of the Research Variables

<table>
<thead>
<tr>
<th>Variables</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
<th>(9)</th>
<th>(10)</th>
<th>(11)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Innovation</td>
<td>1</td>
<td>0.36</td>
<td>0.18</td>
<td>0.40</td>
<td>-0.14</td>
<td>0.05</td>
<td>0.18</td>
<td>0.14</td>
<td>-0.21</td>
<td>0.01</td>
<td>0.15</td>
</tr>
<tr>
<td>IT Investments</td>
<td>0.30</td>
<td>1</td>
<td>0.02</td>
<td>0.28</td>
<td>-0.15</td>
<td>0.00</td>
<td>0.12</td>
<td>-0.13</td>
<td>-0.08</td>
<td>0.01</td>
<td>0.13</td>
</tr>
<tr>
<td>M&amp;A Intensity</td>
<td>0.14</td>
<td>-0.06</td>
<td>1</td>
<td>0.34</td>
<td>-0.19</td>
<td>0.03</td>
<td>-0.16</td>
<td>-0.01</td>
<td>-0.16</td>
<td>-0.06</td>
<td>0.01</td>
</tr>
<tr>
<td>Firm size</td>
<td>0.40</td>
<td>0.25</td>
<td>0.33</td>
<td>1</td>
<td>-0.13</td>
<td>0.03</td>
<td>0.12</td>
<td>0.14</td>
<td>0.15</td>
<td>0.02</td>
<td>0.06</td>
</tr>
<tr>
<td>Debt ratio</td>
<td>-0.19</td>
<td>-0.13</td>
<td>-0.11</td>
<td>-0.18</td>
<td>1</td>
<td>-0.10</td>
<td>0.09</td>
<td>0.16</td>
<td>0.24</td>
<td>0.15</td>
<td>-0.02</td>
</tr>
<tr>
<td>M&amp;A Intensity</td>
<td>0.07</td>
<td>0.12</td>
<td>0.04</td>
<td>0.04</td>
<td>-0.14</td>
<td>1</td>
<td>0.12</td>
<td>-0.13</td>
<td>-0.07</td>
<td>-0.11</td>
<td>0.05</td>
</tr>
<tr>
<td>EU</td>
<td>0.13</td>
<td>0.10</td>
<td>-0.12</td>
<td>0.15</td>
<td>0.04</td>
<td>0.02</td>
<td>1</td>
<td>-0.07</td>
<td>-0.04</td>
<td>-0.03</td>
<td>0.15</td>
</tr>
<tr>
<td>Hi-tech</td>
<td>0.14</td>
<td>-0.15</td>
<td>0.05</td>
<td>0.08</td>
<td>0.14</td>
<td>-0.11</td>
<td>-0.11</td>
<td>1</td>
<td>-0.11</td>
<td>0.233</td>
<td>0.01</td>
</tr>
<tr>
<td>UD</td>
<td>-0.24</td>
<td>-0.02</td>
<td>-0.07</td>
<td>0.11</td>
<td>0.20</td>
<td>-0.06</td>
<td>-0.02</td>
<td>0.01</td>
<td>1</td>
<td>0.16</td>
<td>-0.10</td>
</tr>
<tr>
<td>IC</td>
<td>-0.02</td>
<td>0.04</td>
<td>-0.06</td>
<td>0.08</td>
<td>0.20</td>
<td>-0.02</td>
<td>0.05</td>
<td>0.20</td>
<td>0.13</td>
<td>1</td>
<td>-0.03</td>
</tr>
<tr>
<td>Hi-tech</td>
<td>0.15</td>
<td>0.16</td>
<td>-0.11</td>
<td>0.06</td>
<td>0.001</td>
<td>0.07</td>
<td>0.15</td>
<td>0.08</td>
<td>-0.10</td>
<td>0.05</td>
<td>1</td>
</tr>
</tbody>
</table>

Values higher than 0.07 or lower than -0.07 are significant at the 0.1 level, values higher than 0.09 or lower than -0.09 are significant at the 0.05 level, values higher than 0.13 or lower than -0.13 are significant at the 0.01 level. (2-tailed), N=483

Moreover, firms in high technology (hi-tech) industries showed a propensity to innovate based on the correlation results in Table 5. Also, as predicted, innovation was negatively and significantly related to debt ratio and unrelated diversification.

**Empirical Model**

This research made use of a balanced panel data set to examine the relationship between IT investments and innovation. The study adopted the following cross sectional time series model, $y_{it} = \alpha + X'_{it}\beta + (\mu_i + \omega_{it})$ which estimated variance components for groups and error, while assuming the same intercept and slopes. In this model, $(\mu_i + \omega_{it})$ was the error component and was not correlated to the independent variables. Also, in line with the assumptions of Ordinary Least Square (OLS), the intercept, $\alpha$, was constant and the error variances vary across groups and times (Baltagi, 2005). On substituting the variables from the data into the regression equation, Equation 1 is as shown below.

$$
\text{Innov}_{i,t+n} = \delta_0 + \delta_1\text{ITBGT}_i + \delta_2\text{M&A Intensity}_i + \delta_3\text{Firm Size}_i + \delta_4\text{Dbt}_i + \delta_5\text{Growth}_i + \delta_6\text{Uncertainty}_i + \delta_7\text{RD}_i + \delta_8\text{UD}_i + \delta_9\text{Ind Conc}_i + \delta_{10}\text{Hi Tech}_i + \phi_i
$$

(1)
Equation 1 represents the relationship between innovation and IT investments while controlling for both specific firm and environmental uncertainty variables whereby:

Innov_{i,t+n} = Innovation score for firm i at year t+n where t=0,1,2, and n=1, 2, 3
ITBGT_Sls\_t = IT investments scaled by sales as reported by firm i in year t
M&A\_Intensity\_t = Marketing and Advertising costs scaled by sales as reported by firm i in year t
Firm\_Size\_t = Size of firm measured by log market capitalization for firm i in year t
Dbt\_Rto\_t = Debt ratio of firm i in year t
Gwth\_Sls\_t = Firm growth from sales for t-1 and t for firm i
IndUncnty\_t = Level of environmental uncertainty (standard deviation of industry earnings before extraordinary items for previous 5 years scaled by sales) for firm i in year t
RD\_t = Related diversification based on entropy measures (see appendix for computation) for firm i in year t
UD\_t = Unrelated diversification based on entropy measures (see appendix for computation) for firm i in year t
Ind\_Conctr = Measure of industry concentration and competition for firm i in year t
Hi-tech\_t = Binary value of 1 represents firms in high technology industries and 0 otherwise in year t
\( \eta_{it} \) = Independent and identically distributed error term with zero means

Results
The results from the cross sectional regression analysis are presented in Table 6 on the next page.
### Table 6: Results of a Cross Sectional Regression Analysis

<table>
<thead>
<tr>
<th>Variable</th>
<th>Predicted Sign</th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td></td>
<td>-1.03 (-1.70*)</td>
<td>-1.40 (2.13**)</td>
</tr>
<tr>
<td>M&amp;A_Intensity</td>
<td>+</td>
<td>0.10 (0.03)</td>
<td>2.25 (0.72)</td>
</tr>
<tr>
<td>Firm_Size</td>
<td>+</td>
<td>0.53 (8.94*** )</td>
<td>0.44 (7.39*** )</td>
</tr>
<tr>
<td>Dbt_Rto</td>
<td>-</td>
<td>-1.23 (-2.28**)</td>
<td>-1.05 (-1.97**)</td>
</tr>
<tr>
<td>Gwth_Sls</td>
<td>+</td>
<td>0.31 (0.82)</td>
<td>0.18 (0.50)</td>
</tr>
<tr>
<td>IndUncnty</td>
<td>+</td>
<td>4.39 (1.90*)</td>
<td>4.43 (1.96**)</td>
</tr>
<tr>
<td>RD</td>
<td>+</td>
<td>0.47 (2.26**)</td>
<td>0.69 (3.21*** )</td>
</tr>
<tr>
<td>UD</td>
<td>-</td>
<td>-0.87 (-5.88*** )</td>
<td>-0.82 (-5.66*** )</td>
</tr>
<tr>
<td>Ind_Conc</td>
<td>+</td>
<td>0.37 (1.06)</td>
<td>0.15 (0.44)</td>
</tr>
<tr>
<td>Hi-tech</td>
<td>+</td>
<td>0.27 (2.11** )</td>
<td>0.18 (1.44)</td>
</tr>
<tr>
<td>ITBGT_Sls</td>
<td>+</td>
<td></td>
<td>24.29 (4.84*** )</td>
</tr>
<tr>
<td>Adj_R-squared</td>
<td></td>
<td>0.26</td>
<td>0.30</td>
</tr>
<tr>
<td>Adj_Adj_R-squared</td>
<td></td>
<td>0.04***</td>
<td></td>
</tr>
<tr>
<td>F Value</td>
<td></td>
<td>19.98***</td>
<td>23.40***</td>
</tr>
</tbody>
</table>

Unstandardized regression coefficients are reported and t-values are in parentheses

*** Significant at the 0.01 level, ** significant at the 0.05 level, * significant at the 0.1 level (2-tailed), N=483

- **Innov**: Innovation score firm i at year t=n where t=0,1,2, and n=1,2,3
- **ITBGT_Sls**: IT investments scaled by sales as reported by firm i in year t
- **M&A_Intensity**: Marketing and advertising intensity scaled by sales
- **Firm_Size**: Size of the firm represented by log market capitalization as a ratio of t-1 and t
- **Dbt_Rto**: Debt ratio at time t
- **Gwth_Sls**: Average growth from sales
- **IndUncnty**: Level of industry uncertainty (standard deviation of industry earnings before extraordinary items for previous 5 years scaled by sales) at time t
- **RD**: Related diversification based on entropy measures (see text for computation) at time t
- **UD**: Unrelated diversification based on entropy measures (see text for computation) at time t
- **Ind_Conc**: Measure of industry concentration and competition
- **Hi-tech**: Binary value representing high technology firms in year t, 1 for firms in hi-tech industries.

### Findings and Discussions

A time-series cross sectional regression analysis was carried out to test the effect of IT investments on firm innovation while controlling for both firm and industry factors. As shown in Table 6, the variables statistically significantly predicted firm innovation, ($F(10,472)=23.40, p<0.005$). Specifically, IT investments were positively and significantly (beta=24.29, p<0.001) related to innovations with a change in adjusted R$^2$ equal to 4%. Thus, one unit of IT investments input led to 4 units in innovation outputs. For the control variables, firm size (beta=0.44, p<0.001), uncertainty (beta=4.43, p<0.05), and related diversification (beta=0.69, p<0.01) were positively and significantly related to innovation while debt ratio (beta=-1.05, p<0.05) and unrelated diversification (beta=-0.82, p<0.001) were negatively and significantly related to innovation. On the other hand, marketing and advertising intensity (beta=2.25, ns), firm growth (beta=0.18,50, ns), industry concentration ratio (beta=0.15, ns), and hi-tech (beta=0.18, ns) were positive, as predicted, but not statistically significant.
The support for the research hypothesis suggests that IT investments enable the firms to acquire the capability to test new ideas at faster speeds and at lower prices/costs. This is especially true currently, where firms utilize the internet and other web 2.0 technologies to communicate with their customers and stakeholders in soliciting ideas and inputs on new products or processes. These exchanges, communications, and interactions are accomplished within short time periods, possibly within hours, reducing the cost and time of innovative initiatives. On the other hand, these IT-enabled capabilities make innovations, “the lifeblood of growth, more efficient and cheaper” (Brynjolfsson & Schrage, 2009, p.1). By soliciting customers’ inputs and feedback during the innovation processes, firms generate innovative products and services that are tailored to the needs of the customers, guaranteeing wider acceptance during the diffusion stages and thus, higher economic rents.

IT investments are also used in facilitating and organizing the know-how about a firm’s past projects, expertise, and routines. In addition, investments in IT resources can help in the coordination of knowledge among different people in the firm, as well as between R&D groups in a firm adopting related diversification strategy by offering collaborative capability. IT investments in the form of communication tools such as networks, email, virtual meetings, blogs, and the more recent relation-oriented tools such as wikis, blogs, and social networking resources can also facilitate collaboration and teamwork by reorganizing and recombining the organizational knowledge.

For the control variables, the relationship between M&A intensity and innovation was positive as predicted, but not statistically significant. Also, the relationship between firm size and innovation was found to be positive, although not statistically significant. Large firms tend to be associated with the advantages of superior resources and capabilities that these firms have acquired over time. Also, large firms are more innovative because they tend to have more financial slack, superior marketing skills, and R&D capabilities, as well as product and service development experience (Nord & Tucker, 1987; Zhu & Kraemer, 2005). Hence, large firms can cushion against potential losses associated with unsuccessful innovation project ventures. Some of the IT investments are utilized in acquiring and training IT human resources. Thus, the hiring of IT professionals and skilled workforce with superior technical and business knowledge places large firms at the vanguard of technological development (Ettlie, Bridges, & O’Keefe, 1984; Popadiuk & Choo, 2006).

The negative association between innovation and debt ratio may be explained by the perceived risk associated with innovation that affects the relationship between firm IT investments and commitment to innovation. Innovation involves a number of stages that include ideation, project selection, development, and commercialization and lower firm debt levels are important at each of these stages. Lower debt levels or lower values for leverage (more free cash flows) ensure uninterrupted IT investments in initial innovation initiatives as well as availability of funds during the product testing, launching, and the ultimate commercialization. Also, lower debt levels offer free cash flows that firms can use to expand their knowledge bases, through the hiring of savvy IT professionals, or acquiring IT tech venture firms (O’Brien, 2003). A firm that has a higher debt ratio may not have the required funds to sustain the necessary IT investment levels associated with innovation.
Though indicative results of the relationship between firm growth and innovation were obtained, the lack of significant statistical support might be explained by the fact that not all growth comes from innovation. For instance, top executives seeking prestige and immediate job rewards may grow their firms through mergers and acquisitions (Matsusaka, 1993). Also, firms can grow their sales through competitive attacks such as steep price reductions or other aggressive sales campaigns. Although controlled growth brings with it economies of scale that are conducive to innovation, rapid growth can lead to rapid asset acquisitions, which result in tying-up resources that could be used for other ventures such as IT driven innovations.

The positive and significant relationship between uncertainty and innovation alludes to the fact that higher levels of uncertainty demand greater efforts in coordination and control at the firm level. As such, firms will resort to innovative endeavors – in products, processes or services – which lower the uncertainty levels. For instance, uncertainty requires more complex IT-enabled information processing systems and marketplace volatility is associated with the building of an extensive IT infrastructure (Broadbent et al., 1996). An extensive IT infrastructure such as Enterprise Resource Planning (ERP) or Supply Chain Management (SCM) links the various facets of the organization while also establishing and facilitating timely information gathering and sharing. Thus, firms operating in uncertain environments tend to be more innovative so as to overcome the inherent risks while also staying competitive.

A diversified firm seeks to limit market and operational risks based on the premise that not all products or service offerings move up or down the market simultaneously, allowing for a more consistent performance under various organizational and economic conditions. A firm engaged in related diversification, characterized by similar lines of business, is capable of exploiting economies of scope by sharing physical and human resources. As a result, a consistent revenue stream may be reinvested toward innovation initiatives. Moreover, a firm operating in a number of related business segments may exploit its core capabilities, resulting in economies of scale and scope, efficiency in allocating resources, as well as management synergy through the transfer of technical and management skills across the product or service lines (Rumelt, 1982). The core capabilities resulting from resource sharing and efficient allocation of resources may possibly lead to the positive relationship between related diversification and innovation.

Contrary to expectations, a significant relationship between the concentration ratio and innovation was not found. This was surprising as it was expected that firms in more concentrated industries would be more competitive and hence more innovative to mitigate the effects of market competition. The reason for the lack of significant relationship could be the heterogeneity of the sample space, which was comprised of firms from multiple industries, making it difficult to discern the effect of individual industries. Also, contrary to expectations, a significant relationship between hi-tech firms and innovation was not found. This could be because hi-tech firms are not very adept at using IT for innovation. Hi-tech firms use IT for streamlining and coordinating their business processes.

There is limited empirical research that examines the link between IT investments and innovation. Thus, this research contributed to this line of research by offering results that shed more light on the importance of IT investments in fostering firm
innovations. This paper argued that IT investments enable a firm to reconfigure and recombine knowledge from various diverse sources to promote innovation and also facilitate the organizing of know-how about past projects, expertise, and routines.

Robustness of the Results

As alluded to earlier, the innovation score was computed based on the number of patents applied for and granted to the firm through factor analysis. Assuming that the effects of IT investments take, on average, 3 years to assimilate and yield noticeable business process improvements (Dewan et al., 1998), IT investments were related in year $t$ to applied patents in year $t+n$ ($t=1,2,3$, $n=0,1,2,3,4$), such that IT investments in 1991 were related to patents applied for in 1993. Also, since it takes around 3 years for patents to be approved by the USPTO, the patents applied for in 1993 were typically granted in 1995. Thus, the innovation score associated with IT investments in 1991 was generated from patents that were applied for in 1993 and granted in 1996, based on a 3-year sliding window. To examine the robustness of the results, a 1-year, a 2-year, and a 4-year sliding window were also used, and with the exception of the 1-year sliding window, the results of the cross sectional regression based on the model in Equation 1 were not significantly different. The only results presented were based on the 3-year sliding window to conform with the theory and also for space limitations. Alternative measures and specifications for other variables were also utilized. For instance, the study tested the model in Equation 1 using IT investments scaled by employees rather than sales. The results were not statistically different.

Research Contributions

This study contributes to the literature on the role of IT investments in creating business value through firm innovations in a number of ways. First, researchers have long been motivated by the economic significance of IT investments in studies examining IT business value (Loveman, 1994; Tallon, 2010), but the mechanisms or business processes that yield this value have been understudied. This study brings a closer understanding of this phenomenon by investigating the effects of IT investments on firm innovation, which can lead to business value. This study developed a theoretical framework for IT investment payoff in the context of innovation by specifically aligning the attributes of the KBV theory to the innovation life cycle. The adopted research framework drew from the literature on coordination and control in order to explain payoffs from IT investment in innovation. In this study, the question of whether an IT investment pays-off in the context of innovation was considered to be very significant from an economical perspective. Moreover, the motivation to consider the relationship between IT investments and innovation provides researchers with a firm basis that IT indirectly may yield business value through the commercialization of innovations.

Economists and management scholars agree on the role of innovations in generating economic rents at the firm, industry, or economy level. Firms that are persistent innovators have been demonstrated to appropriate superior economics rents compared to their competitors (Anthony, Johnson, & Sinfield, 2008). In this respect, IT investments played a key role by spurring innovation in the firms that ultimately lead to business advantages. Also, by systematically investigating the relationship
between IT investments and innovation, this research was differentiated from prior research studies, which focused on the direct link between IT investments and business performance. As such, this research offered an explanation for the seemingly conflicting findings about the impact of IT on business performance in the extant literature. The results of a positive relationship between IT investments and innovation added credence to the notion that the impact of IT investments should be carried out at the business process level, where its first order effects are more often realized. This study narrowed that gap by linking IT investments to innovation, which is a key driver of superior business performance.

Limitations

The IT investments data adopted for this study were not based on the actual IT resources specifically allocated to the innovation processes, but were an aggregate value of all the IT investments utilized by the firm. Future studies should try and address this shortcoming. A fine-grained analysis of actual IT investments data dedicated to the firm innovation processes might provide a better understanding of the roles of IT investments in fostering the firm innovation. Also, the sample frame was not randomly selected and was based on a data set comprising firms that appeared in the InformationWeek 500 and for the most part these firms self-reported their IT investments data. As such, the generalizability of these results to other firms is open to scrutiny.

Another limitation of this study was the use of InformationWeek 500 dataset. Although the dataset had been used extensively in previous studies (Kobelsky et al., 2008; Banker et al., 2011; Im et al., 2013), it may be considered dated. However, studies that used duration are better suited to “old” data due to their longitudinal nature that require a couple of years between the investments and the results (Dehning & Stratopoulos, 2003). Future studies should use more recent data to replicate and confirm that the findings still hold after a decade of rapid and widespread use of IT.

The use of patents as a measure of innovation may pose some limitations too. Nevertheless, there is a longstanding debate on the use of raw-patent counts as a measure of innovation output at the firm, industry or economy level (Griliches, 1998). Some critics have argued that patents should be differentiated by value. That is, weights should be assigned based on the economic value of the patent. However, researchers in management and economics have generally accepted raw-patent counts as one indicator of the innovative performance of firms as depicted by new processes, new technologies, and new products. Future studies should seek to use survey data to gather more data on new products and services introduced by firms and the portion of IT investments allocated to each innovation process.

Conclusions

IT has permeated many facets of organizations and is being utilized, for instance, to internally coordinate, control, and facilitate organizational processes and management decision-making processes. Externally, firms have made IT investments that enable and facilitate interactions with customers, suppliers, and other stakeholders as demonstrated in the use of CRM, SCM, or ERP systems respectively. These are organizational day-to-day business oriented processes, which result from IT investments and in one way or
another have a direct or indirect impact on firm innovation. For example, an effective and efficient IT-enabled value chain is an indispensable firm asset that facilitates the generation and capture of ideas on new products, or processes designs, improvements on existing products, and processes as well as retirement of non-rent generating products, services, or business processes. Capturing and understanding valuable knowledge is a firm capability, because these ideas will ultimately be converted into innovative products or services. These ideas also offer a firm several opportunities to identify its strengths and weaknesses. The benefits accruing from innovations are amplified when a firm integrates and aligns its business strategy with IT investment initiatives.

Resources attributed to IT investments have transformed the processes through which firms engage in innovative endeavors (Brynjolfsson & Schrage, 2009). For instance, firms rely on employees, customers, suppliers, and other stakeholders for breakthrough ideas on products, processes, or service innovations. New ideas are generated, shared, and developed through collaborative trial-and-error initiatives by different entities that supersede the Schumpeterian model of lone entrepreneurs (Schumpeter, 1987). Thus, by investing in IT resources, firms can make use of industry value chains that connect the firm with customers, suppliers and other trading partners encapsulating diverse pools of knowledge across the firm, which is an indispensable resource for innovation.

References

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Appendix

Diversification

In measuring business diversification, this study utilized information from Compustat database business segments (Rule 14 of the FASB mandates public firms to disclose information on significant business segments, and a significant business segment is one that accounts for more than 10% of the total firm assets, sales, or profits). The two dimensions of diversification namely, related and unrelated diversifications were computed as shown in the equation below following Jacquemin and Berry (1979), and Palepu (1985).

Figure 2: Equations for Computing Related and Unrelated Diversification Values

\[
\text{Related Diversification} = \sum_{j=1}^{M} \sum_{l=1}^{N_j} S_j^l \ln \frac{S_j^l}{S_j^{l-1}}
\]

\[
\text{Unrelated Diversification} = \sum_{j=1}^{M} S_j^l \ln \frac{1}{S_j^l}
\]

\(N\) is the number 4 – digit SIC industries a firm is active in, indexed by \(i\), which in turn aggregate into \(M\) 2 – digit industry groups, indexed by \(j\), \((M \leq N)\), \(N_j\) is the number of different industries in group \(j\), \(S_i\) is the share of industry \(i\) in total firm sales, \(S_j^l\) is the share of group \(j\) in total firm sales, \(S_j^l\) is the share of firm sales in industry \(i\) of firm sales in industry group \(j\)

Table 6: Diversification Values as Computed from Total Sales for Selected Firms with IT Budgets in 1996

<table>
<thead>
<tr>
<th>Company Name</th>
<th>GVKEY</th>
<th>Total Sales</th>
<th>SEG 1</th>
<th>SEG 2</th>
<th>SEG 1</th>
<th>SEG 2</th>
<th>SEG 1</th>
<th>SEG 1</th>
<th>UD</th>
<th>TD</th>
<th>RD</th>
<th># of SEGs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baxter Int. Inc</td>
<td>2086</td>
<td>5438</td>
<td>5438</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>1</td>
</tr>
<tr>
<td>Bemis Co. Inc.</td>
<td>2154</td>
<td>1655</td>
<td>1180</td>
<td>474</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.000</td>
<td>0.599</td>
<td>0.599</td>
<td>2</td>
</tr>
<tr>
<td>Chevron Corp.</td>
<td>2991</td>
<td>37580</td>
<td>3422</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.313</td>
<td>0.313</td>
<td>0.000</td>
<td>2</td>
</tr>
<tr>
<td>Crane Co.</td>
<td>3580</td>
<td>1865</td>
<td>207</td>
<td></td>
<td>363</td>
<td></td>
<td></td>
<td></td>
<td>1.197</td>
<td>1.197</td>
<td>0.000</td>
<td>4</td>
</tr>
<tr>
<td>Int'l Paper Co.</td>
<td>6104</td>
<td>21400</td>
<td>2665</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.707</td>
<td>1.577</td>
<td>0.870</td>
<td>5</td>
</tr>
</tbody>
</table>

SEG = business segment
The Relationship Between Dispositional Positive Affect and Team Performance: An Empirical Study

Tianjiao Qiu
California State University, Long Beach

Vicki M. Scherwin
California State University, Long Beach

Research has established the impact of affectivity on a range of organizational outcomes. However, empirical works on how dispositional affect—the tendency to experience positive emotions—influences team outcomes are lacking. The purpose of this study is to empirically investigate how dispositional positive affect impacts team performance and how individual team member’s task performance and team interactions, including team learning and interpersonal citizenship behaviors, mediate the relationship. Results from new product student teams demonstrate that dispositional positive affect promotes both individual team member’s task performance and team interactions, yet only team interactions contribute to overall team performance.

Understanding what contributes to the performance of small groups and teams has garnered the attention of scholars and researchers from a variety of disciplines, including psychology, organizational behavior, marketing, and economics (e.g., Grawitch, Block, & Ratner, 2005; Riolli & Sommer, 2010). Among various kinds of teams, new product development (NPD) teams have been widely adopted in organizations to generate product innovation (Edmondson & Nemhhard, 2009; McDonough, 2000). Due to the popularity of NPD teams, a significant amount of research has investigated what contributes to NPD team processes and success (e.g., Troy, Hirunyawipada, & Paswan, 2008; Sethi, Smith, & Park, 2001). The majority of NPD team research focuses on examining how the functional composition of the team—the differing expertise within a team—impacts NPD team performance (e.g., Sethi et al., 2001). This line of research...
has shown that integration through better team communication, team coordination, and team learning is necessary before NPD teams can shorten product development cycles, produce more innovative new product ideas, and generate better product design and quality (e.g., De Luca & Atuahene-Gima, 2007; Troy et al., 2008). Another line of research examines how leadership roles in the NPD process, including team leaders, managers, and champions, enable NPD team success (e.g., Qiu et al., 2009; Sarin & McDermott, 2003). For example, Sarin and McDermott (2003) demonstrated that leadership characteristics in NPD teams significantly impacted team learning, knowledge application, and subsequently, NPD performance. Qiu et al. (2009) found that project managers' interactional fairness promoted both individual team member's task performance and team performance as a whole.

Despite these fruitful findings on NPD teams from the functional composition and leadership perspectives, little empirical research has investigated the individual differences of the members within the team and how these individual differences impact the interactions between the team members. McNally et al. (2009) proposed that a manager's dispositional traits, such as analytic cognitive style, ambiguity tolerance, and leadership style, would be related to his or her decision processes in new product portfolio management. One central dispositional trait, dispositional affect (positive or negative affect), has received little attention in NPD teams. Dispositional affect encompasses a wide range of personality traits (Barsade et al., 2000) and is therefore likely to influence NPD team interactions and ultimately NPD team performance. In this study, how the dispositional affect impacts NPD team performance through individual team member's task performance and interactions with other team members will be empirically examined.

Theoretical Background

Affectivity is generally classified as either positive or negative. Positive affectivity (PA) is described as the experience of engaging pleasurably with one's environment, feeling cheerful, enthusiastic, energetic, confident, and alert (Watson, Clark, & Tellegen, 1988; Wright, Larwood, & Denney, 2002). Conversely, negative affectivity (NA) is the experience of anger, guilt, fear, nervousness, and subjective stress (e.g., Watson & Clark, 1984). The tendency to experience positive or negative feelings consistently across time and a range of situations is defined as dispositional affect—dispositional PA and dispositional NA, respectively. Similar to personality traits, dispositional PA and dispositional NA represent consistent individual differences (Watson & Clark, 1984). They are not opposite ends of a one-dimensional construct. In fact, dispositional PA and dispositional NA operate largely independently and relate to different types of predictor and outcome variables (e.g., Watson et al., 1988).

Given the independence of dispositional PA and dispositional NA, studies have commonly focused on either dispositional PA or dispositional NA in predicting employees' attitudes and behaviors. The meta-analysis of Thoresen et al. (2003) reported that compared to dispositional NA, dispositional PA received disproportionately less attention in organizational research. The existing limited dispositional PA research
primarily focused on organizational outcomes, such as job satisfaction, organizational commitment, and turnover intentions (Thoresen et al., 2003). However, little is known about how individual dispositional PA impacts NPD team outcomes. In this research, the goal is to investigate how individual dispositional PA impacts NPD team performance through individual team member's task performance and team interactions including team learning and interpersonal citizenship behaviors (ICBs).

The research model used integrated insights from motivation research (Elliot, 1999; Elliot & Thrash, 2002; Gable, Reis, & Elliot, 2003), which suggested that motivation consisted of two dimensions: *approach* and *avoidance*. Approach motivation can be described as a tendency toward certain actions (Carver, Sutton, & Scheier, 2000). Action tendencies are “deeply embedded in the nature of human personality” (Carver, 2006, p.109). Approach tendencies prod people to act and trigger behaviors that facilitate their pursuits, whereas avoidance tendencies stimulate inhibition and elicit withdrawal in the face of new opportunities (Gray, 1994).

Scholars from a variety of empirical traditions proposed that these two dimensions served as the foundation for a range of individual differences (Gray 1990, 1994; Elliot & Thrash, 2002; Carver, 2006) including dispositional affect, where positive affect and negative affect were manifestations of approach and avoidance temperaments, respectively. Approach motivated individuals were defined as “highly engaged in the pursuit of whatever incentives arise” (Carver et al., 2000, p. 747). For example, approach motivated individuals could be expected to look forward to an upcoming social event, thrill-seek, act spontaneously, or be excited about an unexpected opportunity (Gray, 1994). More generally, approach motivated individuals enacted behaviors that actively approached their environments, such as fulfilling their responsibilities, intentionally interacting with others, and seeking new experiences and opportunities (e.g., Gable, 2006). Relevant to this research, given that high dispositional PA individuals were likely to be approach motivated (Elliot & Thrash, 2002), they had the tendency to initiate behaviors which supported the task performance, team learning, and interpersonal citizenship behaviors investigated in this study.

Data were collected from teams engaged in the task of designing a new product and corresponding plan as part of an undergraduate product development course. This interactive task (McGrath & Kravitz, 1982), which involved multiple interactions across various product development stages, required the participation of all team members. Because of the level of interdependence inherent in the interactive task (Van der Vegt, Emans, & Van De Vliert, 1999), it was meaningful to examine team members’ behaviors and to explore how these behaviors influenced the relationship between dispositional PA and NPD team performance. Specifically, the study intended to answer the following research questions about teams working on interactive tasks: (1) How did dispositional PA impact individual team member's task performance, team learning, and interpersonal citizenship behaviors? and (2) How did these behaviors contribute to overall team performance?

**Literature Review and Hypotheses**

Although there is an increasing interest in the relationship between personality traits
and individuals' attitudes and behaviors in the work place (see Ng & Sorensen, 2009 for a review), research on how dispositional affect (both positive and negative) impacts NPD team performance has received little attention in the interdisciplinary literature. Research findings have centered on general working teams in the organization. For example, two recent meta-analyses illustrated the range of outcome variables that dispositional affect can influence including: personal accomplishment, organizational commitment, job satisfaction, emotional exhaustion, depersonalization, turnover intentions (Thoresen et al., 2003), global satisfaction, social integration, organizational treatment, job stress, in-role and extra-role performance, and absenteeism (Ng & Sorensen, 2009), among others. Overall findings indicated that dispositional PA and NA were related to many important organizational variables and that dispositional PA had a strong effect on variables related to the job and organizational context (Ng & Sorensen, 2009). Additional research explored affect at the group level which entailed aggregating individual-level dispositional affect (George, 1990) and moods (Bartel & Saavedra, 2000) to investigate, for example, emotional contagion (Hatfield, Cacioppa, & Rapson, 1994) and the effects of affective diversity within a team (e.g. Barsade et al., 2000).

Despite these rich findings, there is a lack of empirical work on the relationship between dispositional PA and NPD team performance. The performance of a NPD team is based on the success of the product(s) that the NPD team develops (Kleinschmidt & Cooper, 1991). Thus, the performance of a NPD team can be assessed in a variety of ways, including external measures, such as product speed to market or timeliness of product introduction (Bstieler & Hemmert, 2010), product quality, and the product’s market performance (Lynn, Skov, & Abel, 1999) or internal measures such as team members’ self-assessments of performance and team member satisfaction (Brockman et al., 2010) along with innovativeness and improvement of the NPD process (Ettlie, Elsenback, & Jorg, 2007).

Regardless of which measure is adopted, NPD performance depends on how well the team members interact and collaborate (Hoegl & Gemeunden, 2001) or in other words, the quality of teamwork (Hoegl & Gemeunden, 2001). Scholars have called for more research into caring and cooperative behaviors and suggest that these behaviors are representative of the quality of team member interactions (Hoegl, Ernst, & Proserpio, 2007) and should be investigated as mechanisms that contribute to NPD team success and efficiency (Bstieler & Hemmert, 2010). Therefore, the question investigated in this study—how specific behaviors mediate the relationship between dispositional PA and NPD team performance—have the potential to yield insights beneficial for both emotion aspects and for NPD team researchers.

Dispositional PA and Task Performance

Task performance refers to individuals enacting role responsibilities (Qiu et al., 2009; Settoon & Mossholder, 2002). Given that individuals with higher dispositional PA are approach motivated (i.e., driven to pursue their goals) and enact approach related behaviors (e.g., actively engage with their environment), they will be more likely to fulfill their responsibilities, perform expected tasks, and complete their duties than those individuals lower in dispositional PA in NPD teams. Howell and Shea (2001) connected approach motivation and task performance by showing that
when individuals were approach motivated, they were likely to be more committed, involved and persistent in working on a product innovation task. Although task focus has never been directly linked to dispositional PA, a recent meta-analysis found that dispositional PA was positively correlated with in-role performance (Ng & Sorensen, 2009). Additionally, research on short-term affect, which demonstrated that individuals in positive moods were found to display task focus (Grawich et al., 2003) and initiative (Den, Hartog, & Belschak, 2007), was relevant in this case because individuals higher in dispositional PA were likely to be experiencing frequent short-term positive feelings. Finally, individuals who experienced more frequent positive emotions across a variety of situations were more likely to have confidence in their performance and were perceived to be more effective in their workplaces than those who experienced positive emotions less frequently (Staw & Barsade, 1993). Therefore, the following is suggested:

**Hypothesis 1:** Team members higher in dispositional PA will demonstrate a higher level of task performance than team members lower in dispositional PA.

**Dispositional PA and Team Learning**

Team learning is one of the most critical drivers of innovation in NPD teams (Clark & Cardy, 2002; Edmondson & Nembhard, 2009). It is defined as “activities by which team members seek to acquire, share, refine, or combine task-relevant knowledge through interaction with one another” (Van der Vegt & Bunderson, 2005, p. 534). This is a key team behavior because teams are unlikely to be able to succeed in new product development if the members do not combine their knowledge. Edmondson and Nembhard (2009) indicated that there was a set of processes that aided in team learning such as seeking feedback and help, experimenting with new approaches, and asking questions. Since approach motivated individuals seek out new opportunities, actively engage with others, and are driven to act in ways that support their goals, these interpersonal learning processes may also be expected from high dispositional PA individuals.

Although no previous research has studied the relationship between dispositional PA and team learning in NPD teams, research on associated behaviors has supported the expectation that team members higher in dispositional PA would engage in team-level processes that contributed to team learning more than those lower in dispositional PA (e.g., D’Zurilla, 2011). For example, individuals with greater dispositional PA performed better on the cognitive processes that were the antecedents to good decision making and constructive problem solving (D’Zurilla, 2011; Staw & Barsade, 1993). Additionally, Levin et al. (2010) found that individuals with a positive affect had a more successful transfer of knowledge than individuals with a negative affect. Individuals’ with high dispositional PA approach motivation, decision making skills, and increased knowledge incorporation all indicated that individuals higher in dispositional PA would benefit from team learning. Thus the following is suggested:

**Hypothesis 2:** Individual team member’s dispositional PA will be positively associated with team learning behaviors.
**Dispositional PA and Person-focused Interpersonal Citizenship Behaviors (ICB)**

Person-focused ICB refers to a type of extra-role behavior in which an individual extends voluntary efforts that go beyond his or her immediate role requirements in order to support fellow team members, enhancing the fabric of social relations in the workplace (Qiu et al., 2009; Settoon & Mossholer, 2002). Person-focused ICB can be exhibited in various forms, such as interpersonal sharing, helping, and facilitation (Bowler & Brass, 2006). Qiu et al. (2009) found that team members’ commitment to NPD teams positively impacts team members’ person-focused ICB.

Approach motivated individuals also have a more positive attitude toward social relationships (Gable, 2006). They experience an increase in relationship quality compared to non-approach motivated individuals (Impett et al., 2010). Therefore, it is expected that individuals higher in dispositional PA will be more willing to contribute beyond their required role responsibilities and enact ICB behaviors, compared to those individuals lower in dispositional PA in NPD teams.

Although no research has specifically addressed the relationship between dispositional PA and person-focused ICB in NPD teams, some research has shown that short-term PA encourages the display of helping others and prosocial behaviors (Isen & Baron, 1991; George, 1991). Dispositional PA can also lead to participation in more social activities (Watson, 1992) and better social judgments (Staw & Barsade, 1993). High dispositional PA members are also better at perceiving the social interaction patterns in groups (Casciaro, Carley, & Krackhardt, 1999) and have the tendency to pay more attention to others’ behavior, consequently allowing them to make more accurate judgments about others than judgments made by individuals with lower dispositional PA (Staw & Barsade, 1993). Accurate judgments and frequent social interactions with team members are necessary precursors of ICB behaviors. Thus it is suggested:

**Hypothesis 3:** Team members higher in dispositional PA will demonstrate higher levels of person-focused ICB than team members lower in dispositional PA.

**Task Performance, Team Learning, and Person-focused ICB as Mediators**

This research explored the relationship between dispositional PA and the team behaviors described above with the ultimate goal of understanding how dispositional PA influenced NPD team performance. Team members were engaged both in their “taskwork” and “teamwork” (Ortiz, Johnson, & Johnson, 1994). Thus, team performance depended on individual task performance, as well as how well the team members learned, interacted and collaborated in NPD process.

Although NPD teams consisted of multiple individuals working toward a common goal, each individual was responsible for exerting effort in order to accomplish his or her assigned tasks. There is general consensus among team researchers that the quality performance of each group member contributes to the overall NPD team performance (Qiu et al., 2009). Specifically, individual task efforts have been found to have a significant positive influence on team performance (Weingart & Weldon, 1991). Previous conceptual arguments stated that task performance may impact team performance in a number of different ways depending on the task type. Task types may have determined whether team performance was affected by interdependent group
efforts or by the efforts of specific individuals within the team (Zaccaro & McCoy, 1988). For example, if performance in a specific task was only based on one team member's solution, then one might argue that the other team members' emotional dispositions would be irrelevant. However, that was not the case for the interactive task assigned to the product teams in this study. Therefore, the expected result was that the greater each team member's task performance, the greater the team performance would be.

_Hypothesis 4a: Task performance will mediate the relationship between individual dispositional PA and team performance._

In addition to “taskwork”, in order to reap the benefits of working in a team, team members need to behave in ways that enhanced team learning. Teams are “key learning units in organizations” (Senge, 1990, p. 236) and they contribute to organizational effectiveness. A significant success factor in NPD teams is whether knowledge shared with the team becomes a part of the team (e.g., Edmondson, 1999; Edmondson & Nembhard, 2009). When team members learn by effectively sharing their information or developing new knowledge, the effectiveness of the NPD team is enhanced (Edmondson, 1999; Edmondson & Nembhard, 2009), in turn leading to improved NPD team performance (Sarin & McDermott, 2003). Knowledge acquisition, implementation, and dissemination, (among other learning sub-concepts) contributes to new product success (Akgün, Lynn, & Yılmaz, 2006). More specifically, since innovation is a consequence of the learning process (Sarin & McDermott, 2003), the more a team learned, the more likely the NPD team would be to perform well. Therefore, it is hypothesized:

_Hypothesis 4b: Team learning will mediate the relationship between individual dispositional PA and team performance._

A harmonious work environment in which team members voluntarily enact supportive and caring behavior is also important in order for teams to achieve a common goal. When constructive and cooperative behaviors occur within NPD teams, the quality and acceptance of the solutions that the teams propose are enhanced (De Dreu & West, 2001; Qiu et al., 2009). Additionally, scholars hypothesize that when team members are in a caring environment they can concentrate more on their tasks, as opposed to having to struggle to be accepted and appreciated, yielding a positive impact for the team (De Dreu & Weingart, 2003). Therefore, this paper suggests that voluntary interpersonal caring behaviors, such as listening, showing concern and helping—investigated in this study as person-focused citizenship behaviors—will mediate the relationship between dispositional PA and team performance.

_Hypothesis 4c: Person-focused ICB will mediate the relationship between individual dispositional PA and team performance._
Method

Sample and Data Collection Procedure

Data were collected from 26 new product development teams consisting of a total of 98 undergraduate senior business majors from two large public universities. 15 new product development teams (56 students) were from a large public university in the Midwestern United States and 11 new product development teams (42 students) were from a large public university in the Southern United States. Approximately 32% of the participants were male and 68% were female. Participants’ ethnicities were as follows: White (85), Hispanic (6), Asian (5), Black (1), and Native American (1). The participants’ ages ranged from 18 to 45 years old, with 88% of the participants having full or part-time work experience.

Given that organizations are increasingly relying on new product development (NPD) teams to leverage employees’ combined expertise and knowledge (McDonough, 2000), NPD teams provide an opportune context in which to empirically investigate the relationships studied in this paper. The study participants were enrolled in NPD courses that required product teams to develop detailed and actionable new product solutions to project ideas provided by corporate sponsors from both manufacturing and service industries. During the first week of the semester, participants were randomly assigned to teams of three or four members to work on this task. Then, following the schedule as outlined in the course syllabus, the student teams engaged in the following new product development activities: 1) identifying market needs, 2) generating new product ideas, 3) evaluating the potential market, 4) conducting cost analysis, and 5) outlining a market launch plan. Team members interacted with each other both in the class work-sessions and during team meetings outside of the class. The course faculty advisors and corporate sponsor representatives guided the teams’ NPD efforts from idea screening to product testing. At the end of the semester, the teams presented their new product solutions and submitted a written report. The faculty advisors and the corporate sponsor representatives then evaluated each team’s new product solution following the Product Development and Management Association’s project success guidelines (Griffin & Page, 1996). Specifically, the faculty advisors and the corporate sponsor representatives evaluated the product solutions along five dimensions: product innovativeness, development cost, how the product met quality specifications, how the product fit with the business strategy, and how the product led to future opportunities.

After all teams submitted their reports (but before the evaluation of their projects), the data for the study were collected via a written survey. Collection occurred before the final project evaluation to avoid retrospective biases in which team members adjusted their responses based on the evaluation results from the faculty advisors. The survey contained measures of each team member’s dispositional PA, task performance, team learning behavior, person-focused ICB, and self-report team performance.

Measures of Key Constructs

The measures employed in the study were adapted from previous scales. The item loadings of all variables were significant at $p < .05$. Cronbach’s reliability statistics showed that all measures had satisfactory convergent reliability. Discriminant validity
between the measures using two approaches was tested. First, a confirmatory factor analysis (CFA) was employed to test the validity of the measures (Anderson & Gerbing, 1988). The model statistics were satisfactory (RMSEA = 0.08; GFI = 0.89; RMR = 0.08; AGFI = 0.85; CFI = 0.90; NFI = 0.86). Second, following the guidelines set by Segars (1997), discriminant validity with a chi-square difference test was tested. Specifically, the study compared the pair-wise chi-square statistics among each possible pair of scales using unconstrained (the correlation between the two constructs is set free) and constrained (the correlation between the two constructs is constrained to one) models. All chi-square statistics in the unconstrained model were significantly lower than the chi-square statistics in the constrained model ($p < .01$), verifying the discriminant validity of the scales.

The study measured dispositional PA by adopting Watson et al.’s (1988) 10-item scale. The instructions asked the respondents to indicate to what extent he/she felt that each of the items was generally descriptive of oneself, not just descriptive of oneself while he/she was working on the team project. The measure used a 5-point Likert scale, with response options ranging from 1 = “not at all”, to 5 = “extremely”. The final measure contained all 10 items, with a reliability level (alpha) of 0.79 in the current study. The following were three sample items: interested, proud, and inspired. Williams and Anderson’s (1991) in-role behavior scale to measure individual team member’s task performance was adapted. This self-report scale contained five items that examined how well the team member completed his/her assigned team duties. The following were two sample items: “I adequately completed my assigned team duties” and “I fulfilled my responsibilities as specified.” The scale had a reliability level of 0.88. Edmondson’s (1999) team learning scale was adapted to measure team learning processes. This scale measured learning as an ongoing process at the group level that enabled team members to acquire, share, and combine knowledge through group interactions. One item in this scale had a loading of less than [.50] and was eliminated (Hair et al., 1998). The final scale contained 6 items, with response options ranging from 1 = “strongly disagree”, to 5 = “strong agree.” The reliability level was 0.73. The following were two sample items: “Our team frequently sought new information that led us to make important changes” and “We regularly took time to figure out ways to improve our team’s work processes.” Settoon and Mossholder’s (2002) scale was used to measure person-focused ICB. This scale measured team members’ social and emotional support of other team members. The scale contained 6 items and had a reliability level of 0.90. The following were two sample items: “I made an extra effort to understand the problems faced by teammates” and “I took the time to listen to teammates’ problems and worries.”

Team performance was measured in two ways: (1) respondents’ self-report rating of their teams’ performance, and (2) faculty advisor’s evaluation of the team performance. For the first measure, existing published research using student samples was followed (e.g., Sarin & McDermott, 2003) and team performance was assessed with self-report ratings of NPD team performance, which included team performance from 5 perspectives: the morale of the team, the efficiency of the team’s operations, the attainment of the goals set for the team, the team’s reputation for work excellence, and the quality of the project (Sethi et al., 2001). This scale used a 5-point Likert scale, ranging from 1 = “far below expectations”, to 5 = “far above expectations”. The
reliability level was 0.91. The limitation of assessing team performance through self-report survey items was recognized, thus the study attempted to address this limitation by including a second, external team performance measure that reflected a combined team evaluation score from the faculty advisors and corporate sponsors. The advisors and corporate sponsors met to discuss and assign a score to each team’s project based on the five-stage development process. Since the student teams worked on mock products and no true product performance data were available, these evaluations captured the qualitative aspect of the project and were project-specific centering around the key criteria of “the degree to which the product provides a competitive advantage” as advocated by Griffin and Page (1996). Specifically, five dimensions of the product solutions: product innovativeness, development cost, how the product met quality specifications, how the product fit the business strategy, and how the product led to future opportunities, were emphasized in the qualitative evaluation.

Finally, the study controlled for three variables: (1) team members’ gender, (2) team members’ ethnicity, and (3) team size, when testing the models due to the possible influence these variables might have had on team interactions and project success.

Tests of Hypotheses

Table 1: Descriptive Statistics and Correlations among Variables

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<td>-.02</td>
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<td>-.11</td>
</tr>
</tbody>
</table>

a Ninety eight senior undergraduate students participated in the study. The items corresponding to each construct/dimension were summed and averaged in order to obtain a summated index. The summary statistics are reported for this index.

b correlations have p < .01

c correlations have p < .05

Before testing the model, an assessment was conducted of the between-group variance in team performance using a null model. The null model is an intercept-only model in which no predictors are specified. The between-group variance ($\tau^2$) in team performance was calculated to be .27, while the variance between members in the same team ($\delta^2$) was .35. In this case, the interclass correlation coefficient was .44, indicating that 44% of variance in team performance resided between groups. This
result indicated that the team level had an important impact on team performance and justified the use of hierarchical linear modeling technique.

The 5 linear mixed equations that were tested in the study are presented in Table 2. Equations 1 to 5 tested the mediating effects of individual task performance, person-focused ICB and team learning on the relationship between dispositional PA and NPD team performance (Krull & MacKinnon, 1999). Analytical procedures recommended by Baron and Kenny (1986) were adopted to test the presence of mediating effects in the model. Equations 1, 2 and 3 examined the direct effects of dispositional PA on the mediating variables: individual task performance, team learning, and person-focused ICB. Equation 4 examined the direct effect of dispositional PA on the dependent variable of the model: NPD team performance. All variables were entered simultaneously in Equation 5 to examine individual task performance, team learning, and person-focused ICBs as mediators of the relationship between dispositional PA and NPD team performance. The hypothesized mediating effects were supported if three criteria were met: (1) if dispositional PA significantly affected individual task performance, team learning, and person-focused ICB in equations 1, 2 and 3, (2) if dispositional PA significantly affected NPD team performance in the fourth equation, and (3) if individual task performance, team learning, and person-focused ICB significantly affected NPD team performance while controlling individual dispositional PA.

Table 2: The Effect of Dispositional Positive Affect (DPA) on Team Performance

<table>
<thead>
<tr>
<th>Equation</th>
<th>Fixed Effects</th>
<th>Random effects</th>
<th>Fit statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\gamma$’s (SE)</td>
<td>$\phi$ (SE)</td>
<td>$\phi^2$ (SE)</td>
</tr>
<tr>
<td>1. Task performance (TP):</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Level 1: $(TP)<em>i = \beta</em>{1i} + \beta_{2i}(DPA)<em>i + \beta</em>{3i}(CV)_i + \epsilon_i$</td>
<td>Int $3.24^{**}$ (45)</td>
<td>$0.00^{*}$ (26)</td>
<td>$0.04^{*}$ (135.1)</td>
</tr>
<tr>
<td>Level 2: $\beta_{1i} = \gamma_{10} + U_{1i}$</td>
<td>DPA $0.43^{**}$ (0.08)</td>
<td>Size $-0.05^{*}$ (0.05)</td>
<td></td>
</tr>
<tr>
<td>2. Team learning (TL):</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Level 1: $(TL)<em>i = \beta</em>{1i} + \beta_{2i}(DPA)<em>i + \beta</em>{3i}(CV)_i + \epsilon_i$</td>
<td>Int $2.58^{**}$ (62)</td>
<td>$0.11^{*}$ (0.07)</td>
<td>$0.39^{*}$ (0.07)</td>
</tr>
<tr>
<td>Level 2: $\beta_{1i} = \gamma_{10} + U_{1i}$</td>
<td>DPA $0.25^{**}$ (11)</td>
<td>Size $-0.05^{*}$ (0.08)</td>
<td></td>
</tr>
<tr>
<td>3. Person-focused ICB (ICB):</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Level 1: $(ICB)<em>i = \beta</em>{1i} + \beta_{2i}(DPA)<em>i + \beta</em>{3i}(CV)_i + \epsilon_i$</td>
<td>Int $2.42^{**}$ (52)</td>
<td>$0.02^{*}$ (0.04)</td>
<td>$0.36^{*}$ (0.06)</td>
</tr>
<tr>
<td>Level 2: $\beta_{1i} = \gamma_{10} + U_{1i}$</td>
<td>DPA $0.30^{**}$ (10)</td>
<td>Size $-0.13^{*}$ (0.06)</td>
<td></td>
</tr>
<tr>
<td>4. Team performance (TAP):</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Level 1: $(TAP)<em>i = \beta</em>{1i} + \beta_{2i}(DPA)<em>i + \beta</em>{3i}(CT)_i + \epsilon_i$</td>
<td>Int $1.70^{**}$ (60)</td>
<td>$0.16^{*}$ (0.08)</td>
<td>$0.31^{*}$ (0.06)</td>
</tr>
<tr>
<td>Level 2: $\beta_{1i} = \gamma_{10} + U_{1i}$</td>
<td>DPA $0.48^{**}$ (10)</td>
<td>Size $0.09^{*}$ (0.09)</td>
<td></td>
</tr>
<tr>
<td>5. Team performance (TAP):</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Level 1: $(TAP)<em>i = \beta</em>{1i} + \beta_{2i}(DPA)<em>i + \beta</em>{3i}(CT)<em>i + \beta</em>{4i}(ICB)_i + \epsilon_i$</td>
<td>Int $-0.58^{**}$ (56)</td>
<td>$0.01^{*}$ (0.03)</td>
<td>$0.23^{*}$ (0.04)</td>
</tr>
<tr>
<td>Level 2: $\beta_{1i} = \gamma_{10} + U_{1i}$</td>
<td>DPA $-0.79^{**}$ (69)</td>
<td>TP $0.10^{*}$ (12)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>TL $0.41^{**}$ (69)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>ICB $0.79^{**}$ (12)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Size $-0.02^{*}$ (0.06)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Ethnicity $-0.03^{*}$ (0.06)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Gender $0.12^{*}$ (14)</td>
<td></td>
</tr>
</tbody>
</table>

*p < .05; **p < .01

Equation 1 showed a significant effect of dispositional PA ($\gamma = .43$, p < .01) on individual team member's task performance, supporting Hypothesis 1. Equation 2 examined the effect of dispositional PA on team learning. The parameter estimate of dispositional PA ($\gamma = .25$, p < .05) was significant. These results demonstrated that...
dispositional PA significantly impacted team learning, which supported Hypothesis 2. Equation 3 examined the effect of dispositional PA on team members’ person-focused ICB. Dispositional PA demonstrated a strong significant effect on person-focused ICB ($\gamma = .39, p<.01$), which supported Hypothesis 3. Equation 4 examined the direct effect of dispositional PA on NPD team performance. Dispositional PA was found to significantly impact NPD team performance ($\gamma = .48, p<.01$).

In Equation 5, dispositional PA ($\gamma = .29, p<.01$), team learning ($\gamma = .41, p<.01$), and person-focused ICB ($\gamma = .29, p<.01$) were found to significantly impact NPD performance. Individual task performance did not show a significant effect on team performance. Taken together, the hypothesized mediating effects of team learning and person-focused ICB were supported. However, although dispositional PA significantly impacted team members’ task performance, team members’ task performance had no direct impact on NPD team performance.

Further, since dispositional PA still significantly impacted NPD performance in Equation 5, this was an indication of a partial mediation. Team learning and person-focused ICB did not fully mediate the relationship between dispositional PA and NPD performance. Using Sobel’s (1982) method, the study further tested the partial mediating roles of team learning and person-focused ICB. The Sobel z-statistics were 2.11 for team learning ($p = .04$) and 3.36 for team members’ person-focused ICB ($p < .001$). These statistics confirmed a partial mediating role of team learning and person-focused ICB on the relationship between dispositional PA and NPD team performance, supporting Hypotheses 4b and 4c.

To address the issue of possible common method bias, the faculty advisors’ aggregated performance evaluation scores were used as an alternative measure of NPD team performance (Podsakoff et al., 2003). Since HLM required that the dependent variables be measured at the lowest level to capture both variance within the lower-level and the variance between the higher-level groups, the faculty advisors’ evaluation scores took into account the advisors’ evaluation not only of each team’s new product solutions, but also of the individual student team member’s contribution to the solution. Consistent with the above findings, dispositional PA significantly impacted NPD team performance ($\gamma = .70, p<.01$). At the same time, both team learning ($\gamma = .33, p<.05$) and person-focused ICB ($\gamma = .54, p<.01$) demonstrated highly significant relationships with NPD performance while controlling for dispositional PA. Thus, the faculty advisor scores provided a version of an external measure of performance to complement the internal measure (Brockman et al., 2010) and through triangulation, supported the validity of the study’s findings (Jick, 1979).

In terms of controls, the findings showed that ethnicity had no significant impact on team learning, individual task performance, and person-focused ICB. Gender had no relationship to task performance either. However, it was found that gender significantly impacted both team learning and person-focused ICB. Female team members demonstrated significantly higher levels of person-focused ICB and promoted team learning better than male team members. Team size demonstrated a significant negative effect on team members’ person-focused ICB. The findings illustrated that smaller team size enhanced interactions and facilitated team members’ interpersonal behaviors.
Discussion

Due to the increased popularity of teams in executing various tasks, such as new product development and sales campaigns in organizations, there is great interest from academics and practitioners alike in the antecedents of team performance. This study contributed to an understanding of the relationship between dispositional PA and NPD team performance and promoted an understanding of both an antecedent to and the mechanisms of team success. Although functional diversity, especially cross-functional diversity in NPD teams, has received wide attention, it has been shown here that the dispositional diversity of team members also has important implications for team interactions. The study highlighted the relationship between dispositional PA and key behaviors integral for NPD team performance. It was also shown that dispositional PA had a direct positive effect on NPD team performance along with having important implications for team learning and ICBs which also contributed to NPD team performance. These results underscored the role of dispositional PA as a critical team stage setting element at the outset of a team project that promoted active learning and influenced project success.

This study illustrated that team members with high levels of dispositional PA acted in ways that corresponded with their approach motive tendencies (e.g., intentionally interacting with others and seeking new experiences and opportunities); namely, they were more willing to fulfill their task responsibilities and go beyond their task specifications to engage in team learning and spontaneous assistance behaviors. These findings were consistent with previous research on dispositional PA that emphasized the positive relationships between dispositional PA and a range of work performance outcomes, such as decision making, interpersonal performance, and managerial potential (Staw & Barsade, 1993; for a review, see Thoresen et al., 2003). Furthermore, the findings demonstrated that dispositional affect may be considered an individual-level team stage setting element. McDonough (2000) described this as an element in place at the outset of the project that influenced project success. Thus, the study illustrated that dispositional affect is an important variable to address because it not only can have a direct impact on individual task performance, it also indirectly influences two mechanisms—interpersonal behavior and team learning—known to drive NPD performance.

The study suggested that the success of NPD teams depended upon how effectively team members were interacting and communicating with each other. Team activities such as communication with other members and showing concern towards others contributed to the performance of NPD teams as a whole, which supported previous research emphasizing the importance of teamwork quality (Hoegl et al., 2007) and internal team factors such as social cohesion (Nakata & Im, 2010) on NPD team success. It was also found that the extent to which team members acquired, shared, and combined knowledge impacted NPD team performance, thereby supporting previous findings (Lynn et al., 1999; Akgün, Lynn, & Yilmaz, 2005) and theorizing (Edmondson & Nembhard, 2009) in regards to the relationship between team learning and NPD team performance.

This study also revealed that dispositional PA and short-term PA had different
consequences. For example, previous research on short-term PA has shown that it had an inhibiting role in individual cognition and the search for information because individuals in positive moods use heuristics and perform less systematic analyses of the information they receive than individuals in negative moods (see Forgas, 2008 for a review). In contrast, it was found that team members high in dispositional PA did not appear to fall prey to this type of limited information search. It seemed that they continued to initiate behaviors that facilitated their pursuits, as their task performance and team learning behaviors were consistently stronger than low dispositional PA team members.

Although dispositional PA had a positive influence on individual team members’ task performance, counter to expectations, individual team members’ task performance did not have a significant effect on team performance. This implies that fragmented individual effort cannot lead to the success of the team as a whole for an interactive task. Instead, success on an interactive task depended on the concerted efforts of all team members through their behaviors that promote team interactions and team synergy.

This study had important implications for practitioners managing NPD teams. The results suggested that it is critical for managers to seek out high dispositional PA individuals in the interest of success of the whole team. Dispositional PA was consistent across situations (Diener & Larsen, 1984) and team members carried their affective history with them when they interacted as a group (Kelly & Barsade, 2001). Thus, dispositional PA, at any time, exerted strong effects on the behaviors of individuals. However, it is also important to note that although team members with high dispositional PA were likely to fulfill their individual task obligations, high dispositional PA individuals’ fragmented efforts could not guarantee the success of the team. Instead, the success of the team relied on the concerted efforts of dispositional PA team members to actively contribute their share of knowledge to the development of the project while at the same time supporting other team members. Taking into account that dispositional PA operates like a personality trait, management may have difficulty changing the team dynamic by adapting individuals’ dispositional affect. Instead, management may want to consider individuals’ dispositional affect when assigning employees to teams. To summarize, this study contributed to a better overall understanding of the relationship between dispositional PA and NPD team performance. This relationship cannot simply be summed up so as to say “positive people create positive outcomes,” but instead that individuals who are more dispositionally positive enhance team effectiveness due to enacting behaviors that support team learning and ICBs.

Limitations and Future Research

This research provided important evidence of the positive effects of dispositional PA on NPD team outcomes, including team learning behavior, ICBs, and overall team performance. Several limitations to the research are worthy of note and efforts that address these limitations may introduce interesting avenues for future study. First, PA from a dispositional perspective was studied while ignoring the possible influences of short-term PA and group-level PA on team outcomes. Future research should try to incorporate individual short-term PA and group-level PA with dispositional PA in order
to enable a better understanding of the effects of various types of PA on team outcomes. For example, do frequent short-term low PA experiences for high dispositional PA individuals negate the benefits of dispositional PA on team performance? Also, what is the impact of different configurations of dispositional PA on how team behaviors are enacted when some team members are high in dispositional PA and other team members are not? Assessing PA as a state and a trait, individually and in different configurations, will likely introduce many other important mechanisms that can influence team performance.

Second, as noted above, the study investigated the mediating roles of task performance, team learning, and ICBs in the relationship between PA and team outcomes. However, previous research has indicated that a wide variety of variables may have moderating/mediating roles such as job type and tenure (Ng & Sorensen, 2009). Future research could expand on the behaviors investigated here to include other team based variables that dispositional PA would be likely to influence, such as group identity, risk taking, conflict resolution, and innovation.

Lastly, the restricted student sample that was used placed a limitation on the study's external validity. The study could be enhanced by collecting data from work teams in a range of real business settings and using a variety of performance indicators. The faculty advisors’ performance evaluations, although incorporating corporate sponsors’ feedback, were still based on only one rater. Thus, the study could be improved by having corporate sponsors be more involved in the student projects and integrating multiple evaluators’ objective evaluations as the index of the final team performance scores. Instead of developing mock products, long-term or permanent teams in organizations engaging in the development of real-world products or promoting a product should be investigated, along with various external performance indicators, such as speed to market, customer satisfaction, and sales volume. Continued research in this area may not only shed new light on the influence of affect on NPD team processes, but also provide practitioners with useful guidelines for boosting NPD team performance.

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Employee Turnover: A Study on Information Technology Sector

Sumana Guha
St. Xavier's College

Subhendu Chakrabarti
Indian Statistical Institute

Under the globalized market, a firm's success depends on its innovativeness, adaptability and speed. These all are derived from its own human resources, but employee turnover can jeopardize a firm's efforts. This study, based on a primary survey, tries to explore the underlying reasons behind the voluntary turnover of Information Technology (IT) professionals. Among the six plausible considered push and pull factors – 'higher-salary', higher-portfolio', 'higher-company-brand-name' – these three pull factors chronologically appear to be responsible for IT professional turnover, regardless of age and gender. From an empirical and turnover model, it appears that an employee's attitude towards life and work is a key parameter affecting employee turnover.

The key players behind the spectacular technological changes in the 21st century are human beings. Human resources are sometimes referred to as human capital by different schools of thought and is considered as intangible intellectual capital with distinctive functional capabilities that control and augment both physical capital and other resources. Consequently, intellectual property has become the obvious concern of the present century, which in turn, has diffused in order to develop hypercompetitive market rivalries in world markets. Pfeffer (1994) argued that success in the present dynamic, hypercompetitive markets depends more on innovation, speed, and adaptability which are largely derived from a firm's own employees and the way in which they are managed. With similar arguments, various scholars (Wernerfelt, 1984; Levine, 1995; Lawler, 1996; Grant, 1996; O'Reilly & Pfeffer, 2000) advocated that for the competitive advantage, a firm should adopt a set of management practices with high involvement from human resources (HR). These arguments are the genesis for the development of today's system of Strategic Human Resource Management (SHRM).
Highly skilled and talented employees are indispensable for achieving or maintaining competitive advantages and are considered as assets to an organization. Therefore, any loss of this resource undoubtedly would be at great cost to the organization. In the present globalized competitive market, firms generally set up their respective HR divisions to promote, protect, and utilize their employee resources. The major problem faced by the firms though, is the departure of these resources, especially skilled ones. The employee turnover cost becomes even greater when efficient and skilled employees leave the firm. On the other hand, most employees will try to optimize their professional career, which is subject to their capability and functional domain. An employee’s career scale is always judged in terms of income, professional position, and the reputation of the organization where the employee works. Therefore, human resources management often confronts two types of problems: recruiting and retaining high-value employees.

The Information Technology (IT) sector is one of the most important sectors of the world, especially in India where the voluntary employee turnover is the highest compared to other sectors. It is therefore pertinent to identify the reasons behind voluntary employee turnover in this changing market environment. This study, based on a primary survey, will endeavor to find the reasons behind the voluntary turnover of IT professionals.

**Literature Review**

*Job Satisfaction, Employees’ Future Expectations and Employee Turnover*

Researchers have tried to unveil the impellent factors behind an employee leaving or choosing to stay with the firm. In this regard, Hom and Griffeth (1991) argued that an employee's job satisfaction or dissatisfaction is what motivates them to stay with or leave the firm. But these work attitudes play a relatively small role (Hom & Griffeth, 1995; Griffeth, Hom, & Gaertner, 2000) in overall employee retention. Instead, various other factors like organizational commitment, the opportunity for job alternatives, etc. are more important in explaining employee turnover. Mobley et al. (1979) observed that there are two factors responsible for employee turnover: one is the employee's evaluation of the firm's future expected value with respect to their own work aspirations, and the other is the tension associated with the employee's present work conditions. Researchers like Becker (1975), Kraut (1975), Stevens et al. (1978) and many others argued that employees make an implicit comparison between expected job benefits and alternative job opportunities. If the offered benefits of the present job are greater than or equal to alternative offers, then they will be less likely to leave the firm. An employees' personal commitment is a completely different aspect which indicates the intention of the employee to continue working in the firm in lieu of accepting an alternative job that may offer potentially better socio-economic benefits.

*Workload, Role Ambiguity and Employee Turnover*

Numerous studies have reported evidence like workload, role ambiguity, and role conflict in determining turnover decisions (Bostrom, 1981; Goldstein & Rockart, 1984; Ivancevich, Napier, & Wetherbe, 1983; Li & Shani, 1991; Sethi, Barrier, & King, 1999;
It has been suggested that IT professionals in many firms are continually asked to take on impossible workloads and deadlines (Bartol & Martin, 1982; Ivancevich et al., 1983). The primary component of job burnout and exhaustion is the depletion of mental resources (Schaufeli, Leiter, & Kalimo, 1995). Consequences of exhaustion include job dissatisfaction (Burke & Greenglass, 1995; Maslach & Jackson, 1984; Pines, Aronson, & Kafry, 1981; Wolpin, Burke, & Greenglass, 1991), reduced organizational commitment (Jackson, Turner, & Brief, 1987; Leiter, 1991; Sethi et al., 1999; Thomas & Williams, 1995), and enhanced turnover intention (Jackson, Schwab, & Schuler, 1986; Jackson et al., 1987; Pines et al., 1981).

**Gender Differentiated Employee Turnover**

Marta M. Elvira (2001) observed that women were less likely to leave when there were other women employed at high levels within the firm. On the other hand, men's turnover was not significantly affected by the proportion of men in their own hierarchical level or immediately above their level, but decreased when more men were employed in executive levels. Again, social structure affects individuals differently, and different aspects of that same social structure have differing effects. Hence, it can be said that women are less likely to leave when they work with more women at their job level (Tolbert et al., 1995). Tsui, Egan, and O'Reilly (1992) observed that men's psychological attachment diminished with an increasing proportion of women. This evidence suggests that men are less likely to exit when more men work at their job level.

**Employee Turnover in the IT Sector**

Voluntary employee turnover of Information Technology (IT) professionals has become one of the persistent challenges faced by technology-based firms, and one of the major problems lies in employee retention. Adams, Clark, and Goldman (2006) argued that IT turnover remains a chronic problem. Despite a significant number of studies on IT turnover that have been conducted in the last two decades; there is no symmetric review of this topic for the collective understanding of accumulated knowledge on the IT turnover phenomenon. Most of the literature on IT professionals' turnover has focused on turnover intentions and very few have examined actual IT turnover behavior. Some IT firm level turnover studies emphasized contextual factors related to IT (Ang & Slaughter, 2000; Cappelli & Sherer, 1991) and focused on the internal labor market (Ang & Slaughter, 2004) and human resource practices' (Ferratt, Agarwal, & Brown, 2005) influence on IT turnover rates. Bacharach (1989) tried to specify interrelationships among the existing antecedents to explain why IT professionals develop turnover intentions. Thus, the crux of the problem therefore lies in the organizational internal environment, external labor market conditions as well as an employee's perception and attitude towards life and work.

**Conceptual Framework**

**Employee Turnover:** Refers to the percentage of employees who have left the organization during a specific period (usually one year) to the average monthly employee strength of the organization.
Employee turnover = \( \frac{y}{\bar{x}} \times 100 \); where \( \bar{x} = \frac{\sum_{i=1}^{12} x_i}{12} \);

\( y \) = Number of employees left in a year

Employee turnover can primarily be classified as voluntary or involuntary. In the case of voluntary, the employee's decision to leave a company is solely that employee's decision. The voluntary turnover occurs, because of various factors like an employee's job dissatisfaction, workload, familial reasons and/or when the employee is attracted by lucrative offers from other similar organizations. In the case of involuntary turnover, the employee's job termination decision is made by the organizational authority. Employee retirement, layoff, etc. are examples of involuntary turnover.

It is apparent that the employee’s decision to leave or not to leave an organization is influenced by either endogenous factors, exogenous factors, or both. Keeping this in mind and for the sake of better understanding, this study classified the underlying reasons of employee turnover into push and pull factors.

**Push Factors**: Push factors are those factors which compel the employee to quit a job (e.g., employee’s job dissatisfaction, breach of commitment, familial compulsion and other like factors).

**Pull Factors**: Pull factors motivate employees to change organizations voluntarily in order to achieve a better and higher position in the professional-hierarchical scale. Pull factors include attractive offers from similar competitive firms, like ‘higher salary’, ‘higher portfolio’, ‘higher company-brand-name’, which are the means of upgrading an employee’s social and economic status.

Theoretical Framework

The employee turnover phenomenon is the consequence of various impulsive factors. These factors are classified into exogenous pull factors (e.g., attraction of a higher salary, higher portfolio, more prestigious company or better brand name) and endogenous push factors (e.g., job dissatisfaction, breach of commitment, familial compulsion, retirement, etc.) which compel an employee to leave an organization voluntarily. For the sake of simplicity, it was assumed that the goal of an employee was to optimize professional achievement and that he/she would always accept any available better offer in order to upgrade their professional career. It was also assumed that alternative job opportunities were available in the market.

\( Q_t \) implies an employee's voluntary decision to leave an organization at time \( t \), and \( P^l_t \) and \( P^h_t \) are the respective impulsive pull and push factors at time \( t \). Then,

\[
Q_t = Q (P^l_t, P^h_t); \quad \frac{dQ_t}{dP^l_t} > 0, \quad \frac{dQ_t}{dP^h_t} > 0 \quad \text{... (1)}
\]

Now,

\[
P^l_t = f (S^*_t, P^*_t, C^*_t); \quad \frac{dP^l_t}{dS^*_t} > 0, \quad \frac{dP^l_t}{dP^*_t} > 0, \quad \frac{dP^l_t}{dC^*_t} > 0 \quad \text{... (2)}
\]
Where, $S_t^*$, $P_t^*$ and $C_t^*$ are the attractions of ‘Higher Salary’, ‘Higher Portfolio’ and ‘Higher Company-Brand-Name’ respectively offered by other organizations at time, $t$.

If $S_t$, $P_t$ and $C_t$ are the ‘Salary’, ‘Portfolio’ and ‘Company-Brand-Name’ enjoyed by employees in the organization where they are working at time, $t$.

Then, $(S_t^* - S_t) = s_t \Rightarrow$ Higher Salary impulsion at time $t$,

$(P_t^* - P_t) = p_t \Rightarrow$ Higher Portfolio impulsion at time $t$, and

$(C_t^* - C_t) = c_t \Rightarrow$ Higher Company-Brand-Name impulsion at time $t$.

Then function (2) becomes,

$$P_t^l = f(s_t, p_t, c_t); \quad \frac{dP_t^l}{ds_t} > 0, \quad \frac{dP_t^l}{dp_t} > 0, \quad \frac{dP_t^l}{dc_t} > 0 \quad \ldots (3)$$

On the other hand,

$$P_t^h = f(B_t, O_t); \quad \frac{dP_t^h}{dB_t} > 0, \quad \frac{dP_t^h}{dO_t} > 0 \quad \ldots (4)$$

Where, $B_t$ and $O_t$ are the ‘Breach of Commitment’ and ‘Others’ factors respectively at time $t$.

Considering $\hat{B}_t$ and $B_t$ as the commitments made and the commitments fulfilled in practice at time $t$ respectively and $\hat{O}_t$ and $O_t$ as the ‘Other’ Expected Employees’ own constraints, and the actual constraints faced by the employee at time $t$ then,

$(\hat{B}_t - B_t) = b_t \Rightarrow$ Breach of Commitment impulsion at time $t$, and

$(\hat{O}_t - O_t) = o_t \Rightarrow$ Other self-constraints impulsion at time $t$.

Then function (4) becomes,

$$P_t^h = f(b_t, o_t); \quad \frac{dP_t^h}{db_t} > 0, \quad \frac{dP_t^h}{do_t} < 0 \quad \ldots (5)$$

Replacing functions (4) and (5) into function (1), then there is,

$$Q_t = Q(s_t, p_t, c_t, b_t, o_t), \quad \ldots (6)$$

where $\frac{dQ_t}{ds_t} > 0, \quad \frac{dQ_t}{dp_t} > 0, \quad \frac{dQ_t}{dc_t} > 0, \quad \frac{dQ_t}{db_t} > 0, \quad \text{and} \quad \frac{dQ_t}{do_t} < 0$

Hence, it can be said that the voluntary decision of employees to quit ($Q_t$) an organization depends on a number of factors and the impact of these varies from employee to employee. If a linear relationship is assumed between $Q_t$ and its predictor variables, then the required equation:

$$Q_t = \alpha + \beta_1s_t + \beta_2p_t + \beta_3c_t + \beta_4b_t - \beta_5o_t + e_t \quad \ldots (7)$$
But, the outcome of $Q_t$ is reflected only when the decision of the employee has been measured, (i.e., either the employee quits or stays in the organization). Then the dependent variable $Q_t$ becomes dichotomous. If values 0 and 1 are assigned to employee’s staying or leaving the organization respectively, then the coefficient of each independent predictor will show their respective contribution to the variation of $Q_t$. From the knowledge of relevant independent predictors and coefficients, the objective becomes not to find a numerical value of $Q_t$ as in linear regression, but the probability ($\theta$) that it is 1 rather than 0. Then outcome will not be a prediction of a $Q_t$ value but a probability value which can be any value between 0 and 1. A log transformation was needed to normalize the distribution and this log transformation of the $\theta$ values to a log distribution enabled the study to formulate a normal regression equation. The log distribution (or logistic transformation of $\theta$ is the log (to base e) of the odds ratio that the dependent variable was 1 and was defined as,

$$\log \left[ \frac{\theta}{1-\theta} \right] = \ln \left( \frac{\theta}{1-\theta} \right), \text{ where } \theta \text{ ranges between 0 and 1}$$

Hence, the required equation becomes,

$$\ln \left[ \frac{\theta}{1-\theta} \right] = \alpha + \beta_1 s_t + \beta_2 p_t + \beta_3 c_t + \beta_4 b_t - \beta_5 o_t + \epsilon_t \quad \ldots \ (8)$$

where $P(Q_t = 1) = \theta$ and $P(Q_t = 0) = (1 - \theta)$

**Methodology**

Primary information regarding causal factors behind employee turnover in the IT sector was collected through a questionnaire given to 460 IT employees working presently in 17 different IT firms in Kolkata, West Bengal. The snowball method was used for sample selection. The questionnaire contained multidimensional questions to capture the behavioral patterns of IT employees under the influence of different push and pull factors. In this study, 420 respondents (out of a total of 460 respondents) had left companies at least once before joining their current company at the time of the survey. The number of companies covered by the survey, including the companies the respondents had left, was approximately 90.

This study was concerned with six plausible factors: 1) ‘higher salary’, 2) ‘higher portfolio’, 3) ‘scope of foreign assignment’, 4) ‘higher company-brand-name’, 5) ‘breach of commitment’, and 6) ‘others’ (which includes employee’s job dissatisfaction, familial obligations, and other factors) which were hypothesized to be influential in causing Indian IT professionals to leave their jobs voluntarily and examine relative factors of dominance across gender and age groups. The respondents were asked to rank these factors according to their reasons for leaving their last company. Thus, respondents’ given ranks expressed their respective motivation behind leaving the last company they worked for.

One of the implicit assumptions made in the study was that an employee’s decisions were strongly affected by their attitudes towards life and work. Research in psychology and organizational behavior, especially the content theories, focused on the needs, wants
and desires of people which were the main impetus for motivational behaviors. The study also incorporated a self-appraisal of the IT employees' attitudes towards life and work and examined its effect on their turnover intent as well as the actual turnover. It appeared that the reasons behind turnover of the two groups of employees [ones who give 'Highest Priority to Work Life' (HPWL) and others who give 'Highest Priority to Social Life' (HPSL) in accordance with employees' self-assessment] were distinctively different. Respondents were classified by gender and age. Frequency and percentage distributions will be presented in tabular form. A correlation matrix and linear regression analysis were done. In addition, this paper developed a theoretical framework for employee turnover and based on that, a turnover model was created. The characteristics of sample respondents are presented below in the form of descriptive statistics.

### Table 1: Descriptive Statistics of Sample Respondents

<table>
<thead>
<tr>
<th>Characteristics of Sample Respondents</th>
<th>Age Group</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Less than 30</td>
<td>30-40</td>
</tr>
<tr>
<td>A. Gender</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>119</td>
<td>27.0</td>
</tr>
<tr>
<td>Female</td>
<td>69</td>
<td>27.4</td>
</tr>
<tr>
<td>Total</td>
<td>188</td>
<td>27.1</td>
</tr>
<tr>
<td>B. Experience in IT (in yrs):</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Less than 1 yr</td>
<td>5</td>
<td>0.4</td>
</tr>
<tr>
<td>1-5 years</td>
<td>144</td>
<td>2.8</td>
</tr>
<tr>
<td>6-10 years</td>
<td>38</td>
<td>6.7</td>
</tr>
<tr>
<td>10 yrs.+</td>
<td>1</td>
<td>29.0</td>
</tr>
<tr>
<td>Total</td>
<td>188</td>
<td>3.7</td>
</tr>
<tr>
<td>C. # of company changes:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 change</td>
<td>38</td>
<td>-</td>
</tr>
<tr>
<td>1 change</td>
<td>41</td>
<td>-</td>
</tr>
<tr>
<td>2 changes</td>
<td>82</td>
<td>3.4</td>
</tr>
<tr>
<td>3+ changes</td>
<td>188</td>
<td>3.4</td>
</tr>
</tbody>
</table>

Note: \(\bar{x}\) = mean; \(\sigma\) = Standard deviation and No. = Number of respondents

### Empirical Observations

The empirical analysis was based on the information collected through a survey of 460 IT professionals in West Bengal. In order to judge the intrinsic factors behind an employee's propensity to leave a company, some endogenous factors [e.g., scope of revealing skill (SRS), professional attitude (PA), locational advantage (LA), experience
in IT (EIT), ‘higher degree of independence leads to greater attachment’ (HIGA)] were obtained from the 460 respondents (40 of which did not change companies at the time of survey), to reveal their plausible response. First, a correlation matrix was computed to see the relationship between these factors and the number of company changes (NCC) made by each respondent. Then a linear regression was estimated by assigning the ‘number of changes’ as the dependent variable (Y). The results of the correlation matrix and the regression analysis are presented below.

**Figure 1: Pearson Correlations Matrix (n=460)**

<table>
<thead>
<tr>
<th>Variables</th>
<th>NCC</th>
<th>SRS</th>
<th>PA</th>
<th>LA</th>
<th>EIT</th>
<th>HIGA</th>
</tr>
</thead>
<tbody>
<tr>
<td>NCC</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SRS</td>
<td>-.098*</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PA</td>
<td>-.326*</td>
<td>.076</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LA</td>
<td>.131*</td>
<td>.061</td>
<td>-.005</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EIT</td>
<td>.128*</td>
<td>.028</td>
<td>.012</td>
<td>-.055</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>HIGA</td>
<td>.127*</td>
<td>.014</td>
<td>-.067</td>
<td>.008</td>
<td>.040</td>
<td>1</td>
</tr>
</tbody>
</table>

* Significant at the 0.05 level (2-tailed). ** Significant at the 0.01 level (2-tailed).

The correlation matrix among the endogenous factors explored the relationship of these factors with the ‘number of company changes’ (NCC) made by each respondent and also the inter-correlation between factors. Most of these endogenous factors appeared to be significantly correlated with ‘number of company changes’, but inter-factor correlations were found to be very insignificant.

**Linear Regression Equation:**

\[
\text{NCC} = 1.853 - 0.123 (\text{SRS}) - 0.393 (\text{PA}) + 0.408 (\text{LA}) + 0.038 (\text{EIT}) + 0.279 (\text{HIGA})
\]

\[
\begin{align*}
5.155^* \\
(-2.033) \\
(-7.258^*) \\
(3.285^*) \\
(3.198^*) \\
(2.321^*)
\end{align*}
\]

(Figures in the parenthesis indicate t value and *, indicates significant at the 0.01 level)

The correlation matrix showed that all the variables were highly correlated with the ‘number of company changes’ (NCC) and from the regression it appeared as expected, that all the predictor variables were significantly related to the predicted variable. The employee's propensity to change companies was negatively related with SRS and PA. This implies that an employee's highly professional attitude combined with the greater scope of revealing skill would reduce their propensity for leaving the company. On the other hand, highly experienced (EIT) employees revealed their preference to locational advantage (LA) and greater freedom of work (HIGA) and if these preferences were not satisfied at their existing company, it increased their propensity to change companies. The reason behind this may as an employee ages, they may be more likely to look for work in a better location in order to avoid non-professional problems as well as have greater freedom to demonstrate their work efficiency and commitment.

Respondents (n = 420) who changed at least one company ranked the given 6 plausible causal factors according to their own rationale of leaving their last company. Respondents' given ranks were arranged in accordance with age groups (‘below 30’,
‘30-40’ and ‘above 40’) and gender. It was apparent that most of the respondents (47.5% male and 49.6% female; overall 48%), irrespective of age and gender, gave rank-1 to ‘higher salary’. This implied that the attraction of a higher salary was the most important factor for IT professionals for joining a new company. After ‘higher salary’, about 32% (27.2% male and 43.7% female) of the respondents ranked ‘higher portfolio’, and over 32% (34.6% male and 40.3% female) ranked ‘higher company-brand-name’ third. It is evident that the three impulsive pull factors, irrespective of age and gender, were mostly responsible for IT employees’ leaving a company. ‘Breach of commitment’, ‘others’, and ‘scope of foreign assignment’ respectively ranked 4th, 5th and 6th. However, it appeared that the top three priority causal factors differed between male and female IT professionals. Male employees’ first concern was ‘higher salary’ followed by ‘higher company-brand-name’ and ‘portfolio’. On the other hand, female employees’ main concern was also ‘higher salary’ but the second concern was ‘portfolio’, followed by ‘higher company-brand-name’. Females appeared to be more concerned about professional hierarchy than their male counterparts.

In order to single out the most important reason among different age groups of IT employees for leaving their last company, the distribution of which of the 6 factors was ranked first was observed. Fifty-one percent of the ‘below 30’ age group of respondents ranked ‘higher salary’ first. The corresponding figures for the ‘30-40’ and ‘above 40’ age groups respectively were around 48% and 33%. After ‘higher salary’, the second highest frequency of factors ranked was to ‘higher company-brand-name’ by the ‘below 30’ group (27%), age ‘30-40’ (22%) and ‘above 40’ (24%) age group of respondents respectively (see Table 2). The third highest frequency of factors ranked was given to ‘higher portfolio’ by 10%, 13.8%, and around 10% of respondents ‘below 30’, ‘30-40’, and ‘above 40’ respectively (see Table 1). One distinctive feature was that the propensity to change companies was much higher among younger IT employees which reflected their zeal to reach the top of the professional-ladder within a short period of time.

**Table 2: Distribution of Highest Rank Given by the Respondents by Age Group**

<table>
<thead>
<tr>
<th>Age Group</th>
<th>Higher Salary</th>
<th>Higher Portfolio</th>
<th>Scope of Foreign Assignment</th>
<th>Higher Company-Brand-Name</th>
<th>Breach of Commitment</th>
<th>Others</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Below 30</td>
<td>82 (51.0)</td>
<td>16 (9.9)</td>
<td>7 (4.4)</td>
<td>44 (27.3)</td>
<td>6 (3.7)</td>
<td>6 (3.7)</td>
<td>161 (100)</td>
</tr>
<tr>
<td>30-40</td>
<td>113 (47.5)</td>
<td>33 (13.8)</td>
<td>8 (3.4)</td>
<td>53 (22.3)</td>
<td>14 (5.9)</td>
<td>17 (7.1)</td>
<td>238 (100)</td>
</tr>
<tr>
<td>Above 40</td>
<td>7 (33.4)</td>
<td>2 (9.5)</td>
<td>2 (9.5)</td>
<td>5 (23.8)</td>
<td>1 (4.8)</td>
<td>4 (19.0)</td>
<td>21 (100)</td>
</tr>
<tr>
<td>Total</td>
<td>202 (48.1)</td>
<td>51 (12.1)</td>
<td>17 (4.0)</td>
<td>102 (24.3)</td>
<td>21 (5.0)</td>
<td>27 (6.5)</td>
<td>420 (100)</td>
</tr>
</tbody>
</table>

**Note:** Figures in the parenthesis are the % of total respondents.

In order to judge attitudinal affect on employee turnover intention, the 460 employees were divided into two groups: 1) ‘Highest Priority to Work-Life’ (HPWL) and 2) ‘Highest Priority to Social-Life’ (HPSL) according to the respondents’ self-evaluation
of their attitudes towards life and work. Each group was then divided into three sub

groups: 1) ‘no change of jobs’, 2) ‘1 or 2 changes of jobs’, and 3) ‘3 or more changes of

jobs’ (see Table 3). Out of a total of 460 respondents, 8.6% did not change companies

(n = 40) at the time of the survey, of which 75% belonged to the HPSL category and the

remaining 25% belonged to the HPWL category. Around 206 respondents had already

made ‘1 or 2 changes of job’ of which 55% belonged to the HPSL category. However,

it is interesting to note that out of those who had already changed 3 or more jobs,

only 29% of them fell into the HPSL category and the remaining 71% were from the

HPWL category. It was observed that for IT employees ‘higher salary’, ‘higher portfolio’

and ‘higher company-brand-name’ were the three primary reasons for them leaving a

company. Therefore, it is evident that for the HPWL categories of employees, financial

gain, professional position, and professional glamour with a more prestigious company

brand name were the most important factors.

Table 3: Distribution of Respondents in Accordance with Their Highest

Priorities between ‘Work Life’ and ‘Social Life’ by Age Group

<table>
<thead>
<tr>
<th>Age Group</th>
<th>Respondents’ Self-Evaluation of Attitudes Towards Their Work and Life</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Highest Priority to Work-Life (HPWL)</td>
<td>Highest Priority to Social-Life (HPSL)</td>
</tr>
<tr>
<td></td>
<td>No Change</td>
<td>1 or 2 Changes</td>
</tr>
<tr>
<td>Below 30</td>
<td></td>
<td></td>
</tr>
<tr>
<td>30-40</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Above 40</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: Figures in the parenthesis are percentage of corresponding totals.

Again, when the respective attitudinal category of respondents was classified

to age group, it became apparent that in the HPWL category, employees of

relatively lower age groups frequently changed jobs (59% of ‘below 30’ and 61% of

‘30-40’ age groups of respondents changed ‘3 or more companies’). On the other hand,

among the HPSL category of employees, only 24% of ‘below 30’ and 33% and of ‘30-

40’ age groups made ‘3 or more changes of jobs’. Respondents who made ‘3 or more

changes of jobs’ among the ‘above 40’ group were equally distributed between HPWL

and HPSL categories (see Table 3). It was also revealed that 91% of ‘below 30’, 99% of

‘30-40’, and 100% of ‘above 40’ age groups in the HPWL category of respondents

changed at least one company. The corresponding figures for the HPSL category of

respondents were 78%, 92% and 79% of the ‘below 30’, ‘30-40’ and ‘above 40’ age

groups respectively. Thus, it appeared that HPWL category of employees irrespective

of their age group generally changed jobs more frequently than those in the HPSL

category. Hence, the role of an employee’s attitude on their turnover decision appeared

to be very much pertinent.
Employee Turnover Model

Dependent Variable (Y)

An employee’s propensity to change companies was the dependent variable of the model. An employee’s propensity to change companies is defined as follows:

\[
\text{Employee’s propensity to change company} = \frac{\text{Employee’s IT experience (in years)}}{\text{Employee’s number of company changes}}
\]

This ratio is the average time that an employee remained in one job. In other words, this ratio is an employee’s average propensity to change a company. A higher value of the above ratio indicates lower propensity to change and vice versa. The respondents were classified into two groups: a high-propensity group and a low-propensity group. The median value of the employee’s propensity was taken as a cut-off value. Employees having a median value of propensity to change or less than median value were assigned 1 (high-propensity group). Values above the median value were assigned 0 (low-propensity group). Therefore, the dependent variable was a dichotomous one by putting 0 for those employees who had a low-propensity to change companies and 1 for those who had a high-propensity to change companies.

The dependent variable (Y) became a dichotomous variable: \( Y = \ln \left( \frac{\hat{p}}{1-\hat{p}} \right) \)

A linear logistic regression model was fit in the following form:

\[
\ln \left( \frac{\hat{p}}{1-\hat{p}} \right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 - \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6
\]

Here, \( \hat{p} \) = Probability \( (Y = 1) \) implied the probability of an employee to quit the company, and \( (1 - \hat{p}) \) = Probability \( (Y = 0) \) implied the probability of an employee to stay in the company.

Explanatory Variables \( (X_i) \)

\( X_1 = \text{Higher Salary (HS)} \); \( X_2 = \text{Higher Portfolio (HP)} \); \( X_3 = \text{Higher company-brand-name (HCBN)} \); \( X_4 = \text{Others (OTH)} \); \( X_5 = \text{Breach of Commitment (BoC)} \); \( X_6 = \text{Age (AG)} \); \( X_7 = \text{Educational Qualification (Edu_Q)} \); \( X_8 = \text{Attitude} \)

Respondents were asked to reveal the reasons for their leaving their last company by assigning ranks (1 for the highest rank and 6 for the lowest) for the 6 possible job change factors: ‘higher salary’, ‘higher portfolio’, ‘company’s brand name’, ‘scope of foreign assignment’, ‘breach of commitment’, and ‘others’. The overall rank of ‘scope of foreign assignment’ appeared as insignificant and therefore this plausible factor was not included in the models. Here, the numerical value of each of the \( X_1 \) to \( X_5 \) explanatory variables varied from 1 to 6. The value of the variable \( X_6 \) was a continuous variable and \( X_7 \) and \( X_8 \) were binary variables.
Output of the Logistic Regression

Table 4: Classification Table

<table>
<thead>
<tr>
<th>Observed</th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bi_prop_change</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Bi_prop_change 0</td>
<td>194</td>
</tr>
<tr>
<td>Bi_prop_change 1</td>
<td>181</td>
</tr>
<tr>
<td>Overall Percentage</td>
<td></td>
</tr>
</tbody>
</table>

a. Constant is included in the model. b. The cut value is .500

Table 5: Variables in the Equation

<table>
<thead>
<tr>
<th>Step 0 Constant</th>
<th>B</th>
<th>S.E.</th>
<th>Wald</th>
<th>Df</th>
<th>Sig.</th>
<th>Exp(B)</th>
</tr>
</thead>
<tbody>
<tr>
<td>-.069</td>
<td>.103</td>
<td>.450</td>
<td>1</td>
<td>.502</td>
<td>.933</td>
<td></td>
</tr>
</tbody>
</table>

Table 6: Omnibus Tests of Model Coefficients

<table>
<thead>
<tr>
<th>Step</th>
<th>Chi-square</th>
<th>Df</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step</td>
<td>407.779</td>
<td>8</td>
<td>.000</td>
</tr>
<tr>
<td>Step 1 Block</td>
<td>407.779</td>
<td>8</td>
<td>.000</td>
</tr>
<tr>
<td>Model</td>
<td>407.779</td>
<td>8</td>
<td>.000</td>
</tr>
</tbody>
</table>

Table 7: Model Summary

<table>
<thead>
<tr>
<th>Step 1</th>
<th>-2 Log likelihood</th>
<th>Cox &amp; Snell R Square</th>
<th>Nagelkerke R Square</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>111.630a</td>
<td>.663</td>
<td>.884</td>
</tr>
</tbody>
</table>

Note: Estimation terminated at iteration number 9 because parameter estimates changed by less than .001

Table 8: Hosmer and Lemeshow Test

<table>
<thead>
<tr>
<th>Step</th>
<th>Chi-square</th>
<th>Df</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.505</td>
<td>8</td>
<td>.993</td>
</tr>
</tbody>
</table>

Table 9: Classification Table

<table>
<thead>
<tr>
<th>Observed</th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bi_prop_change</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Bi_prop_change 0</td>
<td>179</td>
</tr>
<tr>
<td>Bi_prop_change 1</td>
<td>12</td>
</tr>
<tr>
<td>Overall Percentage</td>
<td></td>
</tr>
</tbody>
</table>

a. The cut value is .500
The output of the logistic regression was derived by using the IBM SPSS Statistics version 20 software package. Out of 420 respondents, after the exclusion of the outliers, the number of samples became 375. The aim was to predict an employee's intention to change organizations for 375 IT respondents using 'higher salary' (HS), 'higher portfolio' (HP), 'higher company's brand name' (HCBN), 'breach of commitment' (BoC), 'others' (OTH), employee's 'attitude' (Attitude), 'age' (Age) and the educational qualification (Ed_Q) of the respondents as predictors. A test of the full model against a constant-only model appeared to be statistically significant, indicating that the predictors as a set reliably distinguished between the 'high-propensity group' and the 'low-propensity group' (chi square = 407.779, p < .000 with df = 8). Nagelkerke's $R^2$ of .884 indicated a strong relationship between prediction and grouping. Prediction success overall was 92.8% (92.3% for the 'low-propensity group' and 93.4% for the 'higher-propensity group'). The Wald criteria demonstrated that all the predictors made significant contributions to the prediction ($p = .000, .000, .002, .000, .004, .000, .004, .004, 085$ for HCBN, BoC, OTH, Age, Attitude, Edu_Q, HS, and HP, respectively). It appeared from the outcome of the model results that the model itself could make a correct prediction 51.7% of the time without any predictor variable. By adding the predictors in the model, the study was able to predict 92.8% with accuracy. The Hosmer and Lemeshow (H-L) goodness of fit test had a significance of 0.992 which meant that it was not statistically significant and therefore, the model was quite a good fit. However, it was observed that some of the coefficients [higher portfolio (HP), higher company-brand-name (HCBN), other (OTH)] were opposite of those that would be expected. What is perplexing is that, except HP, all were significantly positive. One possible explanation for these results is that if the existing company failed to fulfill their expected portfolio and company's brand name, and if there were scopes of fulfilling their desired expectation to other companies, then an employee's probability to leave the present company would be much higher. It appeared from Exp (B) of the study's predictors that one unit higher offered in terms 'higher portfolio' (HP) or 'higher company's brand name' (HCBN) or 'other' (OTH) would enhance the probability of an employee changing companies by two or three times.
Concluding Remarks

The attraction of a ‘higher salary’ was the top ranked reason for an employee to leave a company for almost all the IT employees, regardless of gender and age. This reason was followed by ‘higher portfolio’, and ‘higher company-brand-name’. All of these were in the array of pull factors. But, between ‘higher portfolio’ and ‘higher company-brand-name’, the female employees gave more priority to ‘higher portfolio’. IT employees’ attitudes towards life and work which is genetically inherited and determined by the influence of childhood socio-cultural and economic environments was an important parameter for judging the employee turnover phenomenon. Young employees were found to frequently change jobs which may be due to their desire to reach the top of the professional-ladder within a short period of time.

It appeared that lucrative offers from other competitive companies enhanced an employee's propensity to change from their existing company. Therefore, it is imperative to examine the magnitudes of attraction of different pull factors at which an employee finally quit his or her organization. This exercise was not done in the present study and is a limitation of the study. However, this issue could be considered as one for future studies.

Employee turnover models were actually meant for finding ways and means on how to retain skilled and high valued employees. The results in this study also have some policy implications for managers and administrators towards retaining talented employees. It was revealed that employees were very much concerned with their career development. Therefore, the organization should offer them a career path and career development plan. By doing so, an organization will show its commitment to developing its talent which benefits both the organization and the employee. Organizations should try to make employees realize that they are trying to enhance and support their employees’ skills and experience. Again, the compensation structure for employees should be designed by giving salary and perquisites by means of a weighted composite function of qualification, talent, skill, performance and experience, as well as offering a slightly higher salary than the existing industry rates to highly valued employees. In reality, when it is followed, it will go much deeper into the human consciousness and the actions and attitudes that make employees feel successful, secure and appreciated. That in turn will help address the four key elements of a sound retention strategy: performance, communication, loyalty, and competitive advantage.

Above all, for a positive outcome with any retention strategy, it is necessary to mentor relationships with colleagues in order to increase emotional ties to the organization. Such familial relationships among the employees of the organization where each employee feels proud to be associated with the organization and his or her colleagues creates commitment to the organization.
References


Resources and Business Failure in SMEs: Does Size Matter?

Densil A. Williams
UWI, Mona

Almost all analyses that use small and medium-sized enterprises (SMEs) as their unit of analysis treat this group of firms as a homogenous group. However, the literature indicates that the small business sector is more heterogeneous than originally thought. To test this assumption, this study investigates business failure among SMEs controlling for size of the firm. Using data from over 60,000 SMEs in the UK, the study utilizes logistic regression to model business failure with a number of surrogate measures for resources. The analysis is compartmentalized into small and medium-sized firms. The results reveal that the resources that impact business failure do in fact vary based on firm size. The implications of the findings are addressed in the paper.

It is generally argued that firms fail because they lack resources (Ahmad & Seet, 2009; Campbell et al., 2012). However, it is not always clear whether or not these resource deficits are confined to firms of a particular size. The extant literature asserts that larger firms will have more resources, and, as such, should be able to survive while smaller firms with their limited resource stock should fail (Watson, 2007). However, empirical evidence suggests that failure is not confined to small firms but firms of all sizes. It is this observation that has motivated the work presented in this paper. The paper will try to understand whether or not the predictors of business failure, which are generally seen as surrogate for firm resources (Watson, 2007), vary based on the size of the firm. This analysis will be useful in guiding public policymakers to the best way to support firms of different sizes in order to prevent or alleviate failure rates among these enterprises. Similarly, managers in small and medium-sized firms can use the results from this analysis to help them determine the types of resources they should cultivate in the firm in order to minimize the risk of failure.

Resources and Business Failure

The organization ecology (OE) scholars who study business failure, generally argue that firms fail not because of factors external to them, but results directly from poor internal management decisions having to deal with shocks presented in the
external environment (Hannan & Freeman, 1988; Hannan, 1997). In essence, what this school of thought suggests is that failure is an internally driven activity. Contrary to this belief, industrial organizations (IO) scholars believe that firms fail because the environment in which they operate becomes too turbulent and therefore exert pressure on the firm which leads to its failure (Scott, 1992; Zou & Stan, 1998). For example, taking the Schumpeterian thesis of creative destruction as its starting point, industrial organization scholars argue that shifts in the environment caused by things such as technological change, economic or geographic shifts, regulatory changes, etc., are factors which the managers of a firm have no control over and these put pressure on the firm’s strategy, which will lead to it failing. Thus, both schools of thought are at odds in explaining business failure among firms. The IO school blames external factors while the OE school blames internal factors vis-à-vis, management decision making. To reconcile both, this work will look at the resource-based view as the theoretical lens through which to analyze business failure.

The resource-based view of the firm argues that once a firm possesses resources that are scarce, difficult to copy, and measurable, this will lead to a competitive advantage that will ensure the survival of the firm (Amit & Schoemaker, 1993; Barney, 1991). From a reading of this literature, it appears that most scholars writing on the resource-based view of the firm generally infer that resources are only internal to the firm; thus, conflate the resource-based view and the organizational ecology view in explaining firm failure. Resources however, are not only tied to the internal operations of a firm. Resources can be external as well as internal to the firm. In fact, Amit and Schoemaker, (1993) defined resources as a set of factors that are owned or controlled by the firm. Indeed, controlled means that the resources do not have to be directly inside the organization but may be within the wider industry sector. As such, once resources are not conceptualized as only internal to the firm, the resource-based view of the firm will reconcile both the industrial organization view and the organization ecology view of business failure. Therefore, using the resource-based view lens; a number of factors that are generally referred to as surrogates for resources can be analyzed in order to determine their impacts on business failure.

Size

Firm size has been a long standing variable that is used to proxy firm resources (e.g., Bloodgood, Sapienza, & Almeida, 1996; Williams, 2009, 2011). The general argument is that the larger the firm, the more resources it will have, hence, the greater the likelihood of it surviving (Watson, 2007). This logic seems to suggest that with more employees, the firm tends to have a larger stock of resources and, as such, can generate economies of scale and reduce the cost of doing business, thus ensuring its long-term survival (Mittelstaedt, Harben, & Ward, 2003). An even more compelling argument for the importance of size in the survival/failure discourse is that size provides a buffer for the firm to absorb the fixed cost of doing business. Firms of larger size and presumably more resources are better able to absorb certain fixed costs of operations. Small firms do not have this latitude because absorbing large fixed costs can lead to a firm having to exit an industry (Hall & Tu, 2004). As such, overcoming the liability of smallness is important in the future survival of the firm.
In the extensive literature, a number of studies noted a positive relationship between size and firm performance as measured by growth, profitability, survival, or internationalization. For example, Watson (2007) and Calof (1994) noted that large firms are more likely to survive than small ones. This positive relationship between size and performance of the firm seems overwhelming. The general consensus strongly suggests a positive relationship between firm size and firm performance. Indeed, viewing failure through the resource-based view lens, it is expected that larger firms will have a higher stock of resources. Among other things, these resources can be used as a buffer to absorb fixed costs, which generally helps to drive failure and helps the firm to overcome turbulent times in the market.

**Governance**

The organizational structure of the firm is a critical proxy for the access to resources, which can impact the performance of that firm. For example, whether or not the firm is publicly or privately owned can impact the amount of resources it has at its disposal.

Firms that are publicly owned and listed on stock markets are more likely to have access to cheaper sources of finance than firms that are privately owned and depend solely on the small networks of the owner and family members (Brush, 2002; Watson, 2007). Based on this observation, it is logical to expect that firms that are publicly owned and listed, will have a larger stock of resources than those that are privately owned. Following this logic and using the resource-based view lens to analyze business failure, it is expected that publicly-listed firms are more likely to survive than private firms given that the former will likely have more avenues to gather additional resources than the latter.

**Firm Age**

Age is seen as a good proxy for the stock of resources that a firm possesses (Williams, 2009). Researchers have used the age of the firm as a proxy for experience (Autio, Sapienza, & Almeida, 2000). In fact, from a resource-based perspective of the firm, older firms will have considerably more resources than younger firms. This logic is based on the assumption that firms acquire resources over time (Autio, 2005). Because older firms will have a larger stock of resources than younger firms, the resource-based view explains that these firms will stand a better chance of survival than those with a lower stock of resources. This is because the higher stock of resources will provide a stronger buffer for the firms to absorb shocks and unanticipated costs, which can generally lead to business failure. This line of reasoning converges with the expectations of some researchers that older firms are less likely to fail than younger firms. Watson (2007) even found evidence among established firms that the older firms had a greater chance of survival than the younger ones.

**Industry Sector**

The sector in which the firm operates may impact its ability to amass resources. Indeed, researchers who are trying to understand firm performance as measured by success or failure have argued that the industry sectors impact on performance success
(Campbell et al., 2012; Watson, 2007). The argument is that access to resources may differ across industry sectors, and, as such, the performance of the firm may differ across sectors as well (Barney, 1991; Watson, 2007). The level of competition in the industry, the number of firms, and the structure of the industry are all factors that will determine whether or not a firm exits or remains in the sector (Porter, 2008). This observation about industry sectors makes the analysis of sectors important in the performance of business failure. Sectors that are predisposed to a greater stock of resources (maybe due to the make-up of the industries that reside there), will more than likely be better able to support its firms, and, as such, more firms in these sectors will be able to survive compared to those sectors that are informal and resources are hard to come by.

### Financial Resources

Financial resources are generally seen as the most important resource that the firm possesses because they are easily observable and most persons can identify with them (Barney, 1991). These resources, while not the most important for a company to succeed, are an essential part of the resource pool that a company can possess in order to improve its competitive advantage and increase its chances of success. In this study, a number of these measures were used to capture the resource stock of the firms. These include net income, revenue, and return on assets.

Researchers have argued that higher capitalization normally suggests a greater belief in the viability of the business (Caves, 1998). Further, others have suggested that lower capitalization implies that the owner might want to learn from the business instead of wanting to grow the business, thus, embracing the idea that thinly capitalized business is a greater candidate for closure (Bates, 2005). However, this view is challenged by Gimeno et al. (1997). They argued that organizational survival is not exclusively a function of economic profitability but also depends on the firms’ ‘threshold for performance’. Indeed, it is suggested that internal characteristics such as firm size as well as other human capital attributes, like the owner’s interests, are variables which help to define this threshold. It means then that the threshold performance varies across the different types of firms (Gimeno et al., 1997). They argued that the dynamism in the relationship with firm performance is not only dependent on the interest of the owner but also on the influence of outside stakeholders such as shareholders, employees, customers, community members, and the government (Gimeno et al., 1997). The strength of the influence of the external stakeholders tends to vary based on the size of the firm, with the owners of smaller firms having more control over decision-making, bearing in mind that their financial and non-financial resources normally outweigh those of other stakeholders.

### Location

Agglomeration theory is a tool that can be used to better understand the impact of location on the performance of the firm. It hypothesizes that a relationship exists between the geographical location of firms and their competitive positions (Folta, Cooper, & Baik, 2006). It is argued that the performance of geographically clustered firms improve with cluster size (ibid). The theory argues that the ‘economies of
agglomeration’ enhance the firm’s ability to innovate through patenting, attracting alliances, partners, and private equity partners. This suggests that these geographical links, such as those which exist in places like Silicon Valley, benefit small firms by improving the access to and use of information whether it relates to process, company strategy, and knowledge, as well as the ability to attract additional financial resources (Folta et al., 2006, p. 222). McCann and Folta (2011) further argued that firms do not benefit equally from clustering or networks. Before entering the network, it is important to consider the knowledge stocks of the firms as a key determinant of possible clustering.

Location is also a source of human capital resources for the firm. Areas that are more densely populated (e.g., urban areas) generally have more human resources than those that are less populated. For small firms, the recruitment of skilled workers and access to capital are important resources that can determine their survival or failure. If a location possesses these resources in abundance, it may be easier for the firms there to access them. In a recent study analyzing the longevity of small firms in Jamaica, the results showed that firms, which were located in rural areas had a higher chance of survival than those in urban centers (Williams & Jones, 2010). Despite having larger amounts of resources - especially human capital resources, firms in urban centers face a greater level of competition for markets, and so, those firms that do not start with a high stock of resources will eventually exit the market place. Indeed, this increased chance of survival in a rural area appears to stem from the lower levels of competition for market-share which these small firms face despite their small stock of resources. In essence, the location in a rural area provides a competitive advantage for these small firms. The remoteness of some rural locations in Jamaica makes it difficult for a large number of SMEs to operate in those geographic areas, so those that have a first mover advantage are more likely to face less competition for market-share. This lessening of competition thus provides a sort of monopoly status to these SMEs in the rural locations and therefore, increases their chance of survival.

Critically, while it is expected that urban centers will have a greater stock of resources which small firms can access, the cost of accessing these resources may inhibit resource-poor SMEs from actually taking advantage of these resources. With the inability to gain access to these resources, it may result in these firms being unable to compete in a highly competitive market environment. Urban centers that are densely populated with excess demand for labor may not be ideal locations for SMEs because of the high premium they will have to pay to attract human capital resources. Indeed, the locational advantage derived from being rural appears to be context-specific. As such, one can conclude using the lens of agglomeration theory that the impact of the location on the performance of the firm is still uncertain. Merely being located in a geographical area does not automatically lead to strong performance but it is the quality of the resources and levels of competition among the firms in the area that matter.

**Method**

This section describes the method that is used to achieve the aims of the paper.
The Analytical Framework

To motivate this study, a model which captured the relationship between the dichotomous dependent variable and the independent variables had to be derived. To this end, a model from the qualitative genre was used given the dichotomous nature of the dependent variable. The logit model was used because it had the possibility of producing outcomes that were not dependent on the normality assumptions of the population from which the data was drawn (Gujarati, 2003). In its theoretical form, this model is depicted as follows:

\[
\text{Logit } (Y) = \ln \left( \frac{P}{1-P} \right)
\]  

(1)

However, the operational model becomes:

\[
Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \varepsilon_j
\]  

(2)

Where:

\( \hat{Y} \) represents the unbiased estimator of the dependent variable, business failure, which is dichotomous and measured by whether or not the firm is active in the industry; that is, it keeps open or if it’s inactive, meaning it closes its doors.

\( X_1 \) represents size
\( X_2 \) represents governance structure
\( X_3 \) represents age
\( X_4 \) represents industry sector
\( X_5 \) represents net income
\( X_6 \) represents revenue
\( X_7 \) represents return on asset
\( X_8 \) represents location
\( \varepsilon_j \) represents the error term

The model in Equation 2 above was estimated to provide insights into which factors are most important in predicting the likelihood of failure among small firms.

Research Data and Operational Measures for Variables

The data for this study were collected from the Financial Analysis Made Easy (FAME) database, a database with a significant amount of financial and company information on UK firms. The search for firms was narrowed down to those that were active or inactive in all industry sectors in the economy of the United Kingdom (UK) over the period from 1999-2008. This period was chosen because it represented a halcyon period in the contemporary UK economy in terms of economic growth and stability since the early 1990s. The average gross domestic product (GDP) growth over this period was 2.74%; the average inflation rate was 1.75% and interest rate at 4.79%. Also, the exchange rate variation was -0.82. The relative robustness of the economy, it is assumed, would be more amenable to business survival than failure.

Since this study focused on SMEs, a maximum upper bound on the number of employees in the firm was placed at 250. This upper bound of 250 employees
represented the definition for SMEs in the UK (Storey, 1994). As such, the search led to over 63,103 firms that were deemed appropriate for the analysis. The number of inactive firms accounted for 32.8% of the sample while the number of active firms accounted for 67.2%. Similarly, 8 variables that had full information and were used in previous studies as surrogate for resources were collected from the database for analysis. These variables along with their operational measures are listed in the table below.

### Table 1: Variable Measurements

<table>
<thead>
<tr>
<th>Variable</th>
<th>Measurement</th>
<th>Variable Code</th>
<th>Previous Research</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent variable (Output)</strong></td>
<td><strong>Business Failure</strong>&lt;br&gt;Dichotomous variable with the following labels&lt;br&gt;Inactive = 1 Active = 0</td>
<td>CS</td>
<td>Mellahi and Wilkinson (2004)</td>
</tr>
<tr>
<td><strong>Independent Variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firm Size</td>
<td>Latest number of employees</td>
<td>Size</td>
<td>Tang and Murphy (2012)&lt;br&gt;Williams (2011)</td>
</tr>
<tr>
<td>Firm Age</td>
<td>Number of years since incorporation</td>
<td>Age</td>
<td>Semrau and Werner (2012)&lt;br&gt;Autio et al. (2000)</td>
</tr>
<tr>
<td>Location</td>
<td>1 = Urban centres,&lt;br&gt;0 = Rural areas</td>
<td>LC</td>
<td>Williams and Jones (2010)</td>
</tr>
<tr>
<td>Governance Structure</td>
<td>1 = Private limited liability&lt;br&gt;2 = Public listed company</td>
<td>GS</td>
<td></td>
</tr>
<tr>
<td>Industry Sector</td>
<td>Ordinal&lt;br&gt;1 = Services&lt;br&gt;2 = Wholesale and retail&lt;br&gt;3 = Food&lt;br&gt;4 = Manufacturing</td>
<td>IDS</td>
<td>Williams and Jones (2010)</td>
</tr>
<tr>
<td>Net Income</td>
<td>Revenue minus cost</td>
<td>NETI</td>
<td>Bates (2005)</td>
</tr>
<tr>
<td>Revenue</td>
<td>Sales figures</td>
<td>Rev</td>
<td>Bates (2005)</td>
</tr>
<tr>
<td>Return on Asset</td>
<td>Total Asset divided by Profit</td>
<td>ROA</td>
<td>Bates (2005)</td>
</tr>
</tbody>
</table>

### Results

This study aimed to understand whether or not size mattered in relation to the impact of resources on business failure. To do this, it modelled the resources, which impacted business failure among different size categories of the firm. The results below reflect the findings from this analysis.
Table 2: Results from All Firms

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>$\beta$</th>
<th>Wald</th>
<th>Sig.</th>
<th>Exp($\beta$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-0.237</td>
<td>24.335</td>
<td>.000</td>
<td>.789</td>
</tr>
<tr>
<td>Size</td>
<td>0.009</td>
<td>1011.847</td>
<td>.000*</td>
<td>1.009</td>
</tr>
<tr>
<td>Governance Structure</td>
<td>1.754</td>
<td>3127.543</td>
<td>.000*</td>
<td>5.777</td>
</tr>
<tr>
<td>Firm Age</td>
<td>-0.196</td>
<td>3073.00</td>
<td>.000*</td>
<td>.822</td>
</tr>
<tr>
<td>IDS</td>
<td>0.033</td>
<td>17.603</td>
<td>.000*</td>
<td>1.034</td>
</tr>
<tr>
<td>ROA</td>
<td>0.000</td>
<td>24.004</td>
<td>.000*</td>
<td>1.000</td>
</tr>
<tr>
<td>Rev</td>
<td>0.000</td>
<td>67.481</td>
<td>.000*</td>
<td>1.000</td>
</tr>
<tr>
<td>NETI</td>
<td>0.000</td>
<td>78.699</td>
<td>.000*</td>
<td>1.000</td>
</tr>
<tr>
<td>Location</td>
<td>-0.210</td>
<td>86.938</td>
<td>.000*</td>
<td>.811</td>
</tr>
</tbody>
</table>

-2LL (Initial Model) 63683.435

-2LL (Final Model) 54260.290

$\chi^2$ (df) (Final Model) 9423.145 (8)

$\chi^2$ (df) Hosmer-Lemeshow test 240.136 (8)**

Nagelkerke R$^2$ .24

R$^2_L$.15

% Correct Prediction 74.6

Dependent variable is business failure, that is, whether or not the firm is active.

* Variables are significant at the 0.05 level of significance

** Statistic is significant at the 0.05 level of significance

$R^2_L = 1 - \text{Final model -2LL/ Initial model -2LL}.$

When the model was analyzed using all 63,103 firms in the data set without controlling for size, the results reflected that all 8 variables which were proxies for resources had a significant impact on failure in small and medium-sized firms. For example, the results suggested that as firms get older, the likelihood of failure is reduced. This is in keeping with the mentality of the resource-based view of the firm which argued that older firms have more resources than younger firms, and, as such, the likelihood of failure is lower among the former. Further, a look at the model diagnostic statistics also suggested that the results were indeed robust. The model had a predictive accuracy of 74.6%, a high predictive accuracy in this line of research (Watson, 2007). Also, the model had a lower -2log likelihood value when the initial model without the variables was compared with the final model with all variables. This suggested that the model fitted was a better predictor of failure than the previous model. Similarly, the model chi-square value was also significant, which suggested that the fitted model was a better predictor than the model fitted only with the constant. In an ideal world, the Hosmer-Lemeshow test would be expected to be insignificant, which suggested that
the chosen model fit the data well. In this case, the test showed a significant statistic. This meant that the model and the data did not fit well. This is not of major concern since all the other diagnostics show a good fitted model.

**Medium Sized Firms**

The table below shows the results when the data were restricted based on the size of the firm. In this case, firms with employees ranging from 51-250 were classified as medium firms. These results show that the pattern of significant variables does change. Not all variables that were found to be significant in the full model are found to be significant here.

<table>
<thead>
<tr>
<th>Table 3: Results from Medium-sized Firms</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Logistic Regression- Medium- Sized Firms (N=21377)</strong></td>
</tr>
<tr>
<td>Independent variables</td>
</tr>
<tr>
<td>------------------------</td>
</tr>
<tr>
<td>Constant</td>
</tr>
<tr>
<td>Size</td>
</tr>
<tr>
<td>Governance Structure</td>
</tr>
<tr>
<td>Firm Age</td>
</tr>
<tr>
<td>IDS</td>
</tr>
<tr>
<td>ROA</td>
</tr>
<tr>
<td>Rev</td>
</tr>
<tr>
<td>NETI</td>
</tr>
<tr>
<td>Location</td>
</tr>
</tbody>
</table>

-2LL (Initial Model) 9856.072

-2LL (Final Model) 9106.685

\( \chi^2 \) (df) (Final Model) 749.387 (8)

\( \chi^2 \) (df) Hosmer-Lemeshow test 43.114 (8)**

Nagelkerke \( R^2 \) .11

\( R^2_L \) .08

% Correct Prediction 68.3

Dependent variable is business failure, that is, whether or not the firm is active.

* Variables are significant at the 0.05 level of significance

** Significant at the 0.05 level of significance

\( R^2_L = 1 - (\text{Final model } -2LL/\text{Initial model } -2LL). \)

Indeed, when compared to the model with all firms present, the model with medium-sized firms only showed that industry sector and revenue were not significant predictors of business failure. The interpretation here is that for medium-sized firms, failure can happen despite their revenue stock and also the industry sector in which they operate.
Small Firms

Small firms were operationalized as those firms with 50 or less employees. The table below shows the results from the model that was analyzed to determine whether or not the resources that were found to be predictors of business failure in medium-sized firms remain consistent across small firms.

Table 4: Results from Small Firms

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>β</th>
<th>Wald</th>
<th>Sig.</th>
<th>Exp(β)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-.576</td>
<td>121.815</td>
<td>.000*</td>
<td>.562</td>
</tr>
<tr>
<td>Size</td>
<td>.034</td>
<td>860.397</td>
<td>.000*</td>
<td>1.034</td>
</tr>
<tr>
<td>Governance Structure</td>
<td>1.972</td>
<td>3303.867</td>
<td>.000*</td>
<td>7.184</td>
</tr>
<tr>
<td>Firm Age</td>
<td>-.216</td>
<td>2998.424</td>
<td>.000*</td>
<td>.806</td>
</tr>
<tr>
<td>IDS</td>
<td>.004</td>
<td>.179</td>
<td>.672</td>
<td>1.004</td>
</tr>
<tr>
<td>RoA</td>
<td>.001</td>
<td>35.784</td>
<td>.000*</td>
<td>1.001</td>
</tr>
<tr>
<td>Rev</td>
<td>.000</td>
<td>58.701</td>
<td>.000*</td>
<td>1.000</td>
</tr>
<tr>
<td>NET1</td>
<td>.000</td>
<td>30.549</td>
<td>.000*</td>
<td>1.000</td>
</tr>
<tr>
<td>Location</td>
<td>-.096</td>
<td>14.762</td>
<td>.000*</td>
<td>.908</td>
</tr>
</tbody>
</table>

\[ \text{-2LL (Initial Model)} = 52988.990 \]
\[ \text{-2LL (Final Model)} = 43662.030 \]
\[ \chi^2 (df) \text{ (Final Model)} = 9326.960 (8) \]
\[ \chi^2 (df) \text{ Hosmer-Lemeshow test} = 193.865 (8)** \]
\[ \text{Nagelkerke } R^2 = .279 \]
\[ R_L^2 = .18 \]
\[ \text{% Correct Prediction} = 74.6 \]

Dependent variable is business failure, that is, whether or not the firm is active.
*Variables are significant at the 0.05 level of significance
**Statistic is significant at the 0.05 level of significance
\[ R_L^2 = 1 - (\text{Final model -2LL/ Initial model }-2\text{LL}). \]

The results from the model suggested that similar to medium-sized firms, industry sector was not a significant predictor of failure among small firms. However, unlike medium-sized firms, the revenue stock of the small firm was found to be a significant factor in the prediction of failure among small firms. These results were interesting and, in general, suggested that resources as a predictor of failure were contingent on the size of the firm in most respects. The discussion below will shed further light on these findings.
Overall, a look at the model diagnostics for all the models that were analyzed suggested that the results were robust. In all cases, both the model $R^2$ and the Nagelkerke $R^2$ were in line with results from previous works. Similar to a linear regression, both sets of $R^2$ provided a gauge of the significance of the model. The values varied between 0 which meant the model was useless in predicting outcomes to 1 which meant it predicted the outcome perfectly. Further, the Hosmer-Lemeshow test looked at the observed model with the predicted model. A result that was not significant (i.e., $p>0.05$) suggested that the model predicted real world data fairly well.

The Wald statistics, which is similar to the t statistic in linear regression, helped to determine the significance of the variable under investigation. A simple rule of thumb was that when the Wald was greater than 2, the variable had a significant impact on the model. This rule was followed in reporting on variables that impacted business failure/success.

In addition, the expected beta value, which reflected the percentage change in the odds score (i.e., if the beta value of the independent variable, which measured the size of the impact of the variable on the outcomes changed by 1, the expected beta value revealed the odds with which the case could be predicted), showed that the results were indeed robust. Similarly, the model chi-square showed that the results were indeed robust, as in all cases the final model chi-square was significant.

Also, the log likelihood score (-2LL), which showed how much unexplained information was in the model after it had been fitted suggested that the models were all valid as the -2LL for the initial model was less than the -2LL for the final model, which included all the variables.

**Discussion of Results**

The research embodied in this paper was geared towards a better understanding of the factors that impacted business failure among SMEs, using the resource-based view lens as the theoretical underpinning for the analysis of variables and data. Importantly, there was a common assumption in the literature that the same stock of resources would have an equal impact on a firm irrespective of the size of the firm. Most of the works that looked at impact of resources on firm performance had not controlled for firm size as an important variable (Campbell et al., 2012; Watson, 2007). An important contribution that this research has made to the literature was to model the same resources that impact business failure across different sizes of firms, that is, small and medium enterprises, in order to determine whether or not the statistical significance of the resources remained the same. The results from the analysis suggested some interesting findings.

When the data was modeled on all firms pooled together, that is, both small and medium-sized firms, the results suggested that all eight (8) proxies that were used as surrogates for resources were found to be significant in predicting business failure among small firms. Similar to previous works (e.g., Ahmad & Seet, 2009; Campbell et al., 2012; Watson, 2007) the results were in concert with the postulates of the resource-based view theory of the firm. In essence, it took the very general view that firms which had a larger stock of resources would no doubt have a stronger proclivity to survive.
Conversely, the greater the stock of resources, the lower the likelihood of failure among small firms. However, this general view hid the fact that the impact of different types of resources may vary based on the size of the business. One type of resource may have a different impact on failure in smaller firms versus medium-sized firm. This is an observation that the general literature missed. This study advanced this argument by testing the various resources across two categories of firms – small and medium-sized – to determine whether or not the impact of the resources on failure remains the same across the size category.

For firms categorized as medium-sized, the analysis suggested that not all variables that served as surrogates for resources significantly impacted business failure among this category of firms compared to the results for the pooled sample.

In the case of the medium-sized firms, the variables that were not found to be significant predictors of business failure among this group of firms were industry sector and revenue stock. This is to say, despite the amount of money that the firm had and irrespective of the industry sector in which it operated, it was not immune to failure. This is an important observation. Taking the lens of the resource-based view of the firm uncritically, it suggested that firms with large stocks of resources such as revenue found it more difficult to fail. The results here suggested otherwise. When firms reached a certain level of maturity, it required more than a large stock of resources to ensure survival. The continued existence of these firms was heavily dependent on managerial astuteness and leadership. It was how management created effective strategies to use these resources in the most efficient and optimum way that determined which firm survived and which ones would fail.

Similarly, for firms that were designated as small, the results from the analysis found that industry sector and not revenue stock had an insignificant impact on the likelihood of failure among these firms. Again, this result deviated from the findings in the pooled data, which suggested that industry sector was indeed a significant factor that impacted business failure among SMEs. It can be reasoned that the industry sector was found to be insignificant among small firms because all firms, despite their size, must compete in the industry in which they are located in order to survive. This argument was true for manufacturing as well as the services industry. In other words, all firms had to find coping strategies in order to remain open despite the industry sector in which they operated. However, the fact that revenue was significant in the case of the medium-sized firms and not in the category of small firms, suggested that size did impact the types of resources that were required to ensure business survival among the SMEs. For smaller firms that had not reached a mature stage in their life cycle, cash generated from revenue was critical to help them acquire additional physical and human resources that were needed to grow the business and ensure survival. Therefore, those small firms that had less revenue resources tended to find it more difficult to survive than those with a large stock of revenue resources.

**Concluding Thoughts**

The aim of the study was to understand whether size mattered in determining which resources were more critical in diagnosing business failure among SMEs. The
results revealed that indeed, SMEs should not be treated as a homogenous group when trying to understand the impact of resources on their survival or failure. Industry sector was found to not significantly impact business failure among firms that were categorized as small. Similarly, for firms categorized as medium-sized; industry sector and revenue stock were not found to have a significant impact on business failure at that level. Policymakers at the firm level and at the country level should recognize this important finding that small firms are not homogenous, and therefore, policies aimed at reversing the mortality rate among these firms need to be properly contextualized. The study also has implications for future research. Future researchers need to use other surrogates of resources to model whether or not the impact of various types of resources on business failure does vary across firm size. Likewise, future researchers can also use different measures of failure such as bankruptcy or other established measures in the extant literature (Mellahi & Wilkinson, 2004) to test whether or not this result holds.

References


EXTREME LEADERSHIP

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Edited by Cristina M. Giannantonio and Amy E. Hurley-Hanson, Chapman University, US

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