Volume 3, Number 1
Print ISSN: 2574-0474
Online ISSN: 2574-0482

GLOBAL JOURNAL OF ACCOUNTING AND FINANCE

The *Global Journal of Accounting and Finance* is owned and published by the Institute for Global Business Research. Editorial content is under the control of the Institute for Global Business Research, which is dedicated to the advancement of learning and scholarly research in all areas of business.

The *Global Journal of Accounting and Finance* is owned and published by the Institute for Global Business Research, 1 University Park Drive, Nashville, TN 37204-3951 USA. Those interested in communicating with the *Journal,* should contact the Executive Director of the Institute for Global Business Research at info@igbr.org.

EDITORIAL REVIEW BOARD

Sorinel Căpuşneanu
Dimitrie Cantemir Christian University,
Bucharest

Susan Shurden
Lander University

Theresa Tiggeman
University of the Incarnate Word

Xiaoquan Jiang
Florida International University

TABLE OF CONTENTS

A STUDY OF THE DIFFERENCES IN PERCEPTION AMONG GENDERS REGARDING THE EFFECT OF NARCISSISTIC LEADERSHIP ON EMPLOYEE JOB SATISFACTION IN THE ACCOUNTING PROFESSION

Susan Shurden, Lander University
Mike Shurden, Lander University

ABSTRACT

Narcissism is a personality disorder that can often be identified in professionals within the business environment. This paper will specifically focus on the accounting profession. Narcissism is prevalent in many successful leaders and is characterized as both destructive and constructive. The disorder is diagnosed when an individual possesses five of nine characteristics listed in the American Psychiatric Association's Diagnostic and Statistical Manual of Mental Disorders (fourth edition, text revision version). The focus of this paper is to determine if there are significant differences in perception between males and females regarding how narcissistic leadership affects job satisfaction in the accounting profession. The paper will also analyze a very useful theory called leader-member exchange (LMX) which is a dyadic relationship between an employer/leader and employee/subordinate. LMX may play a mediating effect between narcissism and job satisfaction. The primary question in this study is: Do gender differences exist with regard to perception on how leader-member exchange (LMX) and narcissistic leadership affect employee job satisfaction in the accounting profession? This research used a quantitative design with a random sample of 152 accountants, nationwide. The data were analyzed using SmartPLS data software, and the method of analysis was a causal modeling technique called Partial Least Squares, Structural Equation Modeling (PLS-SEM).

INTRODUCTION

Narcissism is a psychological disorder characterized by nine traits as identified by the *American Psychiatric Association's Diagnostic and Statistical Manual of Mental Disorders* (fourth edition, text revision version). If an individual possesses five of the nine characteristics listed below, they are diagnosed as narcissistic. These nine characteristics are:

1. *Has a grandiose sense of self-importance.*
2. *Is preoccupied with fantasies of unlimited success, power, brilliance and beauty.*
3. *Believes that he or she is special and unique.*
4. *Requests excessive admiration.*
5. *Has a sense of entitlement to especially favorable treatment.*
6. *Is interpersonally exploitative.*
7. *Lacks empathy with the feelings and needs of others.*
8. *Is envious of others or believes that others are envious of him or her.*

9. *Shows arrogant, haughty behaviors and attitudes. (Amernic & Craig, 2010, 83).*

LITERATURE REVIEW

A study was done by Shurden (2014) in which she determined that narcissistic leadership does affect employee job satisfaction in the accounting profession through a theory called leader-member exchange (LMX). LMX is based on social exchange theory and relates to the dyadic or reciprocal relationship between a leader (employer) and subordinate (employee). It can be either positive or negative. If the relationship is a positive one, the outcome will generally be a lower turnover rate, higher performance by the employee, stronger commitment to the job, and higher job satisfaction (Himanshu, 2009). The Shurden study (2014) determined that narcissism has a negative (or destructive) indirect effect on job satisfaction through LMX (leader-member exchange). The indicators for this study were affect (interpersonal attraction), loyalty, contribution and professional respect which all have a strong influence on the relationship that an employee has with their employer. If that employer is a narcissistic leader, job satisfaction is significantly decreased.

Leaders in the area of finance, which includes accounting, are believed to have more narcissistic tendencies than in other business-related fields (Schwartz, 1991). Corporate financial accounting allows for a facilitating role by CEOs in the preparation of financial information. Because financial statements are prepared on a regular basis, often quarterly, CEOs have the opportunity to satisfy the "intense need to have [their] superiority continually re-affirmed" (Chatterjee & Hambrick, 2007, p. 354). Likewise, unless the profits are unfavorable, the recurring publication of the profits on a quarterly basis gives the CEOs "frequent applause" (Amernic & Craig, 2010, p. 85).

Consequently, the success of an organization is affected by the performance and level of employee job satisfaction within the business (Godkin & Allcorn, 2011). Tension between individuals intensifies job dissatisfaction, especially if the tension is between an employee and employer. This tension could be the result of a narcissistic leader who may use tactics such as coercion, delay and even slander (Grier, 2008). Therefore, a narcissistic leader may undercut employees because the leader feels threatened (Lubit, 2002). The result is generally absenteeism and employee turnover in an organization. However, productivity and quality are the results of employees who are satisfied in their profession (Koprowski, 1981).

Other negative effects of narcissistic leadership are that they create an imbalance in work and social life by infringing upon the personal and social time of their employees (Kernberg, 2008). Likewise, if individuals are exploited and blamed by the narcissist, these individuals exhibit a loss of identity. They begin to feel disengaged and view themselves as victims who are empty and useless (Godkin & Allcorn, 2011).

In regards to narcissism, who is more narcissistic, men or women? According to Biddle (2015) men are more narcissistic. They contend that differences in narcissistic behavior were accounted for because of several factors, one being entitlement, meaning that men in general feel more entitled to certain privileges. Gender stereotypes also have arisen over time. Women are not expected to display aggression or act in an authoritative manner. Women have been taught from an early age to conform to society's expectations. Therefore, men seem to act more assertively, which in the past has been acceptable because men were to be in a leadership or an authoritative role more so than women (Biddle, 2015).

Gender also has an impact on career advancement in accounting. A study by Morley, Bellamy, Jackson and O'Neill (2018) determined that males have significantly higher levels of ambition and career planning. However, women are not as focused on career progress because their attitudes reflect more emphasis on family and home commitments. The demands from housework and child care consistently seem to hamper the career progression of women. Women often will give up having a successful career for a more "balanced" lifestyle, while men plan for career success; therefore, the gap between professional demands and values of women is greater than that same gap for men, indicating that men value success more than do women. This theory is also evident in the accounting profession. Consequently, men seem to progress faster, and more men become successful leaders (Morley, et al., 2018). Himanshu (2009) also examined the effect of gender on LMX by conducting a study in a large organization in eastern India. He determined that females had a stronger positive impact on leader-member exchange relationships than men.

METHODOLOGY

The purpose of this study is to examine the differences in perception between males and females within the accounting profession with regard to narcissistic leadership, leader-member exchange (LMX), and the effect these two variables have on job satisfaction. The research question this study will answer is:

Do gender differences exist with regard to perception on how leader-member exchange (LMX) and narcissistic leadership affect employee job satisfaction in the accounting profession?

The following are the hypotheses for this study:

Hypothesis 1: There is a significant difference between the perception of males and females in regard to narcissistic leadership and employee job satisfaction within the accounting profession.

Hypothesis 2: There is a significant difference between the perception of males and females in regard to leader-member exchange (LMX) and employee job satisfaction in the accounting profession.

Hypothesis 3: There is a significant difference between the perception of males and females in regard to narcissistic leadership and leader-member exchange (LMX) in the accounting profession.

Hypothesis 4: There is a significant difference between the perception of males and females in regard to the how leader-member exchange (LMX) mediates between narcissistic leadership and employee job satisfaction in the accounting profession.

Initially, a random sample of approximately 1,235 accountants were drawn from the American Institute of Certified Public Accountants CPA/PFS Credential Holder Directory. An additional 3,679 emails were purchased, and surveys were emailed to this larger group as well. A total of 4,914 surveys were sent with an overall response rate of 3.3%. The response rate actually decreased because of the increase in the sample size; however, it was necessary to increase the sample size in order to get an adequate sample to use in this research. The total useable surveys were 152. In order to maintain privacy of the information, research procedures were properly applied. Therefore, both the purpose of the study and the voluntary nature of participating in the study were disclosed to the participants.

This research used a quantitative design with this random sample of 152 accountants, nationwide in which 94 were male and 57 were female. In this sample, one of the accountants did not respond to the gender question. The data were analyzed using SmartPLS data software, and the method of analysis was a causal modeling technique called Partial Least Squares, Structural Equation Modeling (PLS-SEM). Table 1 presents the demographic results of those surveyed. Of note is that a limitation of the study is that some informative demographic data such as level and years of experience of the participants, as well as size of the firms was not requested in the original survey.

Table 1
Demographic Data

Description	**Gender**	**Age**	**Degree**	**CPA**	**Race**
Male	62%				
Female	37%				
No response	1%				
18-30		2%			
31-40		9%			
41-50		18%			
51-60		46%			
Over 60		24%			
No response		1%			
Undergraduate			63%		
Masters			29%		
PhD			7%		
No response			1%		
CPA				91%	
Non-CPA				9%	
White					92.0%
Black					1.3%
Hispanic					2.0%
Asian					.7%
Other					3.0%
No response					1.0%

Shurden, 2014.

DEFINITIONS

Definitions from Hair, Hult, Ringle & Sarstedt (2017) helpful in the following discussion of the PLS model are:

Blindfolding: is a sample reuse technique that omits part of the data matrix and uses the model estimates to predict the omitted part. It indicates a model’s out-of-sample predictive power (p. 312).

Bootstrapping: is a resampling technique that draws a large number of sub-samples from the original data (with replacement) and estimates models for each subsample. It is used to determine standard errors and coefficients to assess their statistical significance without relying on distributional assumptions (p. 313).

Constructs (also called latent variables): measure concepts that are abstract, complex, and cannot be directly observed by means of (multiple) items. Constructs are represented in path models as circles or ovals (p. 314).

Endogenous latent variables: serve only as dependent variables, or as both independent and dependent variables in a structural model (p. 316).

Exogenous latent variable: are latent variables that serve only as independent variables in a structural model (p. 316).

Formative measurement model: is a type of measurement model setup in which the direction of the arrows is from the indicator variables to the construct, indicating the assumption that the indicator variables cause the measurement of the construct (p. 317).

Higher-order component (HOC): is a general construct that represents all underlying LOCs in an HCM (p. 318).

Higher-component model (HCM): is a higher order structure that contains several layers of constructs and involves a higher level of abstraction (p. 318).

Indicators [variables]: are directly measured observations (raw data), generally referred to as either *items or manifest variables*, represented in path models as rectangles (p. 319).

Inner model: see Structural model (p. 319).

Latent variable: see Constructs (p. 320).

Lower-order component (LOC): is a sub-dimension of the HOC in an HCM (p. 320).

Measurement: is the process of assigning numbers to a variable based on a set of rules (p. 320).

Measurement model: is an element of a path model that contains the indicators and their relationships with the constructs and is also called the *outer model* in PLS-SEM (p. 321).

Mediating effect: occurs when a third variable or construct intervenes between two other related constructs. (p. 321)

Moderator effect (moderation): occurs when the effect of an exogenous latent variable on an endogenous latent variable depends on the values of a third variable referred to as a moderator variable, which moderates the relationship. (p. 322)

Outer model: see *Measurement model* (p. 323).

Partial least squares structural equation modeling (PLS-SEM): is a variance based method to estimate structural equation models. The goal is to maximize the explained variance of the endogenous latent variables (p. 324).

Path models: are diagrams that visually display the hypotheses and variable relationships that are examined when structural equation modeling is applied (p. 324).

PLS-SEM: see *Partial least squares structural equation modeling* (p. 325).

Reflective measurement model: is a type of measurement model setup in which the direction of the arrows is from the construct (latent variable) to the indicator variables, indicating the assumption that the construct causes the measurement (more precisely, the covariation) of the indicator variables (p. 326).

Structural equation modeling (SEM): is used to measure relationships between latent variables (p. 328).

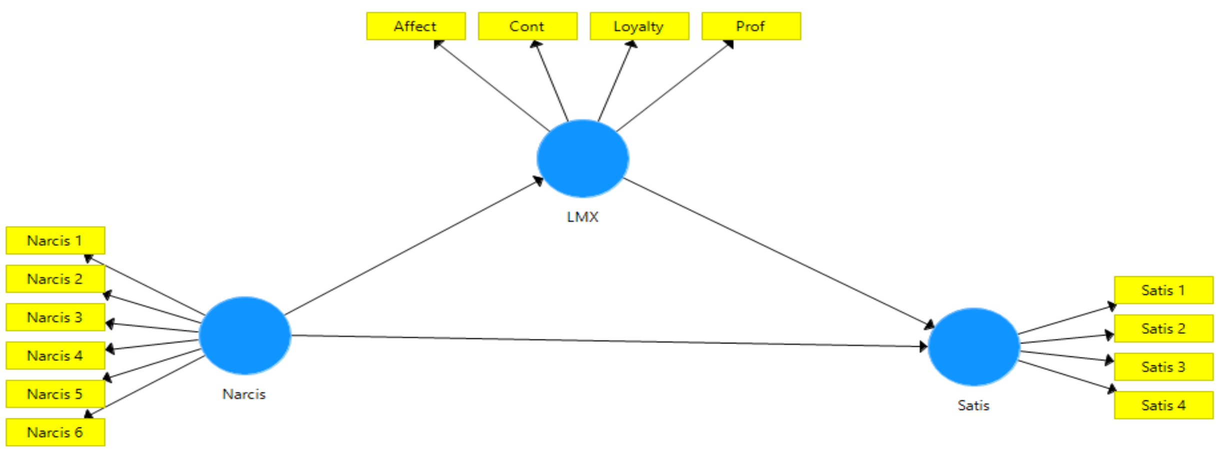
Structural model: represents the theoretical or conceptual element of the path model. The structural model (also called inner model in PLS SEM) includes the latent variables and their path relationships (p. 328).

ANALYSIS

Using Partial Least Squares, Structural Equation Modeling (PLS SEM), the first model produced is shown in Figure 1.1 and indicates the latent variable and the paths under investigation. As can be seen in Figure 1, the circles represent the three latent variables (Narcissistic Leadership, Leader-Member Exchange and Job Satisfaction), while the rectangles represent the survey questions associated with each latent variable. Lower Component Analysis was used to group the survey questions for LMX into four categories: Affect, Contribution (Cont), Loyalty, and Professionalism (Prof). Six survey questions were associated with the latent variable Narcissistic Leadership, and four questions were associated with Job Satisfaction.

The latent variable Narcissistic Leadership (NARCIS) is the exogenous (Independent) variable while leader-member exchange (LMX) and Job Satisfaction (SATIS) are endogenous (dependent or both) variables. NARCIS is an exclusively independent variable while SATIS is an exclusively dependent variable. LMX can be both independent and dependent.

Figure 1.1
Introductory model showing the latent and indicator variables.



Each set of indicator variables must be classified as being reflective or formative in relation to its latent variable. The direction of the arrows from the construct also called the latent variable (circle) to the indicator variables (rectangle) or vice versa is considered either reflective or formative. When the latent variable explains the indicator variables, the arrows point from the circle to the rectangle and are considered to be reflective, while indicator variables are classified as formative when the indicator variables explain the latent variable and point from the rectangle to the circles. In each of these three sets of indicator/latent variables, the assumption was made that the latent variables explain the indicator variables; therefore, the indicator variables were considered reflective. The arrows are shown pointing toward the indicator variables as can be seen in Figure 1.1.

Using the Bootstrapping procedure in SmartPLS, the p-values of the indicator variables along with the correlation and p-value for each latent variable are presented in Figure 1.2. Also, the R^2 values are shown for the latent variables. All of the reflective indicator variables showed significant p-values and were assessed for reliability and validity. Table 2 shows the summary data for the assessment of the reflective latent variables. All of the indicator variables met the requirements for inclusion in the final model.

Figure 1.2
Bootstrapping Results with SmartPLS

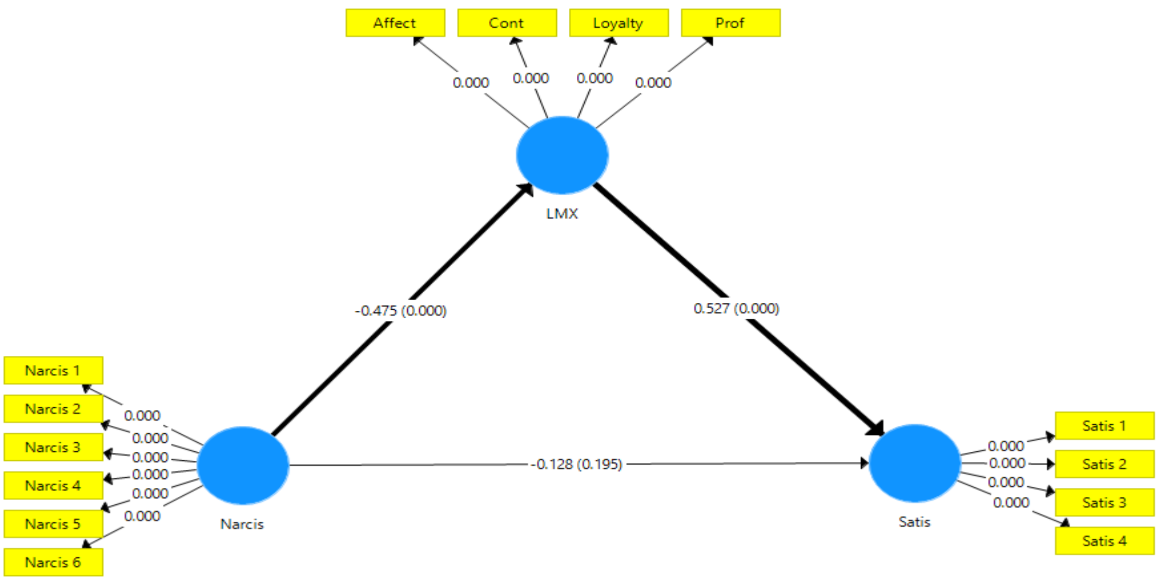


Table 2
Summary of Final Reflective Measurement Model Evaluation/Assessment

Latent Variable	Indicators	Loadings	Indicator Reliability	Composite Reality	AVE Table	Discriminate Validity
Narcis	Narcis 1	.888	.789	.971	.846	Yes
	Narcis 2	.939	.882			
	Narcis 3	.954	.910			
	Narcis 4	.910	.828			
	Narcis 5	.938	.880			
	Narcis 6	.889	.790			
LMX	Affect	.873	.762	.842	.585	Yes
	Cont	.749	.561			
	Loyalty	.901	.812			
	Prof	.453	.205			
Satis	Satis 1	.832	.692	.914	.726	Yes
	Satis 2	.917	.841			
	Satis 3	.813	.661			
	Satis 4	.844	.712			

However, the structural model must be assessed before the final model can be used. Bootstrapping along with a procedure called blindfolding were used to further assess the structural model. The final model was assessed for collinearity, R^2 value, path coefficient significance, effect size, and predictive relevance of the model. The structural model met the assessment requirements and is now ready for further use and interpretation.

Table 3 shows the path coefficient and p-values for the three latent variable paths. Two paths are significant according to the analysis. The path relationship between LMX and (Job) Satis is significant at the .05 significance level as indicated by a p-value of 0.000. Also, the path relationship between Narcis and LMX is significant at the .05 significance level with a p-value of 0.000. The path relationship, Narcis to Satis is not significant at the .05 level because the p-value is 0.195. Although the effect Narcis has on Satis directly is not significant, there is a mediating effect of LMX between Narcis and Satis because the effect of Narcis on LMX is significant, and LMX significantly impacts Satis.

Table 3

Path Coefficient, T-values and P-values for Latent Variables (Construct)

Path	Coefficient	T-values	P-values
LMX ----- Satis	.527	3.6385	0.000
Narcis ----- Satis	-0.128	1.3911	0.195
Narcis ----- LMX	-0.475	8.0571	0.000

MODERATOR EFFECTS “GENDER” MODEL ANALYSIS

Gender was used as the moderator effect in order to determine if there were any differences in the paths of the original model. Figure 1.3 shows the gender moderator effects of the relationship between narcissistic leadership and job satisfaction. The moderator variable had a p-value of 0.962, which indicates there is no significant differences between the perceptions of male or female and the relationship between narcissistic leadership and job satisfaction. This analysis means that neither males or females perceive narcissistic leadership to have a direct impact on employee job satisfaction within the accounting profession.

Figure 1.3
Gender as a moderator effect on Narcissistic Leadership and Job Satisfaction

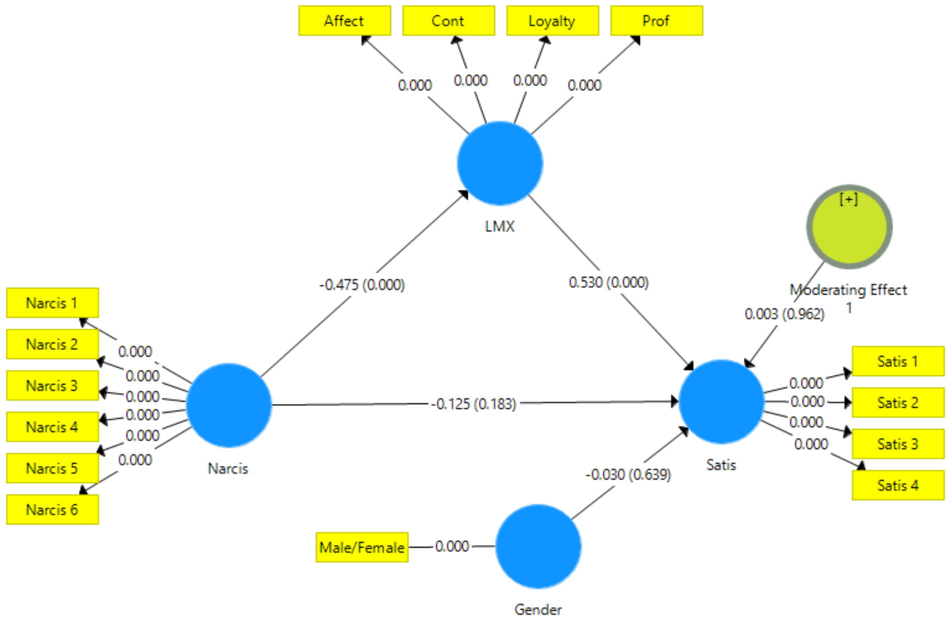


Figure 1.4 reveals the effect of using gender as a moderator between LMX and (Job) Satis. Once again, the moderator effect variable indicates there is no significant difference with a P-value of 0.945 between the perceptions of males and females and their viewpoint of the direct relationship between LMX and Job satisfaction.

Figure 1.4
Gender as a moderator effect on Leader-Member Exchange and Job Satisfaction

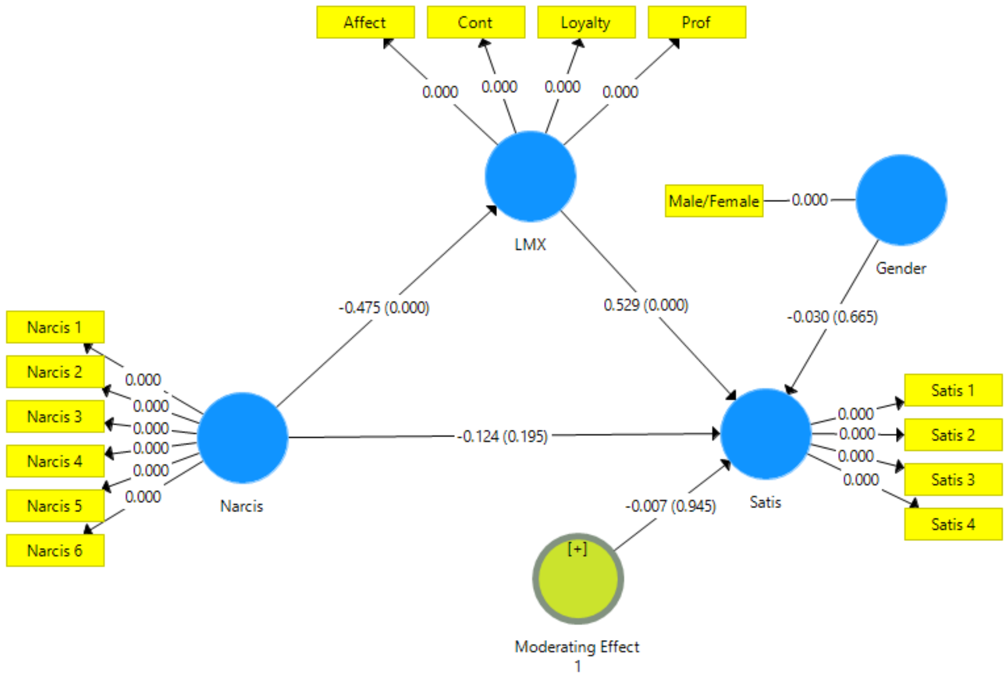
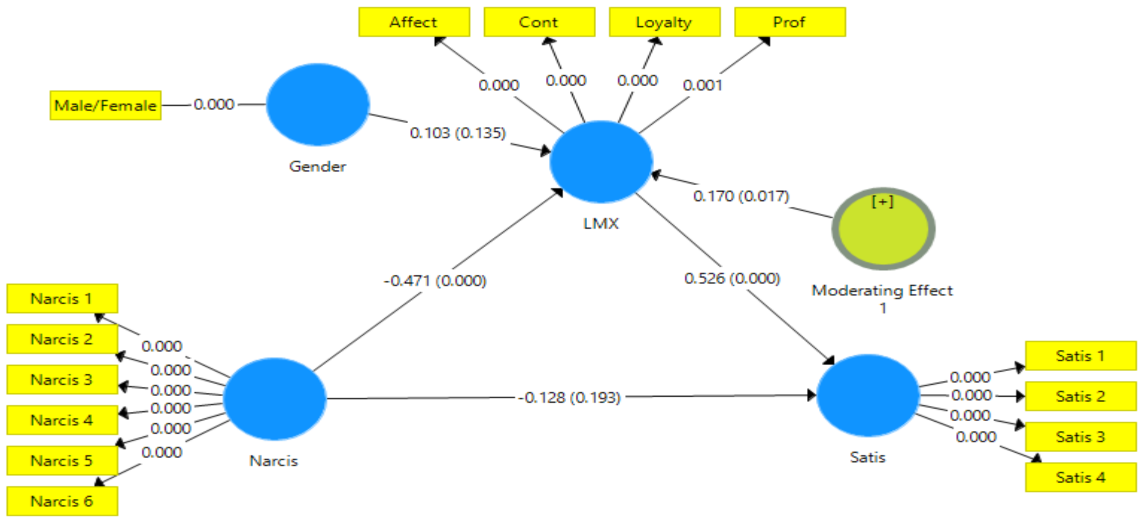


Figure 1.5 shows the PLS results concerning the use of gender as a moderator variable. Gender was used to determine if the perception of male or female is significantly different in relation to narcissistic leadership and leader-member exchange (in the accounting profession). Gender did have a significant moderator effect on the relationship between narcissistic leadership (Narcis) and leader-member exchange (LMX).

Figure 1.5
Gender as a moderating effect on Narcissistic Leadership and Leader-Member Exchange



According to Figure 1.5, the analysis yields a p-value of 0.017 for the path linking the moderator effect variable and LMX. These results provide clear support that Gender exerts a significant effect on the relationship between Narcis and LMX.

Since there is a significant negative relationship between Narcis and LMX, the conclusion is that the perceptions of female accountants exhibit a weaker relationship between Narcis and LMX than males. This conclusion is evidenced in Figure 1.6 and Figure 1.7. The correlation between Narcis and LMX for males was -0.565 (see Figure 1.6) and for females was -0.407 (see Figure 1.7). There is a significant difference between these two groups of accountants at the .05 level of significance. Even though the relationship between Narcis and LMX for females is significant and negative, the relationship is significantly less than males. It is the authors' assumptions that this difference may be explained by the fact that females value more highly the interpersonal relationship between their bosses than do males. Therefore, the fact that females have a narcissistic boss does not have the same degree of negative effect on leader-member exchange (relationship between them). Consequently, because females value the relationship with their boss more than males value this relationship, it does not "bother" females as much if their boss is narcissistic as it does males. Another assumption by the authors' is that males are more competitive; therefore, having a narcissistic leader negatively influences the relationship between leader/subordinate (LMX) to a larger degree than it does with females.

Figure 1.6
Bootstrapping Results with SmartPLS for Males only

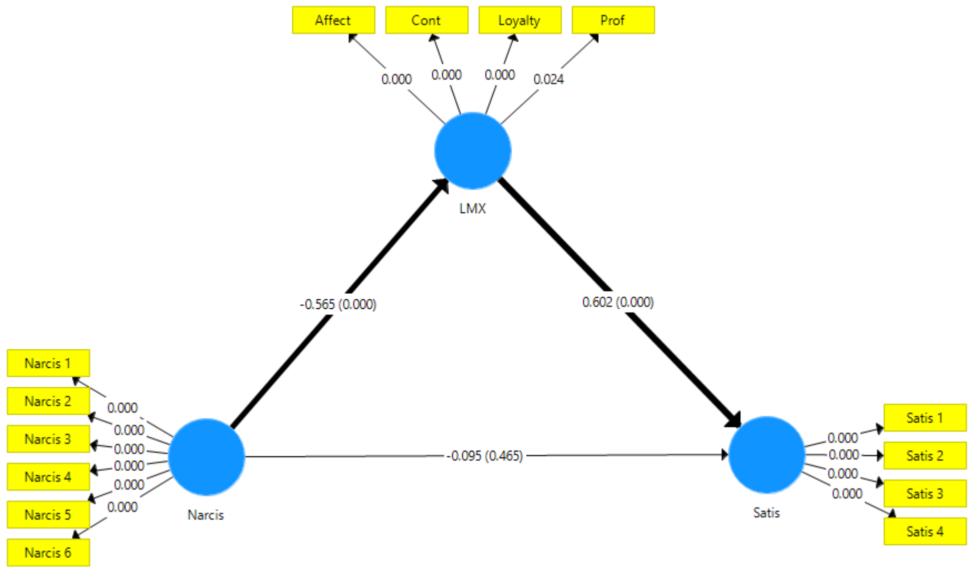
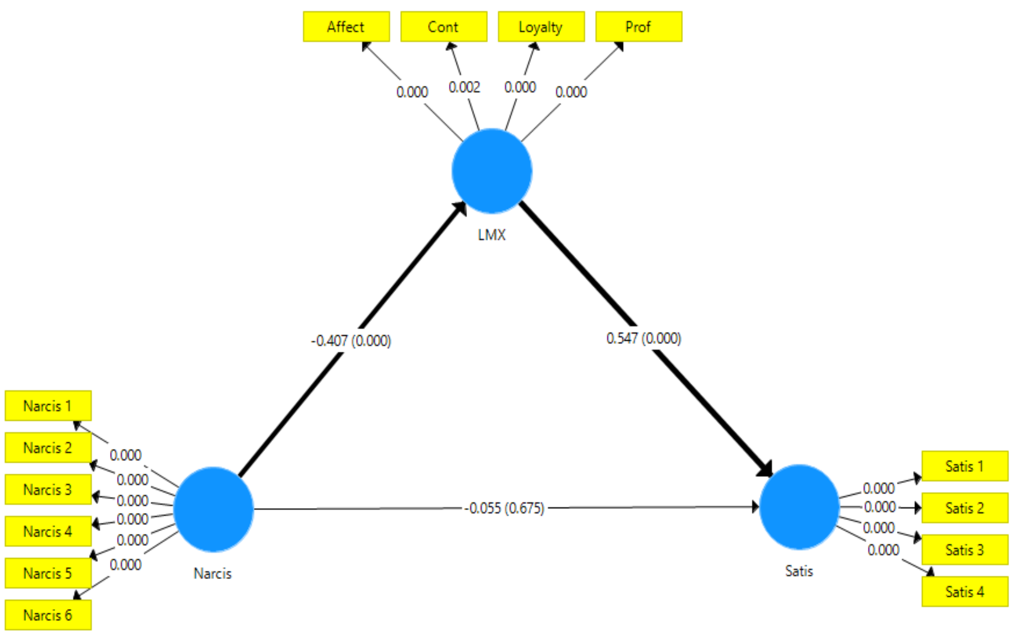


Figure 1.7
Bootstrapping Results with SmartPLS for Females only



FINDINGS AND CONCLUSION

As previously stated, narcissism is a psychiatric disorder that affects professionals in many areas. This paper focused on narcissism and the effect it has within the accounting profession on job satisfaction as related to gender perception. The theory of leader-member exchanged (LMX) is shown to play a significant role in the relationship between narcissistic leaders and employee job satisfaction. Likewise, the question is are there differences in perception between genders in measuring this relationship on job satisfaction? Additionally, does narcissism have a greater effect on job satisfaction with or without LMX moderating between the two?

Consequently, the authors answered the major research question: Do gender differences exist with regard to perception on how leader-member exchange (LMX) and narcissistic leadership affect employee job satisfaction in the accounting profession? The answer is "yes" between LMX and narcissistic leadership because the only path that had a significant difference in regard to gender perception was from narcissistic leadership to leader-member exchange. Males have a higher, negative perception between the two variables indicating they are more affected by narcissist leadership. These results may be because of their competitive nature, while females value a strong leader and are less troubled if that leader is narcissistic.

The following are the findings on the four hypotheses.

Hypothesis 1: There is a significant difference between the perception of males and females in regard to narcissistic leadership and employee job satisfaction within the accounting profession.

In regard to hypothesis 1, there was no significant difference in perception between genders in regard to the direct relationship of narcissistic leadership and employee job satisfaction.

Hypothesis 2: There is a significant difference between the perception of males and females in regard to leader-member exchange (LMX) and employee job satisfaction in the accounting profession.

In regard to hypothesis 2, there was no significant difference in perception between genders in regard to leader-member exchange (LMX) and employee job satisfaction in the accounting profession.

Hypothesis 3: There is a significant difference between the perception of males and females in regard to narcissistic leadership and leader-member exchange (LMX) in the accounting profession.

In regard to hypothesis 3, there is a significant difference in perception between genders in regard to leadership and leader-member exchange (LMX) in the accounting profession.

Hypothesis 4: There is a significant difference between the perception of males and females in regard to how leader-member exchange (LMX) mediates between narcissistic leadership and employee job satisfaction in the accounting profession.

In regard to hypothesis 4, since there is a significant difference in hypothesis 3, there is a significant difference in the perception between genders in regard to how Leader-Member Exchange (LMX) mediates between narcissistic leadership and employee job satisfaction in the accounting profession. Even though LMX mediates the relationship between narcissistic leadership and job satisfaction for both males and females, the degree of mediation for males is significantly greater than for females.

In regard to hypothesis 3 and 4, the coefficient for males was significantly greater with a negative coefficient of -0.565 while females had a negative coefficient at -0.407. This implies that males are more troubled by having a narcissistic leader than are females, again possibly because males are more competitive while females value a strong leader, despite the fact that they may be narcissistic. Another thought by the authors on the subject is that perhaps females do not communicate difficulties to leaders in as vocal a manner as males would communicate.

Being influential is the essence of leadership, and managerial effectiveness is strongly determined by one's ability to influence others, whether they be subordinates or superiors, or even peers. (Himanshu, 2009). Therefore, in regard to being an effective leader, communication is essential, and various styles exist among men and women. Women are better listeners and are more empathetic. When decisiveness is important, men generally are more effective. Men also tend to be better at monologue while women are better at dialogue (Goman, 2016). Other communication strengths for women include the ability to read language and the ability to detect nonverbal cues. They have good listening skills and display more empathy, while men have a very commanding physical presences and display "power" while at the same time being direct and to the point in their conversations. Weaknesses in communication for women are that they can be too emotional, often won't get to the point in a conversation and are not authoritative enough. Communication weaknesses for men are that they can be too blunt and direct, oftentimes too confident in their opinion. They also are not empathetic enough and are often insensitive. (Goman, 2016). Therefore, communication styles, as well as empathy may play a role in explaining these differences in perceptions regarding narcissistic leadership. This observation could be a possible source of future research.

Samier & Atkins (2010) have explored destructive narcissism and how to prevent it within the educational arena. Menon & Sharland (2011) cite that the current college generation exhibits a sense of entitlement and high levels of narcissism. That generation will soon become the leaders in our world, whether it be in business or other areas. Lubit (2002) says that narcissism has become a "significant problem for organization", (p. 127). Of interest is that Baird (1980) notes that students majoring in business tend to be more academically dishonest than majors in other areas. Amernic & Craig (2010) have added to the literature by writing on the relationship between accounting and personality disorders and have cited narcissism; however, there appear to be few published studies solely on the topic of narcissism and accounting (Amernic & Craig, 2010). Additionally, little research exists on the negative effects on employees pertaining to how they are treated by organizations (Gibney, Zagenczyk, & Masters, 2009). It is also noted by the authors that gender topics seems to be prevalent in the news media and literature at the current time; therefore, this study should fill a "gap" in the current research available regarding narcissistic leadership and the effects on employee job satisfaction as it is perceived between genders.

In regards to practice, leadership within the accounting world may have a significant impact on the long-term success of the organization. This success may be linked directly or indirectly to the level of employee job satisfaction. As the authors have previously discussed, there are numerous effects of narcissism within the business world, some of which are lack of job satisfaction, an abnormal imbalance of work and social life, and a loss of identity of employees of identity (Godkin & Allcorn, 2011; Koprowski, 1981; Lubit, 2002; Kernberg, 2008). The understanding of how male and female employees differ in their perception of working relationships may give significant insight to accounting firms on how to attract and keep productive employees that contribute to the future success of the firm.

REFERENCES

American Psychiatric Association. (1994). *Diagnostic and statistical manual of mental disorders* (4th ed. text revision version). Washington, DC.

Amernic, J., & Craig, R. (2010). Accounting as a facilitator of extreme narcissism. *Journal of Business Ethics, 96*(1), 79-93. Dpi:10.107/s10551-010-0450-0.

Baird, J. S. Jr. (1980). Current trends in college cheating. *Psychology in the Schools*. *17*, 515-522.

Biddle, Matthew. (2015, March 4). Study: Men tend to be more narcissistic than women. From University of Buffalo News Center. Retrieved, May 30, 2018 from www.buffalo.edu/news/releases/2015/03/009.html.

Chatterjee, A. & Hambrick, D. C. (2007). It's all about me: Narcissistic chief executive officers and their effects on company strategy and performance. *Administrative Science Quarterly, 52*, 351-386.

Gibney, R., Zagenczyk, T. J., & Masters, M. F. (2009). The negative aspects of social exchange: an introduction to perceived organizational obstruction. *Group & Organization Management, 34*(6), 665-697.

Godkin, L. & Allcorn, S. (2011). Organizational resistance to destructive narcissistic behavior. *Journal of Business Ethics, 104,* 559-570. DOI 10.1007/s10551-011-0930-x.

Goman, Carol Kinsey, (2016, March 31). Is your communication style dictated by your gender? *The Little Black Book of Billionaire Secrets (Forbes).*

Grier, S. (2008). *Narcissism in the workplace.* (no publisher listed).

Hair, J. F., Halt, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). Los Angeles, CA: Sage.

Himanshu, R. (2009). Gender differences: ingratiation and leader member exchange quality. *Singapore Management Review.* Singapore Institute of Management. Retrieved May 27, 2018 from HighBeam Research: https://www.highbeam.com/doc/1G1-192052587.html.

Hochwarter, W. A. & Thompson, K. W. (2012, 8 February). Mirror, mirror on my boss's wall: Engaged enactment's moderating role on outcomes the relationship between perceived narcissistic supervision and work outcomes. *Human Relations, 65*, 335-366. DOI: 10.1177/0018726711430003.

Hoppock, R., *Job Satisfaction*. New York: Harper and Row, 1935

Kernberg, O. F. (2008). The destruction of time in pathological narcissism. *International Journal of Psychoanalysis, 89,* 299-312.

Koprowski, E. J. (1981). Exploring the meaning of "good" management. *Academy of Management Review, 6*(3), 459-467.

Liden, R. C. & Maslyn, J. M. (1998). Multidimensionality of leader-member exchange: An empirical assessment through scale development. *Journal of Management, 24*(1), 43-72.

Lubit, R. (2002). The long-term organizational impact of destructively narcissistic managers. *Academy of Management Executive 16*, 127-138.

Lumpkin, J. R. (1985). Validity of a brief locus of control scale for survey research. *Psychological Reports 57*, 655-659.

McNichols, C. M. Stahl, and T. Manley. (1978). A validation of Hoppock's job satisfaction measure. *Academy of Management Journal*, 737-742.

Menon, M. & Sharland, A. (2011). Narcissism, Exploitative attitudes and academic dishonesty: An exploratory investigation of reality versus myth. *Journal of Education for Business 86*, 50-55.

Morley, C., Bellamy, S., Jackson, M., & O'Neill, M. (2018) Gender difference in career attitudes of accountants and their impact on career progression, Retrieved July 11, 2018 from https://www.researchgate.net/publication/255581633.

Rotter, J. B. (1966). Generalized expectancies for internal versus external control of reinforcement. *Psychological Monographs: General and Applied*, *80*(1), 1-28, Retrieved from http://dx.doi.org/10.1037/h0092976.

Schwartz, H. S. (1991). Narcissism project and corporate decay: The case of general motors. *Business Ethics Quarterly, 1*, 249-268.

Samier, E. & Atkins, R. (2010). Preventing and combating administrative narcissism: Implications for professional programmes. *Journal of Educational Administration, 48*(5), 579-594.

Shurden, Susan B., PhD, Dissertation*: Identifying the Effects of Narcissistic Leadership on Employee Job Satisfaction: A Study within the Accounting Profession*, Clemson University, 2014, 208 pages.

MUTUAL FUND RETURNS AND THE REVERSAL OF THE SIZE AND VALUE PREMIUMS

William J. Trainor, Jr., East Tennessee State University
Changyue Xu, Johns Hopkins University

ABSTRACT

Size, price/earnings (PE), and price-to-book (P/B) anomalies where stocks with smaller values tend to outperform have been known for more than 30 years. Fama & French's (1992) infamous three-factor model was developed as a direct result of these identified premiums. This study examines these anomalies from 1996-2015 to determine if mutual fund returns are consistent with theoretical returns.

Findings show mutual funds weighted toward size and value premiums have returns relatively consistent with theoretical projections after considering expense ratios, although there are major discrepancies in the small value and small growth categories. The bigger issue for investors is these premiums have reversed over the last ten years resulting in negative relative performance instead of positive. Since the size and value "premium" have become so well known, future use of these factors as a long-term investment strategy to attain excess returns seems far less likely.

INTRODUCTION

Market anomalies are generally defined as trading on stock traits that appear to outperform the market after adjusting for risk. This is in direct contrast to the Efficient Market Hypothesis first put forth by Fama (1965), winner of the 2013 Nobel Prize in Economics. Although there is a great deal of research on the existence of anomalies and how excess returns are theoretically available, there is little research on whether equity funds have been able to successfully implement trading strategies to take advantage of these anomalies. This question has been left unanswered mainly due to the relatively short time period that funds dedicated to these strategies have been in existence.

However, some funds based on these anomalies have now been in existence for more than 20 years with a substantial number available for at least 10 years. This is long enough to justify research into whether these funds have been able to replicate the theoretical results found in the academic literature. This study intends to answer two questions: 1) have excess returns been theoretically available from trading on market anomalies during these fund's existence, and 2) have mutual funds based on these trading strategies attained excess returns consistent with theoretical results. These are important questions as some in the academic literature suggest profitable trading on anomalies is unlikely due to anomaly inconsistency and trading costs, Silver (2009).

The remainder of this paper is organized as follows. Section two reviews the literature while Section three describes the data and methodology. Section four presents the results for theoretical portfolios and mutual funds. The paper concludes with a short analysis along with the practical implications of this research.

LITERATURE REVIEW

The most commonly agreed upon anomalies are size, price/earnings (PE) ratio, price-to-book (PB), volatility, and momentum. The first three, (where smaller is better) have been known for more than 30 years, (See Banz 1981 (size); Nicholson, 1960 and Basu, 1977 (PE); Rosenberg, Reid, & Lanstein, 1985 (PB); Jensen, Black, & Scholes, 1972 (volatility)). Jegadeesh & Titman (1993) first identified the momentum anomaly in which stocks that go up the most tend to keep going up, and stocks that fall tend to continue that trend. The interest in low volatility stocks has seen a resurgence in the literature with Ang, et. al. (2006, 2009) studies showing stocks with low volatility tend to generate higher returns than stocks with high volatility. Fama & French (1992, 1996, 2008) have reaffirmed these anomalies. Recent studies suggest these anomalies are still going strong, (Zacks, 2011; Silva, 2012).

Dijk (2011) did an exhaustive study on prior research into the size effect showing the question remains as to whether the size effect is truly an anomaly. Fama & French (2012) find value premiums decrease in size in a variety of international markets, but no size premium per se, while Asness et. al. (2013) also present evidence value and momentum premiums appear to be internationally relevant. Silver (2009) questions whether these anomalies can be taken advantage of in practice. This study tries to answer Silver's question while limiting itself to the size and value premiums as there are significantly more funds with longer histories for these anomalies.

Data & Methodology

This study examines both theoretical portfolio and mutual fund returns based on size and value factors. Theoretical data was attained from Ken French's website. Portfolios are sorted into three value weighted groups, 30/40/30 based on market value of equity, P/B, and P/E ratios. Mutual fund data is based on 96 stock mutual funds from the three largest mutual fund companies ranked by assets (Fidelity Investments, Vanguard Group, and American Fund). Thirty-three of these mutual funds have existed for more than twenty years. Return data for these mutual funds was attained from The Center for Research in Security Prices (CRSP) mutual fund database.

In order to confirm anomalous factors affect returns, the Fama-French three-factor model is applied to mutual funds. This model is a modification of the CAPM and is designed to describe stock returns by using company size, company P/B ratio, and market risk. The model is:

$$R_p - r_f = \alpha + \beta_p(K_m - r_f) + \beta_s(SMB) + \beta_v(HML) + \varepsilon \qquad (1)$$

where R_p is the portfolio's rate of return, r_f is the risk-free return rate, and K_m is the return of the market portfolio. SMB (Small minus Big) is defined by Fama & French as the difference between the average return of three small portfolios and three big portfolios, and HML (High minus Low) is defined as the difference between the average return of two value portfolios and two growth portfolios.

The values of SMB and HML are attained from Ken French's website. Regressions are run for each mutual fund and funds are categorized based on statistical significance at the 5% level. Excess fund returns statistically significant and positive to both factors are classified as small value funds. A fund found statistically negative to both factors is classified as a large growth fund. Funds found to be statistically significant to only one or the other are classified as small (positive to SMB), large (negative to SMB), value (positive to HML), or growth (negative to SMB).

As a final test to insure the mutual fund selection is unbiased, mutual funds in the small value, small growth, large value, and large growth categories as defined by Morningstar are also examined separately to confirm the results. This results in another 516 funds to be examined.

The Jan. 1996 to Dec. 2015 period and the two 10-year sub-periods are examined. This time frame is three years after the Fama & French (1992) study allowing adequate time for managers to implement strategies to take advantage of possible size and value premiums.

To evaluate the risk of these portfolios, both the Sharpe and Sortino (Sortino & Price, 1994) ratios are calculated. The Sharpe Ratio is given as:

$$\frac{R_p - r_f}{\sigma_p} \tag{2}$$

where R_p is the return to the portfolio, r_f is the risk-free rate and σ_p is the annualized standard deviation from the monthly returns. The Sortino ratio is a modification of the Sharpe ratio and focuses on the downside deviation to measure risk-adjusted returns. The larger the ratio, the greater the return per unit of downside risk. The Sortino ratio is calculated as:

$$\mathrm{S} = \frac{R-T}{\mathrm{TDD}} \text{ where TDD} = \sqrt{\frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}}(\mathrm{Min}(0, \mathrm{X_i} - \mathrm{T}))^2} \tag{3}$$

where R = the return, T is the target return (set at zero), N is the total number of returns and X_i is the ith return.

RESULTS

Theoretical SMB and HML Returns

Fama and French's SMB and HML 10-year geometric annualized excess returns are shown in Figure 1 from July 1926 to Dec. 2015. Dates correspond to the end of each 10-year period on a rolling monthly basis. On average, small stocks outperform large cap stocks by 2.01% while the HML value premium is 3.98%. These premiums have varied with the SML factor being more volatile, 3.5% to 2.4% respectively. The value premium has been consistently positive except for the period ending with 2000 tech crash and the 10-year periods ending at the start of 2014.

Whether the disappearance of both premiums has been traded away over the last 10 years due to the anomalies being known, or is a temporary blip remains to be seen. At the very least, it would appear there is increased uncertainty as to whether the premiums will reappear and remain positive over long periods of time in the future. In addition, investors who have been swayed by the historical returns to these factors have certainly been disappointed over the last 10 years.

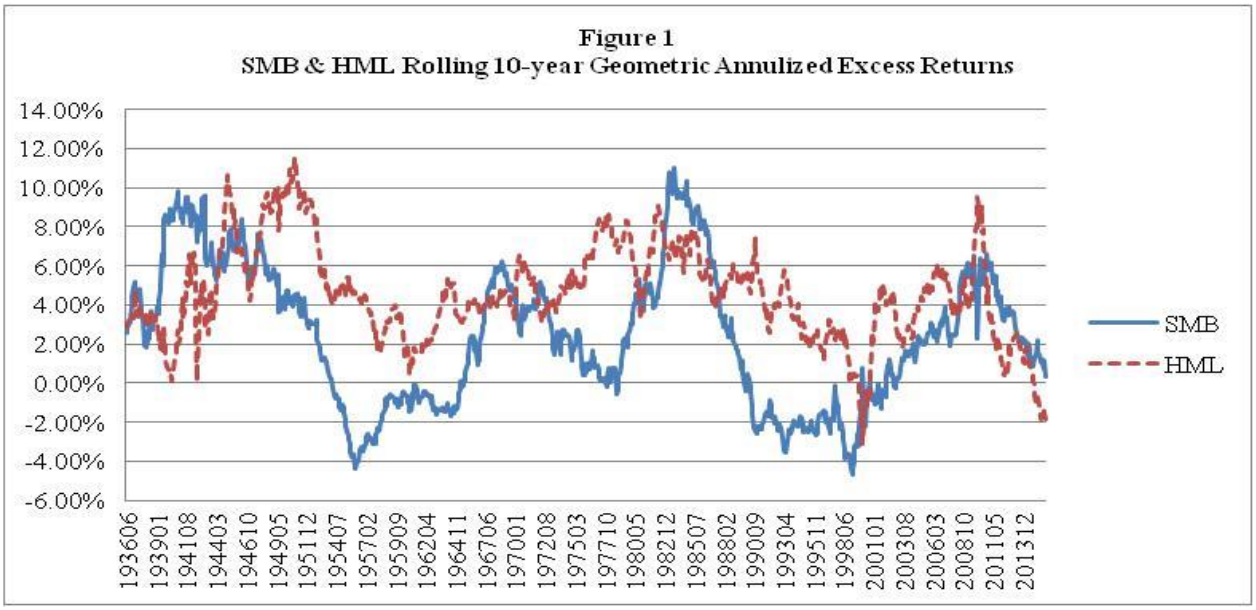
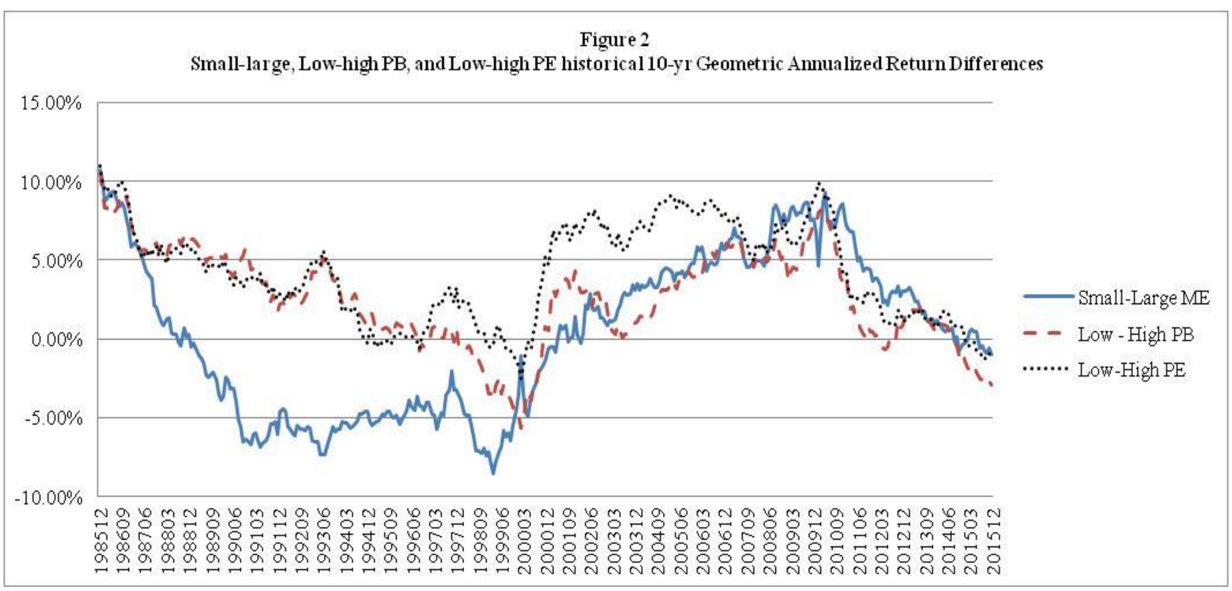


Figure 2 shows rolling 10-year geometric annualized return differences based on small minus large market value of equity, low minus high P/B, and low minus high PE portfolios for the Dec. 1986 to Dec. 2015 period. These results confirm the SMB and HML results above and clearly show there has been no size or value premium over the more recent 10-year holding periods.



Theoretical Size Anomaly

Table 1 shows theoretical returns based on size for the last 20 years along with two 10-year sub-periods. Results for the last 20 years still show a relationship between size and returns, although this is entirely dependent on the first 10 years. For the last 10 years, mid-caps stocks outperform while the small minus large anomaly has completely reversed itself.

Table 1
Annualized 10 year geometric returns for size ranked portfolios

	Low 30		Mid 40		High 30	
Jan. 1996-Dec. 2015	10.09%		9.96%		8.27%	
Jan. 1996-Dec. 2005	13.85%		11.42%		9.10%	
Jan. 2006-Dec. 2015	6.46%		8.52%		7.46%	
Sharpe and Sortino Ratios						
Jan. 1996-Dec. 2015	0.40	0.54	0.45	0.61	0.40	0.57
Jan. 1996-Dec. 2005	0.60	0.71	0.60	0.63	0.28	0.53
Jan. 2006-Dec. 2015	0.25	0.37	0.54	0.58	0.54	0.62

From a risk perspective, both the Sharpe and Sortino ratios generally suggest for the 20-year period small cap stocks are not generating excess returns per unit of risk. In fact, they have smaller Sharpe and Sortino ratios relative to both mid cap and large market value of equity stocks. Thus, even long-term investors are not realizing a size anomaly.

Theoretical P/B Anomaly

Table 2 shows geometric annualized returns for portfolios sorted by P/B. Although the first 10-year period does show lower P/B outperforms the highest, the mid quintile does best. For the last 10 years, high P/B portfolios clearly dominate. Both Sharpe and Sortino ratios are significantly higher over the last 10 years for high P/B portfolios. Even for the 20-year period, "value" stocks do not appear to be associated with anomalous excess returns after adjusting for risk as evidenced by the Sharpe and Sortino ratios.

Table 2
Annualized geometric returns for P/B portfolios

	Low 30		Mid 40		High 30	
Jan. 1996-Dec. 2015	9.10%		9.36%		8.68%	
Jan. 1996-Dec. 2005	12.31%		12.60%		8.44%	
Jan. 2006-Dec. 2015	5.98%		6.22%		8.92%	
Sharpe and Sortino Ratios						
Jan. 1996-Dec. 2015	0.40	0.57	0.45	0.67	0.40	0.60
Jan. 1996-Dec. 2005	0.60	0.96	0.60	0.95	0.28	0.42
Jan. 2006-Dec. 2015	0.25	0.35	0.31	0.44	0.54	0.82

Theoretical PE Anomaly

Another value indicator for stocks is the PE ratio where low PE stocks have been found to outperform high PE stocks. Table 3 shows portfolios with low PEs still outperform. For the 20-year period, low PE portfolios outperform high PE portfolios by 3.27% annually. However, the result is again based on the first 10 years, as the returns reverse over the last 10 years. Sharpe and Sortino ratios are directly related to returns. This suggests the higher returns for low PE stocks in the first 10 years and high PE stocks for the second 10 years are not associated with excess risk.

Table 3
Annualized geometric returns for PE Ranked portfolios

	Low 30		Mid 40		High 30	
Jan. 1996-Dec. 2015	11.49%		9.42%		8.22%	
Jan. 1996-Dec. 2005	16.09%		11.49%		8.13%	
Jan. 2006-Dec. 2015	7.06%		7.38%		8.31%	
Sharpe and Sortino Ratios						
Jan. 1996-Dec. 2015	0.56	0.84	0.49	0.75	0.36	0.54
Jan. 1996-Dec. 2005	0.80	1.30	0.54	0.88	0.27	0.41
Jan. 2006-Dec. 2015	0.35	0.50	0.44	0.63	0.45	0.67

Theoretical Small Value and Growth versus Large Value and Growth

Table 4 shows portfolios sorted by market cap and sorted again by small, mid, and large P/B. The small value (SV), small growth (SG), large value (LV), and large growth (LG) portfolios are shown. For the 20-year period, small value outperforms, and this is especially true over the first 10 years with an annualized return differential of almost 10% a year. However, like above, the last 10 years have shown just the opposite results.

Table 4
Annualized geometric returns Size and value ranked portfolios

	SV		SG		LV		LG	
Jan. 1996-Dec. 2015	12.34%		6.05%		7.93%		8.90%	
Jan. 1996-Dec. 2005	18.72%		4.96%		10.21%		8.75%	
Jan. 2006-Dec. 2015	6.31%		7.15%		5.71%		9.05%	
Sharpe and Sortino Ratios								
Jan. 1996-Dec. 2015	0.51	076	0.15	0.22	0.32	0.46	0.42	0.63
Jan. 1996-Dec. 2005	0.87	1.41	0.05	0.07	0.43	0.67	0.30	0.46
Jan. 2006-Dec. 2015	0.24	0.34	0.30	0.43	0.24	0.33	0.56	0.85

Summary of Theoretical Results

There is a vast literature on the size, P/B, and PE anomalies, but the results over the last 20 years suggest excess returns based on these factors may no longer be consistently available. Although the last 10-year period is not a complete outlier, it is only the second time that a 10- year period since 1936 has seen both the size and value premium turn negative. As these anomalies have been publicized, the number of funds forming portfolios based on these anomalies has increased. At this point, it may be the case the excess returns that were once consistently available may simply have been traded away. The next section shows how mutual funds using these factors have performed.

Mutual Fund Results

Ninety-six (American (16), Fidelity (48), and Vanguard (32)) equity funds are regressed on the Fama-French 3-factor model to identity which funds are based on size, value, or both. As an example, Table 5 shows the regression results for five of these funds. Funds with statistically significant positive coefficients to the SMB and HML factors are assumed to be forming portfolios to some degree based on the size and value anomalies. An asterisk represents significance at the 5% level.

Table 5
Fama-French Three Factor Model regressions

	Mkt-Rf	T-stat	SMB	t-stat	HML	t-stat	Adj R-Sq
FNCMX	1.12	43.47*	0.28	6.21*	-0.37	-8.65*	0.95
FBGRX	1.02	61.38*	-0.07	-2.98*	-0.14	-5.74*	0.95
FLGEX	1.01	70.82*	-0.07	-2.43*	-0.23	-8.83*	0.98
FDSVX	1.00	38.17*	0.01	0.31	-0.20	-5.58*	0.89
VSEQX	1.03	45.28	0.27	8.95	0.35	10.66	0.91

If a fund has both factors significantly positive, it is classified as a small value fund, such as VSEQX in Table 5; if both negative, the fund is classified as a large growth fund such as FBGRX and FLGEX. In sum, there are eight categories, small, large, value, growth (FDSVX for example), small value, small growth, large value, and large growth. Returns from these mutual funds are compared to the theoretical returns reported earlier in this study.

Table 6 shows the results along with the return differences from the theoretical returns. The number of funds for each 10-year period are shown on the top row. Theoretical value returns are based on the average of the P/B and P/E values. For the entire 20-year period, small stock funds outperform large stock funds with similar returns relative to the theoretical numbers after considering expense ratios, 8.92% vs 10.09% and 6.48% vs 8.27% respectively. However, there is only one mutual fund for the 20-year period in the large only category so results should be interpreted cautiously. Interestingly, small cap mutual funds outperform their large only counterparts in both decades, albeit by very little in the 2006-15 decade.

Table 6
Annualized geometric returns and fund minus theoretical return difference

Number of funds in each 10 yr period =	Small 5 & 11	Large 1 & 3	Value 3 & 8	Growth 1 & 3	SV 5 &12	SG 8 &13	LV 18 & 26	LG 5 & 6
Jan. 1996-Dec. 2015	8.92%	6.48%	9.05%	6.48%	9.48%	8.69%	7.87%	7.33%
MF - Theoretical	-1.17%	-1.79%	-1.24%	-1.97%	-2.86%*	2.64%	-0.06%	-1.57%*
Jan. 1996-Dec. 2005	11.81%	7.43%	12.04%	7.43%	12.31%	9.53%	9.49%	7.14%
MF - Theoretical	-2.04%	-1.67%	-2.16%	-0.86%	-6.41%*	4.57%*	-0.72%*	-1.61%
Jan. 2006-Dec. 2015	6.75%	6.61%	6.23%	6.61%	6.67%	8.18%	6.30%	7.67%
MF - Theoretical	0.29%	-0.85%	-0.29%	-2.01%*	0.36%	1.03%	0.59%	-1.38%*

Value mutual funds beat growth which is also found in the theoretical results, although the value funds held their own against growth in the second decade as the three growth mutual funds fell -2.01% short of theoretical returns. Mutual fund results are better than the theoretical P/B returns but worse than the theoretical PE returns. This suggests funds are investing in value stocks based on a combination of P/B and PE and likely other factors as well.

Over the first 10-year period, small value mutual funds perform very well, but completely reverse in the following 10-year period where large growth funds outperform. The largest discrepancy from the theoretical results occurs for small value and small growth mutual funds in the 96-05 decade, with both differences statistically significant. It appears mutual fund managers are using other metrics besides P/B to determine value and growth stocks. Unlike the theoretical results, small growth funds outperform large growth funds in the second decade.

To confirm the above mutual funds results, all small value (50 funds), small growth (96), large value (171), and large growth (199) no transaction fee mutual funds based on Morningstar's fund categorization are also examined. The results are shown in Table 7 for those with complete data that cover the 10-year sub-periods.

Table 7
Annualized geometric returns for Morningstar categorized mutual funds

Number of funds in each 10 yr period =	SV 7 & 27	SG 22 & 64	LV 48 & 88	LG 71 & 134
Jan. 1996-Dec. 2015	9.47%	8.89%	7.34%	7.65%
MF – Theoretical	-2.87%*	2.84%*	-0.59%*	-1.25%*
Jan. 1996-Dec. 2005	11.56%	10.44%	8.95%	7.86%
MF – Theoretical	-7.16%*	5.48%*	-1.26%*	-0.89%*
Jan. 2006-Dec. 2015	5.41%	6.61%	5.73%	7.08%
MF - Theoretical	-0.90%	-0.54%	0.02%	-1.97%*

This broader sample reaffirms the results above where small value and large growth funds switched places over the last 20 years. The returns themselves are generally less than 0.5% different from the funds above with the biggest difference being the small growth funds in the 2006-2015 decade, 8.18% compared to 6.61% for the Morningstar sample.

However, most of the differences between the theoretical returns are quite significant and statistically so with the larger mutual fund sample size. Small value funds fell -7.16% short of the theoretical small value portfolio but are 5.48% better relative to small growth. The same type of result occurred for the funds from Fidelity, Vanguard, and American funds. Thus, the distinction between growth and value seems to be blurred in the small fund category, along with the fact factors in addition to P/B are clearly being used by fund managers to determine value versus growth stocks. If one combines the small value and small growth return differentials, much of the discrepancy can be explained by expense ratios. As an example, small value funds have an average expense ratio of 1.33%.

CONCLUSION

The size and value anomalies have been known for more than 30 years. The infamous Fama & French (1992) three-factor model is based on these known anomalies. However, the value of trading on these anomalies is no longer apparent. Over the last 10 years, large growth has outperformed small value by 2.74% and 1.67% annually based on theoretical portfolios and mutual funds respectively. This is the exact opposite of what one might have expected.

This study initially set out to determine if mutual funds using the small and value premiums could equal the performance of what theoretical portfolios suggest is possible. To match theoretical portfolio returns, funds must overcome several headwinds such as small stock liquidity, tax issues with rebalancing, expense ratios, manager flexibility, and fund flows. Despite these issues, average returns for funds are similar to what is theoretically expected after accounting for expense ratios. The main exception is for small value and small growth funds where small value underperforms substantially, but small growth outperforms. This is likely due to fund managers blurring the distinction between growth and value for small firms, and more relevant, value and growth stocks are chosen based on additional factors other than the P/B used by the Fama-French HML factor. The bigger return issue for investors is the small firm, P/B and PE anomalies reversed themselves during the period of this study.

This study examined the three largest fund providers along with more than 500 funds based on Morningstar's fund categorization starting three years after the Fama-French study was published. Although the first 10 years of this study period did indeed show the small firm and value premium was positive, this was not the case over the last 10 years. It is interesting to note for these three fund companies, only one large growth fund was added from the first 10-year period to the second 10-year period, while eight small value funds were added. It is possible excess returns have simply been traded away at this point. Because so many funds are chasing small value stocks, their prices have been bid up to the point where excess returns have been eliminated. The consistency of the size and value premium over long holding periods may be at an end.

REFERENCES

Ang, A, R.J. Hodrick, Y. Xing, & X. Zhang (2006). The cross-section of volatility and expected returns. *The Journal of Finance*, 61(1), 259-299.

Ang, A, R.J. Hodrick, Y. Xing, & X. Zhang (2009). High idiosyncratic volatility and low returns: International and further U.S. evidence. *Journal of Financial Economics*, 91, 1-23.

Asness, C., T.J. Moskowitz, & H.L. Pedersen (2013). Value and momentum everywhere. *The Journal of Finance*, 68(3), 929-985.

Banz, R.W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics*, 9, 3-18.

Basu, S. (1977). Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis. *The Journal of Finance*, 32(3), 663-682.

Dijk, van M.A. (2011). Is size dead? A review of the size effect in equity returns. *Journal of Banking and Finance*, 35(12), 3263–3274.

Fama, E.F. (1965). Random walks in stock market prices. *Financial Analysts Journal,* 21(5), 55–59.

Fama, E.F. & K.R. French (1992). The cross section of expected stock returns, *The Journal of Finance,* 67(2), 427-465.

Fama, E.F. & K.R. French (1996). Multifactor explanations of asset pricing anomalies. *The Journal of Finance*, 51(1), 55-84.

Fama, E.F. & K.R. French (2008). Dissecting anomalies. *The Journal of Finance*, 63(4), 1653-78.

Fama, E.F. & K.R. French (2012). Size, value, and momentum in international stock returns. *Journal of Financial Economics*, 105(3), 457-472.

Jegadeesh, N. & S. Titman (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance*, 48(1), 65-91.

Jensen, M.C., F. Black, & M.S. Scholes (1972). The capital asset pricing model: Some empirical tests. *Studies in the Theory of Capital Market.* Westport, CT: Praeger Publishers Inc.

Nicholson, F. (1960). Price-earnings ratios. *Financial Analysts Journal*, 16(4), 43-45.

Rosenberg, B.R., KR. Reid, & R. Lanstein (1985). Persuasive evidence of market inefficiency. *Journal of Portfolio Management*, 11(3), 9-17.

Silva, H. (2012). Exploiting the volatility anomaly in financial markets. *CFA Institute Conference Proceedings Quarterly*, March, 47-57.

Silver, T. (2009). Making sense of market anomalies. Retrieved February 19, 2013, from http://www.investopedia.com/articles/stocks/08/market-anomaly-efficient-market.asp

Sortino, F.A. & L. N. Price. (1994). Performance measurement in a downside risk framework, *The Journal of Investing*, 3(3), 59-54.

Zacks, L. (2011). *Handbook of equity market anomalies: Translating market inefficienies into effective investment strategies*, Hoboken, NJ, Wiley.

ACADEMIC R&D ACROSS THE STATES: EFFICIENCY AND ITS DETERMINANTS

Murat Arik, Middle Tennessee State University
Hulya Arik, Middle Tennessee State University
Bronwyn Graves, Middle Tennessee State University

ABSTRACT

A review of the literature suggests that there are few studies on the efficiency of academic research and development (R&D) funding in the United States. Much of the extant literature focuses on efficiency assessments at either the academic department level or the university level. We are not aware of any studies that analyze the efficiency of academic R&D funding at the state level. The purpose of this paper is to fill this void by assessing the efficiency of academic R&D funding at the state level using Data Envelopment Analysis (DEA), a non-parametric efficiency estimation method that can utilize multiple inputs and outputs to create a single efficiency score. The DEA results, along with results in changes in R&D productivity over time, suggest that some U.S. states are relatively better positioned to turn their R&D dollars into academic and business outputs. Tennessee is used as an example to show how to apply the DEA results to guide policy decisions toward efficiency. Tobit model results imply that the diversity of funding source, university R&D intensity, and R&D concentration are key for R&D funding efficiency. The policy implications of the study findings are discussed.

Keywords: Data envelopment analysis (DEA), research and development (R&D), academic efficiency, Tobit model

INTRODUCTION

Research and development (R&D) funding at universities provides the groundwork for increases in local business outputs and economic growth. Following the Arik and Ndrianasy (2018) conclusion that high levels of R&D funding on the state level often correlate with high state Gross Domestic Product (GDP) levels, and with the knowledge that R&D funding leads to business outputs, this paper investigates the efficiency with which universities utilize funding to create these growth-oriented outputs on the state level. This paper aims to create a model for estimating the technical efficiency and productivity growth of state-level R&D funding during the period 2006–2015. To this end, we created a Data Envelopment Analysis (DEA) model to determine efficiency, a Malmquist Index to calculate overall productivity increases, and a Tobit model using the DEA efficiency scores to uncover the determinants of efficiency.

The DEA model has been widely used since the early 2000s to evaluate the efficiency of multiple decision-making units (DMUs), from hotels to universities (Emrouznejad and Yang, 2018). The DEA model has many advantages, outlined in Section 2 below, but central to this paper is its ability to create an efficiency frontier from the data. This efficiency frontier is made up of efficient DMUs, as determined by the model, and can be used as a guide toward efficiency for

DMUs that are not on the efficiency frontier. The efficiency frontier, much like a production frontier, does not assume that one set of inputs and outputs is the best way to achieve efficiency; instead, it allows for many efficient combinations (Cooper et al., 2006).

In this paper, we created an output-oriented DEA model determining the efficiency of R&D funding to universities in creating business outputs. Different from what had been done in previous studies, we modeled R&D funding efficiency at the state level rather than at the academic department or university level. The state-level analysis provides new insights as it is the state economies, rather than universities themselves, that receive the benefits from the efficient transfer of R&D funding into business outputs, including startups and science and engineering graduate students. States, then, should be concerned about their universities' efficiencies as a whole and how they compare to other states with the goal of striving toward higher levels of efficiency. Our DEA model will serve to provide a new framework for R&D funding efficiency, and as we use a time frame of about ten years, historical comparisons and state comparisons will give decision makers new information about the efficiency of universities at the state level.

Additionally, though it has many sources, R&D funding comes primarily from private industry and the federal government (National Science Foundation). Any new insight into academic R&D efficiency will provide support for efficient states to prove that they can indeed turn increases in industry or federal R&D funding into business outputs. On the other hand, inefficient states apply a DEA model like the one provided below to determine how best to become efficient based on our DEA model's specified outputs.

With the knowledge that academic R&D plays a role in growing regional economies, the study of the logistics and efficiencies of R&D funding to universities will provide a foundation for understanding and improving the academic community's positive impact on the business community at the state level. Moreover, data on state-level R&D efficiencies can aid state- and federal-level decision makers as they determine which states receive federal R&D funding.

The paper is organized as follows. Section 2 discusses the background of DEA usage in various disciplines. Section 3 describes the methodology and research questions used by the models for efficiency estimates, productivity changes, and Tobit regression. The results are presented in Section 4. In Section 5, implications and limitations are discussed. Section 6 concludes the paper.

BACKGROUND

Academic R&D Overview

Academic R&D is an important determinant of GDP growth at the state level (Arik and Ndrianasy, 2018). Although total dollar amounts spent on academic R&D are important, whether the states use those academic research dollars efficiently has not received enough attention in the literature. As laid out in Table 1, Federal University R&D spending in the U.S. was around $37.9 billion in 2015, representing about 0.21 percent of the U.S. GDP, a decline from 0.25 percent in 2010. Because a significant amount of taxpayer dollars is invested in the process, an examination of the issue at the state-level rather than the university-level has important public policy implications.

Table 1: Federal University R&D

	2010	2015
Total University R&D	$61.2 billion	$68.7 billion
Total Federal University R&D	$37.5 billion	$37.9 billion
Federal University R&D as a percent of the U.S. GDP	0.25%	0.21%

Source: Authors, BEA, and National Science Foundation

DEA Literature Review

Data Envelopment Analysis (DEA) modeling is widely used to measure the relative efficiency of decision-making units (DMUs). Over the years, the number of published studies using DEA as a method of analysis has grown dramatically, as shown in Figure 1 below. The recent trend suggests that the top five heavily-focused topical areas are agriculture, banking, supply chain, transportation, and public policy (Emrouznejad and Yang, 2018).

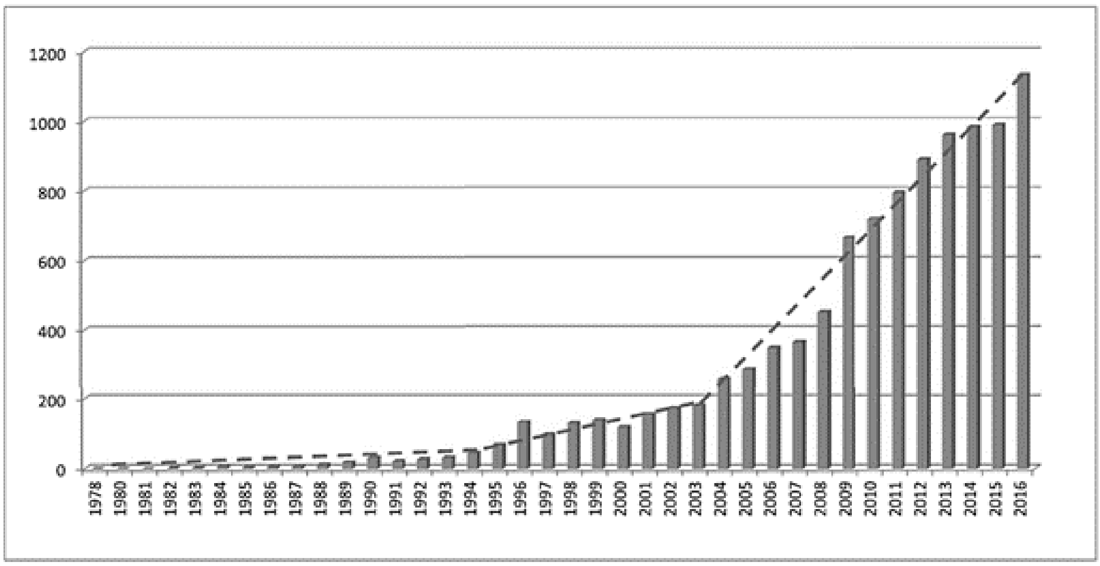


Fig. 1: Distribution of DEA-related articles by year (1978–2016). Source: Emrouznejad and Yang (2018)

A careful review of the titles of approximately 11,000 articles related to DEA reveals that a small fraction (83) of those articles deals strictly with either R&D efficiency in general or university-related efficiency measures. Among those 83 articles, only a handful are directly related to academic R&D at the state level. Table 2 breaks down the types of R&D efficiency-related DEA articles.

Table 2: R&D Efficiency-Related DEA Articles

Unit of Analysis	Number of Articles
Country	10
Country/Industry	13
Country/University	17
University-Department	4
General R&D	13
Industry R&D	13
International R&D Comparison	3
University Efficiency	10
Total	83

Source: Author's Review

DEA is a non-parametric mathematical procedure used to measure and assess the efficiency of a DMU, such as a firm or a university, when compared to other DMUs in the same category. DEA uses input and output ratio data for the DMUs to construct relative efficiency scores for all DMUs and from those scores creates an efficiency frontier. Efficiency scores range from zero (0) to one (1), with one (1) marking efficiency and all other scores marking inefficiency. DMUs on the efficiency frontier have a score of one (1), and efficient DMUs become the "benchmark" peers for the inefficient DMUs. For each inefficient DMU, based on its input-output data, at least one efficient peer DMU is calculated. That peer can be a guide toward efficiency, for example, by showing that an increase in a particular output would be the best choice. The goal of using DEA is to provide data that will show inefficient DMUs how to perform more efficiently with their available resources (Cooper et al., 2006).

"DEA has two primary advantages: It does not require a specification of either the production function form or the weights of different inputs and outputs, and it provides detailed information on the efficiency of the unit relative to specific efficient units as comparators" (Chen et al., 2011). Variations on the DEA model structure have been made, including those that re-evaluate efficient DMUs to determine if inputs can be even further decreased (Zhu, 2001) and those that use hierarchal methods to evaluate better the input-output combinations themselves (Inoue et al., 2015). DEA is widely used in areas such as manufacturing, banking, education, health care, management evaluation, and commerce.

In a broader application, DEA can be used to evaluate data in fuzzy environments. Fuzzy set theory is a method to quantify imprecise and vague data in DEA models. When compared with fuzzy linear programming, the efficiencies of DEA proved the better measurement for quantifying fuzzy data. The subsequent results of this comparison introduced the possibility for using a new α-level based approach and a numerical method for ranking DMUs with fuzzy data (Raeinojehdehi and Valami, 2016). In a fuzzy environment, different decision makers have different attitudes toward which inputs they want to evaluate. The significance of using a fuzzy number is that the decision-makers can make decisions based on their own preferences and in real-world situations. DEA evaluations make it possible for decision-makers to use the information they select (Chen and Wang, 2016; Liu, 2011).

DEA has been successfully used in many studies in the following ways:

Industry

In the travel industry, DEA has been used to evaluate the efficiency of hotels (Lei and Liu, 2018), airliners (Pisarek and Zoltaszek, 2016), and cruise ships (Demirer et al., 2017). A common finding in these studies is that increasing the size of the DMU often does *not* translate to increased efficiency.

In health care, nonprofits such as the Red Cross, large health care systems, and individual hospitals have been evaluated using DEA to determine inefficiencies (Rauner and Sommersguter-Reichmann, 2015; Abeney and Yu, 2015; Chen et al., 2011). In the insurance industry, DEA provided insight into microinsurance, showing that due to the wide variety of program performance, a comprehensive "best practice" benchmark is needed (Biener and Eling, 2011).

In the banking and finance industries, DEA has been used to determine institutional efficiencies in banking in Nigeria (Avinde, 2017), to help managers monitor exchange and interest rates (Zakaria, 2017), and to show that the overall efficiency scores of IPO firms are dismal (Anjum and Sohail, 2016).

Despite their complexity, DEA has also been used to pinpoint inefficiencies in supply chains (Chern and Chou, 2016) and to determine efficiencies in areas lacking research attention, such as sports sponsorships (Bijmolt et al., 2016). DEA has been validated as an appropriate method for "identify[ing] efficient discrete-event simulation software" (Lall and Moreno, 2011) and has even been used to formulate a new method for calculating the human development index (Eren et al., 2017).

Academic Institutions

DEA has the ability to rank overall measure of quality, an important measure for higher education, and the DEA method has been validated in many papers as suitable for the assessment of higher education institutions (Bougnol and Dulá, 2006; Johnes, 2006). In many studies and in various countries, DEA is used to determine the efficiency scores of academic institutions with multiple specifications. Among country-level studies are those in South Africa (Taylor and Harris, 2004), the Czech Republic (Mikusova, 2015), England (Bradley et al., 2010; Thanassoulis et al., 2011), Canada (Datta and McMillan, 1998), Turkey (Bursalioglu and Selim, 2013), France (Barros et al., 2011), and Europe as a region (Veiderpass and Mckelvey, 2016).

Some additional applications of DEA in institutions of higher education include determining "best buy" universities (Eff et al., 2012), "improving estimates of per-student education costs" (Salerno, 2006), evaluating a country's "perceived" top universities and liberal arts colleges (Breu and Raab, 1994; Eckles, 2010), evaluating a country's top business schools (Palocsay and Wood, 2014), and determining efficiencies of specific academic departments (Cimpoies et al., 2016; Dogan et al., 2014; Duguleana and Duguleana, 2015). A common theme among these studies is providing a scientific method for ranking institutions rather than relying solely on subjective or survey rankings.

Academic R&D

In addition to DEA studies that focus on higher education institutions themselves, DEA has also been used to determine the efficiency of those institutions' outputs, namely R&D outputs. DEA has been verified as an appropriate tool for quantifying research efficiency in academia, identifying benchmarks, and contrasting research efficiency with other traditional rankings (Korhonen et al., 2011; Munoz, 2016). As with studies of academic institutions, DEA-based academic R&D efficiency analyses involve many specifications. Among country-level studies published are a Taiwanese study of team communication and its relevance to academic R&D efficiency (Hung et al., 2013), several Chinese investigations into general research performance (Chuanyi et al., 2016; Johnes and Yu, 2008; Ng and Li, 2000), a study of "efficiency and technological change" for U.S. universities (Barham et al., 2011), and one in Malaysia examining measures for "knowledge management performance" (Kuah and Wong, 2013).

Other regional or multi-country studies have been realized as researchers attempt to uncover different facets of academic R&D efficiency by changing the scope of their analysis. These include studies of a single Italian region (Agasisti et al., 2011), of incoming European Union (EU) member states (Aristovnik, 2012), and of the higher education systems of the Organization for Economic Co-operation and Development (OECD) countries (Bayenet and Debande, 1999). In the same way, the current study aims to provide information on U.S. state-level academic R&D efficiency, a facet that has not yet been given intense research attention.

Research and Development (R&D)

In fields and institutions heavily involved in R&D activities, evaluating the outputs of R&D funding is crucial. As is the case for academic R&D, DEA has been used frequently to evaluate the efficiency of non-academic R&D institutions as well, on many levels and with various goals. DEA has been broadly proven to be a suitable method for evaluating R&D activities across multiple research subjects (Dilts et al., 2015; Lee et al., 2011; Li et al., 2014; Sengupta, 1999; Sharma and Thomas, 2008; Wang and Huang, 2007). National R&D investment efficiency and effectiveness have been evaluated using DEA (Jiménez-Sáez et al., 2011; Lee et al., 2009; Shi and Yang, 2008). As R&D is often funded wholly or in part by government agencies, the need to assess the efficient use of public funds has led to many DEA-based studies on government-subsidized R&D efficiency (Hsu and Hsueh, 2009; Lee and Lee, 2015; Park, 2015). Additionally, how the efficiencies of both parties are affected by the partnership between the public and private R&D sectors has been studied using DEA (Revilla et al., 2007). DEA has also been used to create "guidelines" for R&D policy-makers by addressing the question: "Who leads productivity growth?" (Jiménez-Sáez et al., 2013).

DEA has been used in many regional- and provincial-level studies to determine R&D efficiency, such as those looking at regional investments (Zhong et al., 2011), the "transformation of knowledge-based economies" (Afzal and Lawrey, 2014), regional technical efficiency (Bergantino et al., 2013), and "production frontier performance" at the province level (Guan and Chen, 2010). R&D efficiency has been examined using DEA on the institutional level as well, in a study of "scope economies" at U.S. research universities (Chavas et al., 2012) and a study of the growth involved with scientific R&D institutes in China (Meng and Wang, 2014).

R&D efficiency has been evaluated on the industry level using DEA in such industries as pharmaceuticals (Hashimoto and Haneda, 2008), information technology (Sueyoshi and Goto, 2013), and manufacturing (Dočekalová and Bočková, 2013). DEA has been used to evaluate the "returns to growth" for technology-based firms "facing hyper-competition" (Sahoo et al., 2011). DEA has similarly played a part in determining efficiencies in agricultural research on the country-level (Gomes et al., 2011; Hartwich and von Oppen, 2006), within a single region (Rehber and Tipi, 2006), and between firms (Oztop and Ucak, 2017). DEA has been used to determine the impact of barriers to entry on R&D efficiency (Cullmann et al., 2012) and to solve "target-setting difficulties" through "technology forecasting" (Anderson et al., 2012). DEA has likewise been applied to determine the efficiency of networks in "evaluating the R&D linking efficiency of innovation ecosystems" (Chen and Hung, 2016).

As shown by these and other previous studies, DEA calculations are useful in identifying efficiencies that can affect the performance of an organization. These efficiency findings can reveal potential areas of improvement that decision-makers can use to reduce risk and better their organization. The current analysis uses DEA to determine state-level efficiency of academic R&D funding in providing desirable business outputs.

METHODOLOGY

Research Questions

Federal funding represents a large portion of total funding for R&D at government and academic institutions alike. Academic institutions that receive federal funding for R&D programs are often closely examined to determine their ability to produce desired outputs. In this study, we follow this vein of the investigation, with the additional emphasis on whether R&D at academic institutions on the state-level is *efficient* in creating the desired outputs.

Research Question 1: *Are states efficient in converting taxpayer dollars into business outputs?*

Next, we further look into the historical state-level academic R&D efficiency levels and their components to discover whether and how they have changed.

Research Question 2: *How has the productivity of academic R&D at the state level changed over time?*

Lastly, we delve into the environmental factors that contribute to R&D efficiencies and attempt to learn whether those states with efficient academic R&D share similar environmental characteristics.

Research Question 3: *What are the determinants of the efficiency of academic R&D?*

Efficiency Estimates

To determine whether states are efficient in converting taxpayer dollars into business outputs, we use an output-oriented DEA model to create efficiency estimates. We use the model below, as specified by Cooper et al. (2006):

$$\begin{aligned} &\mathrm{Max}_{\emptyset,\lambda}\ \emptyset, \\ &\mathrm{st} \quad -\emptyset y_i + Y\lambda \geq 0, \\ &\qquad x_i - X\lambda \geq 0, \\ &\qquad \mathrm{N1'}\lambda=1 \\ &\qquad \lambda \geq \theta, \end{aligned}$$

To estimate the maximum efficiency of R&D, represented by $\mathrm{Max}_{\emptyset,\lambda}\,\emptyset$,, the output-oriented, variable returns to scale (VRS) model is used where 1≤Ø≤∞ and Ø-1 indicate the proportional increase in outputs that could be achieved for the i-th firm with input quantities held constant. The output-oriented nature of the model tests to what level inputs y can be reduced without changing the quantity of outputs x. Yλ and Xλ represent the efficiency reference set for the corresponding variables. The constraint, N1'λ=1, accounts for differences in whether or not firms are operating at an optimal scale. The projected point of each institution can then be benchmarked against others, where the DEA frontier is a convex combination rather than a linear one. Thus, the output-oriented model offers insight into the measurement of technical inefficiency as a proportional increase in output production for firms with a fixed quantity of resources. This provides for an accurate evaluation of relative efficiency that takes into account both technical and scale efficiencies.

Productivity Change

To observe changes in state-level academic R&D productivity over time, we use an output-based Malmquist Index and decompose the overall total factor productivity (TFP) results into categories such as scale efficiency and technical efficiency as in Orea (2002).

$$m_o(y_{t+1}, x_{t+1}, y_t, x_t) = \left[\frac{d_o^t(x_{t+1}, y_{t+1})}{d_o^t(y_t, x_t)} \times \frac{d_o^{t+1}(x_{t+1}, y_{t+1})}{d_o^{t+1}(y_t, x_t)}\right]^{1/2}$$

The output-based Malmquist TFP Index measure was used to determine the productivity change index when *x* and *y*, again, represent outputs and inputs, respectively. The model represents the productivity of the production point (x_{t+1}, y_{t+1}) relative to the production point (y_t, x_t). A value greater than one (1) indicates positive TFP growth from period *t* to period *t*+1. The index is the geometric mean of two output-based Malmquist TFP indices. One of these indexes uses period *t* technology and the other period *t*+1 technology. This is determined based on the four linear programming problems that calculate each of the component distance functions; $d_o^t(x_{t+1}, y_{t+1})$, $d_o^t(y_t, x_t)$, $d_o^{t+1}(x_{t+1}, y_{t+1})$, $d_o^{t+1}(y_t, x_t)$. Each linear programming equation was calculated for each DMU for every time period measured.

Tobit Model

To address any environmental factors that could affect the efficiency of a firm, we used Stata software to run a second stage Tobit regression. This captures the effects of influences from environmental factors such as R&D intensity, state-level GDP, or the state's R&D-related startups. Unlike a traditional OLS regression model, the Tobit model, or censored regression model, estimates linear relationships between variables with left- or right- censoring in the dependent variable and is able to account for truncated data. It also served to identify and counteract any biases resulting from our first methodological step, the DEA model, which gives an efficiency score that is both left- and right-censored (bounded between zero (0) and one (1)). In this stage, the efficiency scores from the first analysis are regressed on the chosen environmental variables. The signs of the coefficients of these variables indicate the direction of the influences. The Tobit model then uses the regression's estimated coefficients and their random errors to adjust efficiency scores for censor-based bias. This helps to address both continuous and categorical variables affecting the outcomes of the efficiency tests.

Data

Data comes from the Association of University Technology Managers (AUTM) surveys, the National Science Foundation (NSF), the Bureau of Economic Analysis (BEA), and the National Center for Educational Statistics (NCES).

The DEA model's two input variables are (1) real university R&D (in 2009 dollars) and (2) total faculty and science and engineering (S&E) research staff (in number of persons). The seven output variables are (1) total patents, (2) total licenses, (3) total startups, (4) doctorate degrees, (5) master's degrees, (6) S&E graduate students, and (7) S&E postdocs. Table 3 reports the correlations between the DEA model variables. Though the variables exhibit signs of strong correlations, the DEA model's nonparametric specification alleviates estimation bias due to multicollinearity, unlike the bias seen in linear models (Akazili et al., 2008).

Table 3: Correlations Between Model Variables

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Output									
[1] All Patents (AUTM)	1								
[2] Licenses Issued (AUTM)	0.63	1							
[3] Startups Formed (AUTM)	0.87	0.84	1						
[4] Doctorate Degrees (NCES)	0.78	0.81	0.94	1					
[5] Master's Degrees (NCES)	0.75	0.80	0.92	0.98	1				
[6] S&E Grad Students (NCES)	0.85	0.76	0.95	0.97	0.95	1			
[7] S&E Postdocs (NCES)	0.84	0.76	0.92	0.85	0.84	0.89	1		
Input									
[8] Total R&D University Expenditures (2009)	0.84	0.80	0.95	0.93	0.92	0.97	0.92	1	
[9] Faculty and SE Non-Faculty Research Staff	0.80	0.80	0.94	0.97	0.95	0.98	0.85	0.96	1

Estimation Method

This study used Multi-stage Data Envelopment Analysis (DEA), Malmquist Productivity Index, and Tobit Model to estimate (a) relative efficiency of each state; (b) changes in efficiency measures by state; (c) projected (target) output values to reach efficiency level; (d) peer state DMUs for Tennessee, as an example; (e) productivity change over the years studies; and (f) determinants of relative efficiency.

This study utilized an output-oriented approach: given the input level, how much of an increase in outputs can be made to increase efficiency.

RESULTS

Efficiency Results

Table 4: Key Terms

Output-oriented model	This model is used to test whether a decision-making unit (DMU) can increase its output while keeping the input fixed
Constant Returns to Scale (CRS)	Changes in inputs and outputs are proportional
Variable Returns to Scale (VRS)	Production technology may be increasing, constant, or decreasing in terms of returns to scale
Technical Efficiency (TE)-Constant Returns to Scale (CRS)	Ability of a DMU to get the maximum output given the input levels under the VRS technology
Technical Efficiency (TE)-Variable Returns to Scale (CRS)	Ability of a DMU to get the maximum output given the input levels under the CRS technology
Scale Efficiency (TE-CRS/TE-VRS)	The component of technical efficiency associated with the scale of operation

Table 4 provides definitions for the key terms used in the DEA output tables. For purposes of this paper, the relative efficiency score used is the variable returns to scale technical efficiency (TE-VRS). This category is shaded in Table 5, which shows the states ranked by TE-VRS score for the years 2006, 2009, 2011, and 2015. These years were chosen for the study to account for the impact of the 2007-2009 major recession, where the year 2006 represents "before," the year 2009 represents "during," and the year 2011 represents "after." The year 2015 is included as it was the last year the data were available.

Table 5 provides annual efficiency scores of all states in the four years covered in this study. In 2006, as seen on the table, only 12 states in the U.S. were operating efficiently in terms of maximizing the academic outputs given the amount of R&D spending and academic employment (shown by the box around all TE-VRS that equal one (1)). As has been mentioned, technical efficiency that allows variable returns to scale (VRS) is the measure of pure efficiency. A score of one (1) is deemed efficient, and any score of less than one (1) is efficiency-deficient. The rankings indicate how a state compares to the rest in terms of pure efficiency. Interestingly, efficient states show constant or increasing returns to scale. The inefficient states (except Georgia and Wisconsin) show decreasing returns. For example, Tennessee (in bold) ranked 28th in terms of pure efficiency and shows decreasing returns to scale.

The 2009 column of Table 5 shows that in that year 15 states were operating efficiently in terms of maximizing the academic outputs given the amount of R&D spending and academic employment. Though the number of the efficient states increased from 2006, more efficient states showed decreasing returns to scale in 2009 than in 2006. Given the efficiency scores shown in Table 5, we can see that states often maintain their place in the ranking over time, usually only moving a few places up or down. For example, Tennessee ranked 28th in pure efficiency in 2006 and moved to 31st in 2009. South Carolina is an example of a large decrease in efficiency, moving from 25th in 2006 to 38th in 2009. Studying the efficiency scores for a longer time frame would shed more light onto the patterns of change in state R&D efficiency.

Table 5: Annual Efficiency Scores, 2006-2015

2006

State	TE (CRS)	TE (VRS)	Rank (VRS)	SE	Return to Scale
CA	1.000	1.000	1	1.000	-
FL	1.000	1.000	1	1.000	-
IL	1.000	1.000	1	1.000	-
MA	1.000	1.000	1	1.000	-
MI	1.000	1.000	1	1.000	-
NC	0.834	1.000	1	0.834	irs
NE	0.355	1.000	1	0.355	irs
NJ	1.000	1.000	1	1.000	-
NY	1.000	1.000	1	1.000	-
OH	1.000	1.000	1	1.000	-
VA	1.000	1.000	1	1.000	-
WA	1.000	1.000	1	1.000	-
TX	0.905	0.959	13	0.943	drs
PA	0.833	0.955	14	0.872	drs
GA	0.726	0.877	15	0.828	irs
WI	0.765	0.870	16	0.879	irs
AZ	0.015	0.465	17	0.032	drs
UT	0.035	0.419	18	0.083	drs
MD	0.367	0.418	19	0.876	drs
IA	0.031	0.389	20	0.079	drs
MN	0.023	0.346	21	0.068	drs
IN	0.020	0.298	22	0.067	drs
MO	0.011	0.292	23	0.036	drs
CO	0.028	0.266	24	0.106	drs
SC	0.050	0.260	25	0.192	drs
CT	0.062	0.251	26	0.246	drs
OR	0.039	0.251	26	0.156	drs
TN	**0.053**	**0.246**	**28**	**0.217**	**drs**
DC	0.014	0.232	29	0.060	drs
ID	0.044	0.188	30	0.234	drs
AL	0.019	0.161	31	0.116	drs
NM	0.045	0.158	32	0.286	drs
LA	0.008	0.148	33	0.052	drs
ND	0.024	0.127	34	0.186	drs
KY	0.010	0.126	35	0.082	drs
KS	0.007	0.107	36	0.065	drs
OK	0.005	0.106	37	0.049	drs
HI	0.019	0.085	38	0.225	drs
MT	0.005	0.077	39	0.064	drs
MS	0.005	0.068	40	0.068	drs
DE	0.065	0.066	41	0.997	-
NH	0.010	0.063	42	0.153	drs
AR	0.003	0.055	43	0.049	drs
WV	0.003	0.050	44	0.067	drs
RI	0.002	0.043	45	0.039	drs
NV	0.004	0.040	46	0.094	drs
VT	0.007	0.038	47	0.180	drs
ME	0.003	0.026	48	0.129	drs
SD	0.012	0.024	49	0.481	drs
AK	0.001	0.014	50	0.061	drs
Average	0.309	0.431		0.412	

2009

State	TE (CRS)	TE (VRS)	Rank (VRS)	SE	Return to Scale
AZ	0.220	1.000	1	0.220	drs
CA	1.000	1.000	1	1.000	-
CO	0.936	1.000	1	0.936	irs
FL	1.000	1.000	1	1.000	-
IL	1.000	1.000	1	1.000	-
IN	1.000	1.000	1	1.000	-
MA	1.000	1.000	1	1.000	-
MD	0.756	1.000	1	0.756	drs
MI	1.000	1.000	1	1.000	-
MO	1.000	1.000	1	1.000	-
NY	0.901	1.000	1	0.901	drs
OH	1.000	1.000	1	1.000	-
TX	0.786	1.000	1	0.786	drs
VA	1.000	1.000	1	1.000	-
WA	1.000	1.000	1	1.000	-
PA	0.796	0.977	16	0.814	drs
GA	0.830	0.960	17	0.865	irs
NC	0.723	0.925	18	0.781	drs
WI	0.638	0.778	19	0.819	irs
UT	0.022	0.393	21	0.055	drs
MN	0.016	0.328	22	0.049	drs
NJ	0.016	0.314	23	0.050	drs
KY	0.018	0.289	24	0.062	drs
OR	0.014	0.253	25	0.054	drs
IA	0.009	0.235	26	0.038	drs
VT	0.090	0.229	27	0.392	drs
DC	0.007	0.214	28	0.034	drs
ND	0.007	0.214	28	0.034	drs
NV	0.096	0.212	30	0.455	drs
TN	**0.005**	**0.206**	**31**	**0.023**	**drs**
AL	0.004	0.172	32	0.024	drs
CT	0.010	0.154	33	0.068	drs
AR	0.006	0.136	34	0.041	drs
LA	0.003	0.135	35	0.025	drs
NM	0.008	0.114	36	0.067	drs
KS	0.009	0.111	37	0.084	drs
OK	0.003	0.098	38	0.029	drs
SC	0.004	0.098	38	0.045	drs
NE	0.003	0.083	40	0.040	drs
MS	0.002	0.068	41	0.030	drs
ME	0.004	0.067	42	0.054	drs
WV	0.003	0.065	43	0.052	drs
MT	0.002	0.055	44	0.036	drs
NH	0.008	0.050	45	0.166	drs
ID	0.007	0.046	46	0.151	drs
RI	0.005	0.046	46	0.105	drs
HI	0.004	0.045	48	0.089	drs
SD	0.003	0.045	48	0.062	drs
DE	0.002	0.036	50	0.056	drs
AK	0.001	0.016	51	0.057	drs
Average	0.340	0.463		0.388	

2011

State	TE (CRS)	TE (VRS)	Rank (VRS)	SE	Return to Scale
CA	1.000	1.000	1	1.000	-
CO	0.880	1.000	1	0.880	irs
FL	1.000	1.000	1	1.000	-
GA	0.989	1.000	1	0.989	irs
IL	1.000	1.000	1	1.000	-
MA	1.000	1.000	1	1.000	-
MO	1.000	1.000	1	1.000	-
NJ	1.000	1.000	1	1.000	-
NV	0.829	1.000	1	0.829	irs
NY	1.000	1.000	1	1.000	-
PA	1.000	1.000	1	1.000	-
TX	0.886	1.000	1	0.886	drs
VA	1.000	1.000	1	1.000	-
WA	1.000	1.000	1	1.000	-
IN	0.827	0.972	15	0.850	irs
AZ	0.872	0.904	16	0.965	irs
MI	0.884	0.887	17	0.996	irs
OH	0.834	0.844	18	0.988	drs
NC	0.772	0.779	19	0.991	drs
WI	0.673	0.760	20	0.886	irs
MD	0.562	0.563	21	0.998	irs
MN	0.082	0.359	22	0.229	drs
UT	0.065	0.313	23	0.209	drs
OR	0.077	0.309	24	0.250	drs
AL	0.143	0.252	25	0.569	drs
CT	0.118	0.243	26	0.487	drs
DC	0.125	0.237	27	0.528	drs
IA	0.120	0.213	28	0.561	drs
ND	0.046	0.206	29	0.224	drs
TN	**0.049**	**0.183**	**30**	**0.266**	**drs**
KS	0.169	0.174	31	0.973	drs
LA	0.032	0.139	32	0.234	drs
VT	0.127	0.129	33	0.986	irs
ID	0.107	0.122	34	0.880	drs
KY	0.022	0.121	35	0.180	drs
ME	0.038	0.113	36	0.339	drs
OK	0.017	0.096	37	0.180	drs
SC	0.022	0.095	38	0.233	drs
MS	0.050	0.089	39	0.555	drs
AR	0.081	0.087	40	0.939	drs
NE	0.019	0.086	41	0.225	drs
WV	0.013	0.084	42	0.149	drs
NM	0.015	0.072	43	0.206	drs
MT	0.029	0.060	44	0.474	drs
RI	0.024	0.051	45	0.475	drs
NH	0.017	0.050	46	0.346	drs
HI	0.028	0.046	47	0.601	drs
DE	0.021	0.039	48	0.555	drs
SD	0.006	0.023	49	0.284	drs
AK	0.004	0.018	50	0.217	drs
Average	0.414	0.474		0.652	

2015

State	TE (CRS)	TE (VRS)	Rank (VRS)	SE	Return to Scale
CA	1.000	1.000	1	1.000	-
CO	0.964	1.000	1	0.964	irs
CT	0.603	1.000	1	0.603	irs
FL	1.000	1.000	1	1.000	-
IL	1.000	1.000	1	1.000	-
IN	1.000	1.000	1	1.000	-
MA	1.000	1.000	1	1.000	-
MI	1.000	1.000	1	1.000	-
NJ	1.000	1.000	1	1.000	-
NY	0.934	1.000	1	0.934	drs
OH	1.000	1.000	1	1.000	-
PA	1.000	1.000	1	1.000	-
TX	0.827	1.000	1	0.827	drs
VA	1.000	1.000	1	1.000	-
WA	1.000	1.000	1	1.000	-
GA	0.873	0.956	16	0.913	irs
NC	0.706	0.758	17	0.931	drs
MN	0.075	0.717	18	0.105	drs
WI	0.633	0.703	19	0.900	irs
AZ	0.145	0.579	20	0.250	drs
OR	0.133	0.528	21	0.252	drs
MD	0.463	0.496	22	0.934	drs
MO	0.068	0.372	23	0.182	drs
TN	**0.356**	**0.362**	**24**	**0.984**	**drs**
NH	0.032	0.301	25	0.106	drs
UT	0.086	0.287	26	0.298	drs
IA	0.021	0.265	27	0.081	drs
ME	0.057	0.227	28	0.253	drs
DC	0.028	0.185	29	0.150	drs
KY	0.035	0.174	30	0.204	drs
AL	0.025	0.173	31	0.146	drs
ND	0.022	0.161	32	0.134	drs
WV	0.071	0.158	33	0.448	drs
LA	0.019	0.142	34	0.136	drs
NE	0.039	0.131	35	0.297	drs
KS	0.020	0.120	36	0.163	drs
ID	0.034	0.108	37	0.315	drs
SC	0.020	0.106	38	0.186	drs
NM	0.018	0.095	39	0.193	drs
OK	0.014	0.092	40	0.150	drs
AR	0.014	0.080	41	0.169	drs
MS	0.014	0.078	42	0.176	drs
RI	0.045	0.076	43	0.593	drs
NV	0.019	0.066	44	0.287	drs
DE	0.017	0.063	45	0.277	drs
MT	0.009	0.046	46	0.200	drs
VT	0.012	0.038	47	0.316	drs
HI	0.008	0.035	48	0.237	drs
SD	0.004	0.027	49	0.145	drs
AK	0.004	0.019	50	0.233	drs
Average	0.369	0.474		0.513	

Note: TE (CRS) stands for technical efficiency with constant returns to scale, TE (VRS) stannds for technical efficiency with variable returns to scale, and SE stands for scale efficiency

For returns to scale: irs= increasing returns to scale
drs= decreasing returns to scale
- = constant returns to scale

In 2011, 14 states were operating efficiently in terms of maximizing the academic outputs given the amount of R&D spending and academic employment, though the number of efficient states with increasing and constant returns to scale returned to what it had been in 2006. More non-efficient states showed increasing returns to scale as well. The increasing returns to scale showed that inefficient states seemed to be striving toward efficiency. Again, overall states moved only slightly in terms of pure efficiency ranking. For example, Tennessee ranked 30th for pure efficiency in 2011 (28th in 2006 and 31st in 2009).

In 2015, 15 states were operating efficiently in terms of maximizing the academic outputs given the amount of R&D spending and academic employment, and fewer of the non-efficient states had increasing returns to scale compared to 2011. Tennessee ranked 24th in terms of pure efficiency.

The DEA state-level R&D efficiency scores for the four years presented above show that states which comprise the efficiency frontier have generally remained efficient throughout the years of this study. This result is not surprising. It makes sense that it is more likely for an efficient state to remain efficient over a few years' time than for an inefficient state to become efficient in the same amount of time.

Tennessee and Neighboring States as a Case Study

Examining the historical scores of geographical neighbors can be another way for states to benchmark and measure their R&D efficiency as characteristics of universities show geographical clustering. In this case study, we used Tennessee and its neighboring states as an example. Tennessee's scores and its peers' scores are detailed in Table 6. Among Tennessee's neighboring states, Florida, North Carolina, Virginia, and Georgia have scored consistently either on or near the efficiency frontier in the years of the study, while Tennessee's efficiency scores have been consistently below the 50-state average. This suggests that these neighboring states' universities have some sort of institutional advantage over the universities in Tennessee, whether this be the number of R&D-focused institutions or the intensity of the R&D focus in those institutions. By this comparison, one can see that Tennessee ranks in the middle of this Southeast state cluster. However, geography might not be the best criterion for comparison, as the ranks and efficiency scores fail to delve into the reasons for state efficiency. To find more appropriate comparisons, we return to the DEA model.

Table 6: Academic R&D Efficiency: Tennessee vs. Its neighbors

	2006		2009		2011		2015	
	TE-CRS	TE-VRS	TE-CRS	TE-VRS	TE-CRS	TE-VRS	TE-CRS	TE-VRS
Florida	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Virginia	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
North Carolina	0.834	1.000	0.723	0.925	0.772	0.779	0.706	0.758
Georgia	0.726	0.877	0.830	0.960	0.989	1.000	0.873	0.956
South Carolina	0.050	0.260	0.004	0.098	0.022	0.095	0.020	0.106
Tennessee	**0.053**	**0.246**	**0.005**	**0.206**	**0.049**	**0.183**	**0.356**	**0.362**
Alabama	0.019	0.161	0.004	0.172	0.143	0.252	0.025	0.173
Kentucky	0.010	0.126	0.018	0.289	0.022	0.121	0.035	0.174
Mississippi	0.005	0.068	0.002	0.068	0.050	0.089	0.014	0.078
Average	0.309	0.431	0.340	0.463	0.414	0.474	0.369	0.474

Note: States are sorted from highest TE-VRS in 2006 to lowest. TE-CRS is Technical Efficiency-Constant Returns to Scale; TE-VRS is Technical Efficiency-Variable Returns to Scale.

The DEA model itself formulates a unique set of efficient "peer" states for each inefficient state. These peer states provide information about options to achieve efficiency for the inefficient states. The DEA model accomplishes this through "slacks." The slacks are model-determined variables that, when changed, could result in the state becoming efficient. Using the slack information in combination with the input-output ratios for each state, the model matches an inefficient state with peers, those that have a similar input-output structure.

The DEA model creates slacks to show what variables a state could change to become efficient. For Tennessee to be efficient given the level of academic R&D input and staff for 2015, it may be able to increase S&E postdocs, S&E graduate students, and patents. Table 7 shows the original value and the slacks for Tennessee's outputs. For example, in 2015, the state had large output slacks in patents, meaning that these are the outputs that are leading to Tennessee's inefficiency.

Table 7: Academic R&D Efficiency: What It woud take for Tennessee to be efficient?

	2006		2009		2011		2015	
Output	Original Value	Slacks	Original Value	Slacks	Original Value	Slacks	Original Value	Slacks
[1] All Patents (AUTM)	669	2,468	647	11,467	969	14,827	1,009	1,087
[2] Licenses Issued (AUTM)	86	0	80	0	74	15	122	39
[3] Startups Formed (AUTM)	8	19	3	57	0	0	14	20
[4] Doctorate Degrees (NCES)	2,354	0	2,503	1,174	2,989	0	3,679	0
[5] Master's Degrees (NCES)	9,047	4,182	10,144	0	11,099	6,357	11,839	3,951
[6] S&E Grad Students (NCES)	8,051	5,535	8,075	19,415	8,167	21,000	8,204	7,509
[7] S&E Postdocs (NCES)	763	2,752	801	4,990	1,098	1,824	909	119

Peers are determined by the DEA model as the efficient states that have input-output ratios which best fit a target state's original and slack values. Based on the 2015 efficiency assessment, Pennsylvania and California are Tennessee's aspirational peers in terms of the input-output ratios. In Table 8, notice that the slacks for each of these efficient peer states are zero (0), meaning the model can find no way for them to improve. The DEA model assumes that there exist more than one path to attain efficiency; instead, the model creates a "frontier" of efficiency possibilities.

Table 8: Academic R&D Efficiency for Tennessee and Its Peers (2015)

	Tennessee		Pennsylvania		California	
Output	Original Value	Slacks	Original Value	Slacks	Original Value	Slacks
[1] All Patents (AUTM)	1,009	1,087	3,825	0	40,196	0
[2] Licenses Issued (AUTM)	122	39	376	0	464	0
[3] Startups Formed (AUTM)	14	20	59	0	149	0
[4] Doctorate Degrees (NCES)	3,679	0	10,158	0	18,296	0
[5] Master's Degrees (NCES)	11,839	3,951	36,628	0	70,761	0
[6] S&E Grad Students (NCES)	8,204	7,509	30,111	0	83,680	0
[7] S&E Postdocs (NCES)	909	119	2,620	0	10,601	0
Input						
[8] Total R&D University Expenditures (2009)	959,057,450		3,056,045,054		7,767,003,691	
[9] Faculty and SE Non-Faculty Research Staff	12770		32521		63186	

This efficiency frontier is similar to a production possibilities frontier. A production frontier shows the combination of production outputs that are possible for a firm given inputs and costs, while the output-oriented efficiency frontier shows the different combinations of outputs that can be considered efficient. It follows, therefore, that one state could have more patents and fewer startups than another efficient state while still being on the "frontier" of efficiency.

Productivity Change

Following the Malmquist Index methodology outlined previously, we created two tables breaking down the efficiency (or productivity) change over time. The first table (Table 9) shows averages of productivity changes between the time periods used in the present study as well as the separated factors of the total changes. The second table (Table 10) shows state averages for productivity changes over the entire span from 2006 to 2015.

Overall, since 2006, states experienced the greatest change in efficiency in the period 2009-2011, as shown in Table 9. This efficiency change was driven by a large increase in scale efficiency. Increasing returns to scale was highlighted previously in the discussion of the DEA output for 2011. Additionally, pure technical efficiency was on the increase in all three periods.

Table 9: Malmquist Index Summary of Annual Means

Year	Efficiency Change (Effch)	Technical Efficiency Change (Techch)	Pure Technical Efficiency Change (Pech)	Scale Efficiency Change (Sech)	Total Factor Productivity Change (Tfpch)
2006/2009	0.789	**1.379**	**1.073**	0.735	**1.087**
2009/2011	**3.536**	0.293	**1.045**	**3.385**	**1.036**
2011/2015	0.706	**1.523**	**1.028**	0.686	**1.075**
Average	**1.253**	0.850	**1.049**	**1.195**	**1.066**

Note: Efficiency change larger than 1 (e>1) = increasing productivity, Efficiency change less than 1 (e<1) = decreasing productivity, Efficiency change equal to 1 (e=1) = no change in productivity

Technical and scale efficiency seem to be opposite in terms of increasing and decreasing productivity, meaning that when technical efficiency increases in productivity, scale efficiency decreases in productivity.

Examining changes in efficiency provides a case for encouraging productivity growth even in states that are not efficient. These results provide a clearer insight into states' efficient use of R&D funding. For example, in the DEA results above, Tennessee's ranking varies from 24th to 31st in the nation in terms of R&D efficiency. However, by the Malmquist Index results shown in Table 9, Tennessee ranks 6th among U.S. states in terms of productivity gains between 2006 and 2015. In Table 10, shaded cells represent efficiency scores of one (1) or above. Therefore, while Tennessee is average among the states in terms of institutional R&D efficiency, its productivity changes show the state is indeed above average among the states in improving efficiency.

Table 10: Malmquist Productivty Index: Summary of State Averages (2006-2015)

State	Efficiency Change (Effch)	Technical Efficiency Change (Techch)	Pure Technical Efficiency Change (Pech)	Scale Efficiency Change (Sech)	Total Factor Productivity Change (Tfpch)	Tfpch Rank	State	Efficiency Change (Effch)	Technical Efficiency Change (Techch)	Pure Technical Efficiency Change (Pech)	Scale Efficiency Change (Sech)	Total Factor Productivity Change (Tfpch)	Tfpch Rank
AK	1.732	0.653	1.105	1.568	1.131	19	MS	1.437	0.726	1.047	1.372	1.043	25
AL	1.105	0.696	1.023	1.081	0.769	43	MT	1.226	0.981	0.841	1.458	1.203	15
AR	1.711	0.756	1.134	1.509	1.294	11	NC	0.946	0.967	0.912	1.038	0.915	38
AZ	2.140	0.658	1.075	1.990	1.409	9	ND	0.972	0.965	1.084	0.897	0.939	35
CA	1.000	1.058	1.000	1.000	1.058	22	NE	0.479	0.817	0.508	0.942	0.391	50
CO	3.240	1.031	1.554	2.085	3.339	2	NH	1.494	0.775	1.686	0.886	1.157	17
CT	2.136	0.674	1.586	1.347	1.440	8	NJ	1.000	0.912	1.000	1.000	0.912	39
DC	1.261	0.695	0.927	1.360	0.876	40	NM	0.740	0.867	0.843	0.878	0.642	45
DE	0.643	0.719	0.985	0.653	0.462	49	NV	1.723	0.687	1.187	1.451	1.183	16
FL	1.000	1.051	1.000	1.000	1.051	23	NY	0.977	0.949	1.000	0.977	0.927	37
GA	1.064	1.056	1.029	1.033	1.123	20	OH	1.000	1.069	1.000	1.000	1.069	21
HI	0.759	0.819	0.746	1.017	0.621	47	OK	1.388	0.733	0.955	1.454	1.018	26
IA	0.886	0.918	0.880	1.007	0.813	42	OR	1.502	0.863	1.281	1.173	1.296	10
ID	0.918	0.694	0.831	1.105	0.637	46	PA	1.063	1.181	1.015	1.047	1.256	12
IL	1.000	0.999	1.000	1.000	0.999	27	RI	3.010	0.669	1.211	2.485	2.014	4
IN	3.695	1.044	1.498	2.467	3.859	1	SC	0.734	0.918	0.742	0.989	0.674	44
KS	1.413	0.691	1.040	1.359	0.977	32	SD	0.695	0.708	1.037	0.670	0.492	48
KY	1.509	0.754	1.113	1.355	1.137	18	**TN**	**1.884**	**0.906**	**1.138**	**1.656**	**1.707**	**6**
LA	1.362	0.730	0.986	1.381	0.994	28	TX	0.971	1.015	1.014	0.957	0.985	31
MA	1.000	0.987	1.000	1.000	0.987	30	UT	1.350	0.908	0.882	1.531	1.226	13
MD	1.081	0.862	1.058	1.022	0.932	36	VA	1.000	0.970	1.000	1.000	0.970	33
ME	2.578	0.840	2.060	1.251	2.165	3	VT	1.204	0.698	0.999	1.205	0.841	41
MI	1.000	0.994	1.000	1.000	0.994	28	WA	1.000	1.051	1.000	1.000	1.051	23
MN	1.477	0.826	1.276	1.158	1.220	14	WI	0.939	1.010	0.931	1.008	0.948	34
MO	1.860	0.880	1.084	1.715	1.637	7	WV	2.761	0.685	1.468	1.881	1.892	5
							Average	1.253	0.850	1.049	1.195	1.066	

Note: Efficiency change larger than 1 (e>1) = increasing productivity, Efficiency change less than 1 (e<1) = decreasing productivity, Efficiency change equal to 1 (e=1) = no change in productivity

When comparing Tennessee to its neighboring efficient states, one can see that Florida, Georgia, North Carolina, and Virginia all rank at or below 20 in terms of increases in productivity change. In general, for the information presented in Table 10, states that are efficient lack large increases in productivity when compared to the nation. However, the opposite does not hold true: inefficient states do not consistently show large increases in productivity over time. Mississippi, South Carolina, and Kentucky—Tennessee's non-efficient neighboring states—all rank at or below 18 in terms of productivity. In the Tennessee example, one can see that, though inefficient, Tennessee outranks its neighbors, both the efficient and non-efficient states, in terms of productivity changes. These comparisons imply that Tennessee is making strides toward academic R&D efficiency, though it remains in the category of non-efficient.

Determinants of Efficiency

To understand the determinants of the efficiency scores of the states, we used a Tobit random effect panel model for the years 2006, 2009, 2011, and 2015. The dependent variable is the relative efficiency value extracted from the DEA analysis above. The model is both right- and left-censored, as dependent variable values are bounded between zero (0) and one (1). At least four Tobit model variations were tested. Dependent and independent variables are listed in Table 11.

We chose independent variables for determining efficiency through two assumptions: one is that efficiency is determined by the existing institutional and state environment and the other is that the type or distribution characteristics of the R&D funding can influence efficiency. The environmental variables are the number of Faculty and S&E Non-Faculty Research Staff, number of R&D-related startup companies, and State Gross Domestic Product per capita. We expect these variables to be high when efficiency is high, as the higher levels of these variables imply that R&D funding would be high and that business outputs would be more efficiently produced.

Table 11: Tobit Model Variables Used

Dependent	
Efficiency	State DEA efficiency score, $0 \leq$ efficiency ≤ 1
Independent	
FSENFRS	Number of Faculty and S&E Non-Faculty Research Staff
STARTUPS	Number of R&D-related start-up companies
GDPPC	State Gross Domestic Product per capita
RDINTEN	R&D Intensity measured as All Academic R&D/Total GDP
RDDIV	R&D Diversity, measured by sources of academic R&D (industry, federal, state, and federal research institute)
CONIDIV	Interaction term between concentration and diversity
RDINSDIV	R&D Institutional diversity
RDINSD2	R&D Intensity, squared
RDCONC2	R&D State Concentration, squared
RDCONC	R&D State Concentration
RDDIV2	R&D Diversity, squared

For funding, we defined four characteristics: concentration, diversity, institutional diversity, and intensity. Concentration measures a state's ratio of federal funding compared to the national federal funding ratio. Diversity measures R&D funding source diversity (e.g., federal, state, and institutional sources). Institutional diversity measures the number of institutions that receive R&D funding in a state. Intensity measures a state's academic R&D funding as a share of the state GDP. We expected concentration and intensity to correlate positively with efficiency. Funding diversity was expected to correlate negatively with efficiency, as different sources of funding (government or industry) might seek different outcomes for their funds and these differences could cause inefficiency when, for example, multiple entities are funding the same program or department. We also expected institutional diversity to correlate negatively with efficiency according to the assumption that a single institution receiving more funds would likely produce a greater number of outputs than multiple institutions receiving much lesser amounts of funding.

The independent variables include the number of faculty and science and engineering non-faculty research staff per million dollars of R&D funding (FSENFRS), the number of R&D-related startup companies per million dollars of R&D funding (Startups), and state gross domestic product per capita (GDPPC). The other independent variables, described below, have to do with measures and indices of intensity, diversity, and concentration of R&D funding.

R&D intensity is measured as a state's total academic R&D funding normalized by the state's GDP (RDINTEN). Diversity has two meanings and measures in this model. The first is R&D source funding diversity, which measures how many different sources contribute to a state's R&D funding, such as federal or institutional sources (RDDIV). This funding source diversity is set up as a diversity index, as described by Arik and Livingston (2014):

$$RDDIV = 1 - \sum S_u^2,$$

where RDDIV represents the sum of state-level funding diversity, and S(u) represents each source's fraction of a university's R&D funding. By this equation, if a university has a single source of funding—source gives 1.0 (or 100 percent) of funding—its score will be zero (0), so scores closer to zero (0) imply low diversity and scores closer to one (1) imply high diversity.

The second diversity variable measures the institutional diversity of R&D funding in a state (RDINSDIV). This shows the share of the total state R&D funding received by a university or institution. Barring notation, the formula is the same as the diversity formula above:

$$RDINSDIV = 1 - \sum F_u^2,$$

where RDINSDIV is the state-level sum of institutional shares of a state's R&D funding, and F(u) represents the fraction of funding received by a given university. If a single university receives all R&D funding in a state—1.0 (or 100 percent) of funding—the state's score will be zero (0). Scores close to zero (0) indicate low diversity, while scores close to one (1) indicate high diversity.

R&D concentration (RDCONC) is measured using a location quotient, where the relative concentration of academic R&D funding in a state is compared with the relative academic R&D funding in the entire United States.

$$RDCONC = \frac{FFRD_{STATE}/TRD_{STATE}}{FFRD_{US}/TRD_{US}},$$

where $FFRD_{STATE}$ is the federally-funded R&D in a state, TRD_{STATE} is the total R&D in a state, $FFRD_{US}$ is the total federally-funding R&D in the U.S., and TRD_{US} is the total R&D funding in the U.S. If RDCONC is less than one (1), the state's ratio is less than the national ratio. If RDCONC is greater than one (1), the state's ratio is greater than the national ratio and that the state receives a proportionally greater amount of federal funding than do other states. The closer RDCONC is to one (1), the closer the state is to the national ratio of federal to total R&D funding.

This concentration measure of federal funding is important since, after the Bayh-Dole Act of 1980, universities that receive federal funding can take out licenses and patents on the research discoveries they make (Arik and Ndrianasy, 2018).

The final independent variable is an interaction term between R&D concentration and funding source diversity. The equation is simply:

$$CONIDIV = RDDIV * RDCONC,$$

where CONIDIV is the interaction term, RDDIV is source diversity, and RDCONC is a state's R&D concentration relative to the U.S.

We tested four models, and model results are presented in Table 12. Results significant at the 99 percent significance level are outlined in bold.

Table 12: Tobit Random Effect Panel Data Assessment: Determinants of Relative Efficiency

Efficiency	(1)	(2)	(3)	(4)
Constant	0.6840**	0.2530	-0.4210	-0.5014
	0.2694	***0.2287***	***0.3649***	***0.3246***
FSENFRS	-0.0137	-0.0096	-0.0074	-0.0065
	0.0078	***0.0065***	***0.0064***	***0.0061***
STARTUPS	4.6189***	4.4711**	3.5707	3.7123***
	2.5007	***2.2655***	***2.2176***	***2.1983***
RDINTEN	-2.7636	-7.5909**	-5.8188***	-5.6658***
	3.4170	***3.1676***	***3.1359***	***3.1250***
GDPPC			0.000	
			0.000	
RDDIV	0.0770	0.2248	3.7798**	3.8853*
	0.3197	***0.2839***	***1.2408***	***1.2232***
RDCONC		40.5011*	46.9816*	46.8982*
		9.2187	***9.1633***	***9.1465***
CONIDIV	26.3367*	-13.6122	-19.9494***	-19.4538***
	6.5468	***11.1604***	***10.9909***	***10.933***
RDINSDIV	-1.2488***	-0.8231	-0.821	-0.7785
	0.6973	***0.5748***	***0.5483***	***0.541***
RDDIV2			-4.5334**	-4.6464**
			1.5262	***1.5102***
RDINSD2	1.0352***	1.0032***	1.0115***	0.9643***
	0.6268	***0.5446***	***0.5238***	***0.5143***
RDCONC2	-67.5186	-81.4838*	-81.3011*	-82.7077*
	87.1010	***16.8192***	***16.3791***	***16.1359***
Sigma u	0.2274	0.1488	0.1315	0.1311
Sigma e	0.2236	0.2272	0.2247	0.2251
Rho	0.5083	0.3002	0.255	0.2535
Predicted*Observed Efficiency	0.6856	0.8048	0.8147	0.8139
r^2	0.47	0.6477	0.6637	0.6624

Note: Robust standard errors are reported in bold and italics.

*,**,*** indicate significance at 99%, 95%, and 90% levels, respectively

Sigma u and *sigma e* represent the panel-level and overall variance of the model, respectively. All four models had *sigma u* and *sigma e* variances with p-values at the 99 percent significance level. Additionally, the coefficients' signs remain the same across all models, with the exception of CONIDIV, which was positive in the first model and subsequently negative for the last three models.

Model 1 has a correlation of 0.6856 between its predicted values and the observed values. The only 0.05-level significant determinant of efficiency is CONIDIV, which is the interaction term between the concentration ratio of R&D funding and the diversity of the source of R&D funding. The relationship between efficiency and CONIDIV is positive. FSENFRS, RDINTEN, RDINSDIV, and RDCONC2 all correlate negatively with efficiency. Startups, RDDIV, and RDINSD2 positively correlate with efficiency. This implies that faculty and staff, R&D intensity, institutional diversity, or squared concentration correlate with a decrease in efficiency. Increases in startups, R&D diversity or squared institutional diversity would correlate with an increase in efficiency.

Model 2 adds a non-squared R&D concentration term (RDCONC). This addition increases the correlation to 0.8048, with the added term significant at the 0.05 level. Startups, RDINTEN, and RDCONC2 also are significant at the 0.05 level. Startups positively correlate with efficiency, meaning that the more startups there are in a state, the more efficiently the state is able to use university R&D to produce business outputs. RDINTEN, measuring R&D intensity, negatively correlates with efficiency. This means that as the ratio of academic R&D to total (state) GDP goes up, efficiency decreases. RDCONC correlates positively with efficiency, but RDCONC2 correlates negatively with it.

After the concentration variable is added, the models' correlation between the predicted and the observed values hover around 0.81. In Model 3 there is added a squared version of the R&D diversity score (RDDIV2) and a variable for GDP per capita (GDPPC). At 0.8147, this model has, of all the models tested, predicted values that correlate best with the observed values. In this model, RDDIV, RDDIV2, RDCONC, and RDCONC2 are all significant at the 0.05 level or lower. RDINSD2 is significant at the 0.053 level, and thus will be counted as significant. As seen in Model 2, the concentration variable follows the same correlation pattern, where RDCONC is positively correlated, and RDCONC2 is negatively correlated. The normal and squared terms for R&D funding diversity follow the same pattern. The R&D intensity and its square also have opposite signs, where RDINTEN is negatively correlated, and RDINSD2 is positively correlated. This means that in cases of R&D intensity, while intensity negatively correlates with efficiency, there might be a point that increasing intensity does lead to higher levels of efficiency. However, RDINTEN is not significant at the 0.05 level, and thus there can be no strong conclusion drawn.

Model 4 has the next best correlation of 0.8139. Model 4 is the same as Model 3 except for the removal of the variable GDPPC. Without the insignificant variable GDPPC, IDINSD2 is not significant, but the startups variable becomes significant at the 0.10 level. Additionally, RDDIV becomes significant at the 0.01 level. The other significant variables have the same signs and remain as significant as in Model 3.

The addition of a squared term for many of the significant variables suggests levels of the variables that optimize the efficiency score for R&D funding. This is especially true because, for these variables with significant squared terms, the squared term correlates with efficiency in the opposite direction from the non-squared term (e.g., RDCONC correlates positively, and RDCONC2 correlates negatively). This implies that the concentration of R&D funding has a positive effect on efficiency. However, as the concentration increases the effect of concentration on efficiency is lessened.

Across the models tested, those variables we identified as "environmental" variables were not significant or barely significant in one or two models. In the model with the best R-square, none of the environmental variables were consistently significant. This suggests that environmental effects could be captured by other unknown variables.

STUDY IMPLICATIONS, LIMITATIONS AND FUTURE RESEARCH

This analysis of academic R&D funding efficiency suggests that only about 30 percent of states may be considered relatively efficient. When analyzed historically, the same states consistently operated at the efficiency frontier.

Study Implications

Since a significant portion of academic R&D is financed by the taxpayers, a state by state efficiency analysis may provide better insights for policymakers to make responsible choices. Efficiency scores alone, however, do not provide the full picture, as many efficient states remain efficient over time. A more comprehensive understanding comes from examining total factor productivity as it relates to R&D funding efficiency and its changes on the state level. Together, these provide state policymakers with the basis to make a case for increases in their states' portion of federal funding or, in some instances, to make the case to an industry that the investment in a state's universities will lead to increased business outputs in that state.

The key determinants of relative efficiency are diversity, intensity, and concentration variables. These variables all relate to the type and distribution of R&D funding; none of the environmental variables we tested proved consistently significant. This implies that those who provide the funding have an impact on the efficiency of the funding, as funding diversity and funding concentration are directly under the control of the funding decision-makers. R&D intensity and R&D institutional diversity are, similarly, variables over which the DMU (the state) has little control. This means that states should be doing all they can to make their universities attractive to funding entities, namely the federal government and private industry.

Study Limitations and Improvements

One of the limitations of the current study was in the outputs of the DEA model. Though empirically supported by a previous study (Arik and Ndrianasy, 2018), the business outputs used in creating the efficiency scores were hardly all-inclusive. There may be different factors that support local economies, but that were not captured in this study. Furthermore, economies often improve due to factors that are difficult to measure. Thus academic R&D could have effects on local economies that have not yet been measured.

One of the major potential improvements to the study is covering a longer time frame. This would shed more light on the efficiency status of states, as we noted that a ten-year time frame might not reveal incremental increases in efficiency. Increasing the number of years analyzed would allow us to construct a more clear pattern of efficiency and would allow us to consider whether the first-mover advantage is important in efficiency, i.e., once a state achieves efficiency, how likely is it to stay efficient?

Another potential improvement to the study would be to include different environmental factors in the Tobit regression for efficiency determinants. The variable for startups proved minimally significant, and the variable for science and engineering faculty was never significant. In other words, we have not yet found the variables that capture the environmental impact on R&D efficiency, if indeed they exist.

Future Research

In order to expand beyond the bounded DEA efficiency score, a DEA model based on "super efficiency" could give a fuller picture of the states on the efficiency frontier (Zhu, 2001). With the DEA model used in this paper, efficient states are not provided any "decision points," while inefficient states are provided, through slacks created by the model, more than one means by which to increase efficiency.

CONCLUSION

States vary in how much R&D funding they receive and in the amount of business outputs they produce. Our output-oriented data envelopment analysis model uses input-output ratios of state-level university data to create an efficiency frontier. DEA efficiency tables from 2006, 2009, 2011, and 2015 show the changes in state efficiency and highlight that over time the same states remain on the efficiency frontier. Our Tennessee example demonstrates the efficient peers and slacks that are determined by the model to provide directions toward efficiency. In Tennessee's case, the state could seek to increase S&E post docs, S&E graduates, and patents.

Our Malmquist Index breaks the increases in total factor productivity into four types of productivity—efficiency change, technical efficiency change, pure technical efficiency, and scale efficiency—in order to show which type drove increases in TFP over the years 2006 to 2015. We find that the 2009 to 2011 period had the largest scale efficiency and the smallest technical efficiency. We show that state-level TFP measures can serve as evidence for states that want to demonstrate that their academic R&D efficiency is improving even if they are not operating on the efficiency frontier.

The Tobit regression of determinants of efficiency highlights the importance of federal R&D funding ratio (RDCONC), R&D source diversity, and R&D intensity in a state. The environmental factors tested were lowly significant or not significant. This implies that universities can produce business outputs efficiently even in states lacking large numbers of R&D-related startups or high GDP levels. These results also suggest that funding decision- makers (federal government or industry groups) play a role in the efficiency of state-level academic R&D through the variables of concentration and funding diversity.

REFERENCES

Abeney, A. & Yu, K. (2015). Measuring the Efficiency of the Canadian Health Care System. *Canadian Public Policy, Vol. 41, No.4*, 320-331.

Afzal, M. N. I. & Lawrey, R. (2014). Measuring the Importance and Efficiency of Research and Development Expenditures in the Transformation of Knowledge-Based Economies: A Case Study of the Asian Region. *International Journal of Asia-Pacific Studies, 10(1),* 33-47.

Agasisti, T., Dal Bianco, A., Landoni, P., Sala, A., & Salerno, M. (2011). Evaluating the Efficiency of Research in Academic Departments: An Empirical Analysis in an Italian Region. *Higher Education Quarterly, 65(3),* 267-289.

Akazili, J., Adjuik, M., Jehu-Appiah, C., & Zere, E. (2008). Using data envelopment analysis to measure the extent of technical efficiency of public health centres in Ghana. *BMC International Health and Human Rights, 8*.

Anderson, T. R., Daim, T., & Lamb, A. (2012). Research and Development Target-Setting Difficulties Addressed Through the Emergent Method: Technology Forecasting Using Data Envelopment Analysis. *R&D Management 42, 4,* 327-341.

Anjum, M. S. & Sohail, M. K. (2016). Efficiency Dynamics of Initial Public Offerings Using Data Envelopment Analysis and Malmquist Productivity Index Approach. *Engineering Economics, 27(2),* 175-184.

Arik, M. & Ndrianasy, E. (2018) Federally Funded R&D Fuels Regional Economies: A Panel Data Analysis. *Global Journal of Accounting and Finance, 2(1),* 15-36.

Arik, M. & Livingston, S. G. (2014). *Understanding and Analyzing Competitive Dynamics: Methods, Processes, and Applications to a Regional Setting*. New York: Lexington Books.

Aristovnik, A. (2012). The Relative Efficiency of Education and R&D Expenditures in the New EU Member States. *Journal of Business Economics and Management, 13(5),* 832-848.

Ayinde, T. O. (2017). Deposit Money Banks' Efficiency and Financial Inclusion in Nigeria: A DEA Approach. *The IUP Journal of Applied Finance, 23(3),* 28-46.

Barros, C. P., Guironnet, J. P., & Peypoch, N. (2011). Productivity Growth and Biased Technical Change in French Higher Education. *Economic Modelling, 28(1-2),* 641-646.

Barham, B. L., Chavas, J., Foltz, J. D., & Kim, K. (2011). Efficiency and Technological Change at US Research Universities. *Journal of Productivity Analysis, 37,* 171-186.

Bayenet, B. & Debande, O. (1999). Performance of Education and Research Activities of Higher Education Systems of the OECD. *Annals of Public and Cooperative Economics, 70(4),* 659-686.

Bergantino, A. S., Capozza, C., & De Carlo, A. (2013). The Role of Accessibility in Determining Technical Efficiency in R&D Activity of Italian Regions. *International Journal of Transport Economics, 40(3*), 381-399.

Biener, C. & Eling, M. (2011). The Performance of Microinsurance Programs: A Data Envelopment Analysis. *The Journal of Risk and Insurance, 78(1),* 83-115.

Bijmolt, T., Koning, R. H., Los, B., & Walraven, M. (2016). Benchmarking Sports Sponsorship Performance: Efficiency Assessment with Data Envelopment Analysis. *Journal of Sport Management,* 411-426.

Bougnol, M. L., & Dulá, J. H. (2006). Validating DEA as a Ranking Tool: An Application of DEA to Assess Performance in Higher Education. *Annals of Operations Research, 145(1),* 339-365.

Bradley, S., Johnes, J., & Little, A. (2010). Measurement and Determinants of Efficiency and Productivity in the Further Education Sector in England. *Bulletin of Economic Research, 62(1),* 0307-3378

Breu, T.M. & Raab, R.L. (1994). Efficiency and Perceived Quality of the Nation's "Top 25" National Universities and National Liberal Arts Colleges: An Application of Data Envelopment Analysis to Higher Education. *Socio-Economic Planning Sciences, 28(1),* 33-45.

Bursalioglu, S. A. & Selim, S. (2013). Analysis of the Determinants of Universities Efficiency in Turkey: Application of the Data Envelopment Analysis and Panel Tobit Model. *Procedia – Social and Behavioral Sciences, 89,* 895-900.

Chavas, J. P., Barham, B., Foltz, J., & Kim, K. (2012). Analysis and Decomposition of Scope Economies: R&D at US Research Universities. *Applied Economics, 44(11),* 1387-1404.

Chen, L. & Wang, Y. (2016). Data Envelopment Analysis Cross-Efficiency Model in Fuzzy Environments. *Journal of Intelligent & Fuzzy Systems.* 2601-2609.

Chen, C. P., Hu, J. L., & Yang, C. H. (2011). An International Comparison of R&D Efficiency of Multiple Innovative Outputs: Role of the National Innovation System. *Innovation: Management, Policy and Practice, 13(3).*

Chen, P. C. & Hung, S. W. (2016). An Actor-Network Perspective on Evaluating the R&D Linking Efficiency of Innovation Ecosystems. *Technological Forecasting and Social Change, 112*, 303-312.

Chen, Y., Chou, S., Du, J., & Wang, J. (2011). Incorporating Health Outcomes in Pennsylvania Hospital Efficiency: An Additive Super-Efficiency DEA Approach. *Annals of Operations Research, 221,* 161-172.

Chern, C. & Chou, T. (2016). Assessing the Efficiency of Supply Chain Scheduling Algorithms Using Data Envelopment Analysis. *Information Systems and e-Business Management, 14,* 823-856.

Chuanyi, W., Xiaohong, L., & Shikui, Z. (2016). The Relative Efficiencies of Research Universities of Science and Technology in China: Based on The Data Envelopment Analysis and Stochastic Frontier Analysis. *Eurasia Journal of Mathematics, Science and Technology Education, 12(10)*, 2753-2770.

Cimpoies, D., Racul, A., & Sirbu, A. (2016). Use of Data Envelopment Analysis to Measure the Performance Efficiency of Academic Departments. *Agriculture and Agricultural Science Procedia, 10,* 578-585.

Cooper, W., Seiford, L., & Tone, K. (2006) *Introduction to Data Envelopment Analysis and Its Uses: with DEA-Solver Software and References*. New York: Springer.

Cullmann, A., Schmidt-Ehmcke, J., & Zloczysti, P. (2012). R&D Efficiency and Barriers to Entry: A Two Stage Semi-parametric DEA Approach. *Oxford Economic Papers, 64(1),* 176-196.

Datta, D. & McMillan, M. L. (1998). The Relative Efficiencies of Canadian Universities: A DEA Perspective. *Canadian Public Policy, 24(4),* 485-511.

Demirer, I., Gregoriou, G. N., & Gultek, M. M., (2017). Efficiency of Cruise Ships: A Data Envelopment Analysis Approach. *International Journal of Global Business, 10(1),* 8-25.

Dilts, D. M., Orwoll, E., & Zell, A. (2015). A Novel Approach to Measuring Efficiency of Scientific Research Projects: Data Envelopment Analysis. *CTS Journal, 8(5).* 495-501.

Dočekalová, M. & Bočková, N. (2013). The Use of Data Envelopment Analysis to Assess the R&D Effectiveness of the Czech Manufacturing Industry. *Business: Theory and Practice, 14(4),* 308-314.

Dogan, O., Goksen, Y., & Ozkarabacak, B. (2014). A Data Envelopment Analysis Application for Measuring Efficiency of University Departments. *Procedia Economics and Finance, 19,* 226-237.

Duguleana, C. & Duguleana, L. (2015). Data Envelopment Analysis for the Efficiency of Academic Departments. *Bulletin of the Transilvania University of Brasov, Series V: Economic Sciences, 8,* 453-468.

Eckles, J. E. (2010). Evaluating the Efficiency of Top Liberal Arts Colleges. *Research in Higher Education, 51(3),* 266-293.

Eff, E. A., Klein, C. C., & Kyle, R. (2012). Identifying the Best Buys in U.S. Higher Education. *Research in Higher Education, 53(8),* 860-887.

Emrouznejad, A. & Yang, G. (2017). A Survey and Analysis of the First 40 Years of Scholarly Literature in DEA: 1978-2016. *Socio-Economic Planning Sciences, 61,* 4-8.

Eren, M., Eren, M., & Basar, S. (2017). Measuring of Human Development through the Output-Oriented Super Efficiency vrs. DEA Model without Inputs. *Serbian Journal of Management, 12,* 255-270.

Gomes, E., Souza, G., & Souza, M. (2011). Computing Confidence Intervals for Output-Oriented DEA Models: An Application to Agricultural Research in Brazil. *Journal of the Operational Research Society,* 1844-1850.

Guan, J. & Chen, K. (2010). Modeling Macro-R&D Production Frontier Performance: An Application to Chinese Province-level R&D. *Scientometrics, 82(1),* 165-173.

Hartwich, F. & von Oppen, M. (2006). Who Contributes Efficiently to Development? Evaluating Agricultural R&D in Cameroon and Tanzania. *Quarterly Journal of International Agriculture, 45(1),* 47-70.

Hashimoto, A. & Haneda, S. (2008). Measuring the Change in R&D Efficiency of the Japanese Pharmaceutical Industry. *Research Policy, 37(10),* 1829-1836.

Hsu, F. M. & Hsueh, C. C. (2009). Measuring Relative Efficiency of Government-sponsored R&D Projects: A Three-stage Approach. *Evaluation and Program Planning, 32(2),* 178-186.

Hung, C. L., Kuo, S. J., & Dong, T. P. (2013). The Relationship between Team Communication, Structure, and Academic R&D Performance: Empirical Evidence of the National Telecommunication Program in Taiwan. *R and D Management, 43(2),* 121-135.

Inoue, K., Aoki, S., Fukuoka, K., & Tsuji, H. (2015). Data Envelopment Analysis for Evaluating Structure of Input and Output Items. *Electronics and Communications in Japan, Vol. 134-C.* 138-147.

Jiménez-Sáez, F., Zabala-Iturriagagoitia, J. M., & Zofío, J. L. (2013). Who Leads Research Productivity Growth? Guidelines for R&D Policy-Makers. *Scientometrics, 94(1),* 273-303.

Jiménez-Sáez, F., Zabala-Iturriagagoitia, J. M., Zofío, J. L., & Castro-Martínez, E. (2011). Evaluating Research Efficiency within National R&D Programs. *Research Policy, 40(2),* 230-241.

Johnes, J. (2006). Data Envelopment Analysis and Its Application to the Measurement of Efficiency in Higher Education. *Economics of Education Review, 25(3),* 273-288.

Johnes, J. & Yu, L. (2008). Measuring the Research Performance of Chinese Higher Education Institutions Using Data Envelopment Analysis. *China Economic Review, 19(4),* 679-696.

Korhonen, P., Tainio, R. & Wallenius, J. (2001). Value Efficiency Analysis of Academic Research. *European Journal of Operational Research, 130(1),* 121-132.

Kuah, C. T., & Wong, K. Y. (2013). Data Envelopment Analysis Modeling For Measuring Knowledge Management Performance in Malaysian Higher Educational Institutions. *Information Development, 29(3),* 200-216.

Lall, V. & Moreno, A. (2011). Decision Model for Selection of Discrete-Event Stimulation Software – A Data Envelopment (DEA) Approach. *IJGMSP, 3(2),* 29-39.

Lee, H., Park, Y., & Choi, H. (2009). Comparative Evaluation of Performance of National R&D Programs with Heterogeneous Objectives: A DEA approach. *European Journal of Operational Research, 196(3),* 847-855.

Lee, H., Kim, M. S., Yee, S. R., & Choe, K. (2011). R&D Performance Monitoring, Evaluation, and Management System: A Model and Methods. *International Journal of Innovation and Technology Management, 8(2),* 295-313.

Lee, S. & Lee, H. (2015). Measuring and Comparing the R&D Performance of Government Research Institutes: A Bottom-Up Data Envelopment Analysis Approach. *Journal of Informetrics, 9(4),* 942-953.

Lei, H. S. & Liu, J. (2018). Applications of Network Data Envelopment Analysis to Explore the Operational Efficiencies of International Five-Star Hotels. *International Journal of Organizational Innovation, 10(3),* 64-87.

Li, R., Li, Y., & Cui, Z. (2014). Application of Data Envelopment Analysis to Efficiency Evaluation on R&D Input and Output. *Open Automation and Control Systems Journal, 6(1),* 194-199.

Liu, C. C. (2011). A Study for Allocating Resources to Research and Development Programs by Integrated Fuzzy DEA and Fuzzy AHP. *Scientific Research and Essays, 6(19),* 3973-3978.

Meng, H. & Wang, Y. (2014). R&D Growth and Efficiency of Scientific Research Development Institutes In China. *Journal of Chemical and Pharmaceutical Research, 6(4),* 182-187.

Mikusova, P. (2015). An Application of DEA Methodology in Efficiency Measurement of the Czech Public Universities. *Procedia Economics and Finance, 25,* 569-578.

Munoz, D.A. (2016). Assessing the Research Efficiency of Higher Education Institutions in Chile: A Data Envelopment Analysis Approach. *International Journal of Educational Management, 30(6),* 809-825.

Ng, Y.C. & Li, S. K. (2000). Measuring the Research Performance of Chinese Higher Education Institutions: An Application of Data Envelopment Analysis. *Education Economics, 8(2),* 139-156.

Orea, L. (2002). Parametric Decomposition of a Generalized Malmquist Productivity Index. *Journal of Productivity Analysis, 18(1),* 5-22.

Oztop, A. O. & Ucak, H. (2017). Evaluation of Firms of Agriculture and Food Sectors Quoted at Borsa Istanbul (Bist) by DEA-Based Malmquist Total Factor Productivity Index. *Acta Scientiarum Polonorum Oeconomia, 16 (1),* 73-82.

Palocsay, S. W. & Wood, W. C. (2014). An Investigation of US Undergraduate Business School Rankings Using Data Envelopment Analysis with Value-Added Performance Indicators. *Journal of Education for Business, 89,* 277-284.

Park, S. (2015). Evaluating the Efficiency and Productivity Change within Government Subsidy Recipients of a National Technology Innovation Research and Development Program. *R And D Management, 45(5),* 549-568.

Pisarek, R. & Zoltaszek, A. (2016). Effectiveness of National Airlines in Europe – The DEA Approach. *Folia Oeconomica Stetinensia.* 103-118.

Raeinojehdehi, R. & Valami, H. B. (2016). Ranking Units in Data Envelopment Analysis with Fuzzy Data. *Journal of Intelligent and Fuzzy Systems.* 2505-2516.

Rauner, M. S. & Sommersguter-Reichmann, M., (2015). Benchmarking the Rescue Departments of the Austrian Red Cross Using Data Envelopment Analysis and Fractional Regression Models. *International Journal of Production Research, 53(24),* 7271-7285.

Rehber, E. & Tipi, T. (2006). Measuring Technical Efficiency and Total Factor Productivity in Agriculture: The Case of the South Marmara Region of Turkey. *New Zealand Journal of Agricultural Research, 49(2),* 137-145.

Revilla, E., Sarkis, J., & Modrego, A. (2007). Exploring Public and Private R&D Partnership Performance: A Knowledge-Based View of Inter-Organizational Alliances. *International Journal of Services and Operations Management, 3(4),* 371-393.

Sahoo, B. K., Kerstens, K., & Tone, K. (2011). Returns to Growth in a Nonparametric DEA Approach. *International Transactions in Operational Research, 19,* 463-486.

Salerno, C. (2006). Using Data Envelopment Analysis to Improve Estimates of Higher Education Institution's Per-student Education Costs. *Education Economics,14(3),* 281-295.

Sengupta, J. K. (1999). Efficiency Measurements with R&D Inputs and Learning by Doing. *Applied Economics Letters, 6(10),* 629-632.

Sharma, S. & Thomas, V. J. (2008). Inter-country R&D Efficiency Analysis: An Application of Data Envelopment Analysis. *Scientometrics, 76(3),* 483-501.

Shi, P. & Yang, J. (2008). The Effectiveness of National R&D Investment - An Empirical Investigation in China. *Problems and Perspectives in Management, 6(4),* 4-11.

Sueyoshi, T. & Goto, M. (2013). A Use of DEA-DA to Measure Importance of R&D Expenditure in Japanese Information Technology Industry. *Decision Support Systems, 54(2)*, 941-952.

Taylor, B. & Harris, G. (2004). Relative Efficiency among South African Universities: A Data Envelopment Analysis. *Higher Education, 47(1),* 73-89.

Thanassoulis, E., Kortelainen, M., Johnes, G., & Johnes, J. (2011). Costs and Efficiency of Higher Education Institutions in England: A DEA Analysis. *Journal of the Operational Research Society, 62(7),* 1282-1297.

Veiderpass, A. & McKelvey, M. (2016). Evaluating the Performance of Higher Education Institutions in Europe: A Nonparametric Efficiency Analysis of 944 Institutions. *Applied Economics, 48(16),* 1504-1514.

Wang, E. C. & Huang, W. (2007). Relative Efficiency of R&D Activities: A Cross-Country Study Accounting for Environmental Factors in the DEA Approach. *Research Policy, 36(2),* 260-273.

Zakaria, S. (2017). The Use of Financial Derivatives in Measuring Bank Risk Management Efficiency: A Data Envelopment Analysis Approach. *Asian Academy of Management Journal, Vol. 22, No. 2,* 209-244

Zhong, W., Yuan, W., Li, S. X., & Huang, Z. (2011). The Performance Evaluation of Regional R&D Investments in China: An Application of DEA Based on the First Official China Economic Census Data. *Omega, 39(4),* 447-455.

Zhu, J. (2001). Super-efficiency and DEA Sensitivity Analysis. *European Journal of Operational Research, 129(2),* 443-455.

FRAUDS, EMBEZZLERS, THIEVES, AND OTHER BAD ACTORS: HOW CRIMINALS STEAL YOUR PROFITS AND PUT YOU OUT OF BUSINESS

Martin S. Bressler, Southeastern Oklahoma State University
Linda Bressler, Southeastern Oklahoma State University

ABSTRACT

Shoplifting, fraud, embezzlement, and now cybercrimes are only a few of the many types of crimes business owners lose sleep over. Business owners lose profits, sometimes significant profits, and small businesses are affected to any even greater extent. Small businesses often lack the resources to defend their business against various criminal activities and may not be able to recover from large losses. The U.S. Chamber of Commerce reports that as many as 30% of small business failures could be attributed to embezzlement or employee theft. And to make matters worse, thieves are becoming more sophisticated in the use of high-tech tools to steal. In this paper, the authors provide an overview of current criminal activity and offer several ways to address the situation.

Key words: business crime, fraud, embezzlement, white-collar crime, prevention-paradox

INTRODUCTION

According to the U.S. Small business Administration (SBA Small Business Facts), only two-thirds of small businesses will survive the first two years and only about half will survive beyond the first five years of operation. Many others offer an even more gloomy estimate. According to Wagner (cited in Forbes Online, 2013) as many as eight in ten new business fail within the first eighteen months. There might not be agreement on the number of small business failures but certainly, the numbers are cause for concern. Likewise, there is considerable discussion on the causes of small business failure. However, little attention is paid to one of most important causes of small business failure. The U.S. Chamber of Commerce (cited in Simon, 2016) reports that 30 percent of business failures are the result of embezzlement or employee theft.

INTERNAL CRIMES

In the context of small business, white collar crimes typically take the form of fraudulent record keeping, sometimes referred to as "cooking the books". In many instances, business figures or sales receipts are changed to falsely represent the business as earning less profit than it really is. Small Business Digest reports that the typical business or organizations loses about 5% of revenues to various fraud activities each year (smallbusinessmagdigest.com). For some small businesses, losing 5% of their revenues could mean the difference between profitability and business failure

Crimes committed against businesses

EXTERNAL	INTERNAL
Robbery	Theft
Burglary	Embezzlement
Fraud	Fraud
Vandalism	Identity theft
Ponzi schemes	Sabotage
Computer hacking	
Shoplifting	
Counterfeiting	
Piracy	

White collar crimes

White collar crimes include bribery, extortion, theft, tax evasion, embezzlement, and miscellaneous frauds, including payroll fraud and pharmacy fraud. In some instances, fraud occurs over long periods of time. A CNBC report on white collar crime cites data from the global insurance specialty company Hiscox, that finds for embezzlement and fraud occurring five or more years, the average loss for was $2.2 million, and for fraud or embezzlement lasting 10 years or more the loss was $5.4 million (www.cnbc.com). Losses exceed $1 million in 20% of cases (www.cnbc.com).

Verschoor (2018) refers to the 2018 Global Economic Crime and Fraud Survey, conducted by Price Waterhouse Coopers, one of the Big 4 accounting and consulting firms. Their survey of more than 7,200 respondents across 123 different territories uncovered some very important findings. The largest cause of fraud (59%) is weak internal controls and only 54% of respondents reported that they conducted a general fraud or economic crime risk assessment within the past 2 years. As the respondents are larger companies, we can assume that small businesses would be even less likely to have conducted a crime risk assessment.

Examples of white-collar crime
Bribery
Extortion
Theft
Tax evasion
Embezzlement
Miscellaneous including payroll fraud and pharmacy fraud

Source: www.legalmatch.com

Embezzlement cases often occurred when an employee would repeatedly divert small sums of money over time, thereby making their theft very difficult to detect. In 28.7 percent of fraud or embezzlement incidents, employee theft took happened over the course of five years or more (Hiscox, cited in CNBC).

Instances of business fraud last an average of 18 months and average $573,000 for executives and $60,000 for other employees. Research found that the longer an incident of fraud lasts and the higher the position in the organization, the greater the losses. In the United States, fraud loss estimates range from $300 to $600 billion. This estimate highlights the difficulty in uncovering and confirming all instances of fraud that occur. In many instances, recovering the funds can be more difficult than finding, researching and prosecuting fraud. More than half (58%) of companies that uncover cases of fraud recover none of the money and overall, only 39% of embezzled funds were recovered on average, through settlements, restitution or insurance (HISCOX, 2018).

The 2018 HISCOX Embezzlement Study research uncovered some interesting findings and although the findings differ somewhat from other studies, nevertheless the results are important to note. Some key findings include: more than one perpetrator in 79% of all cases, with an average of three perpetrators; 33% of cases involved someone employed in the accounting or finance department.

The Association of Certified Fraud Examiners (ACFE) reports the median fraud loss in a small business of fewer than 100 employees to be $200,000 (Report to the Nations, 2018). The most common means of fraud or theft were found to be corruption, billing, check payment tampering, expense reimbursements, skimming, cash on hand, non-cash theft, financial statement fraud, payroll fraud, and register disbursements (Fraud in small business, 2018).

Small Business	Less than 100 employees	Greater than 100employees
Median loss	$200,000	$104,000
Frauds detected by tip	29%	44%
Frauds caused by lack of internal controls	42%	25%
Frauds perpetrated by owner/executive	29%	16%

Source: Report to the Nations, the Association of Certified Fraud Examiners

EXTERNAL CRIMES

External crimes, those committed by persons outside the company, include burglary, robbery, larceny (theft), cybercrime, shoplifting, vandalism, and cargo theft. In addition to the financial cost to the business, sometimes financial crimes are accompanied with other violent crimes including assault or murder.

Burglary-The FBI Uniform Crime Reporting Data indicates that in 2017, there were more than 1.4 million burglaries reported to various law enforcement agencies, resulting in $3.4 billion in property losses (Crime in the United States, 2017). These crimes resulted in an average financial loss of $2,416 per occurrence (Crime in the United States, 2017). Although only about a third of these burglaries (32.8%) occur in businesses, the resulting financial loss can significantly impact smaller businesses.

Larceny-theft-This crime category includes a wide range of thefts ranging from bicycles, auto parts, and other property including pickpocketing and shoplifting, totaling more than 5 ½ million thefts. Together, these thefts $5.6 billion, with an average theft of $1,007 (Crime in the United States, 2017).

Cargo theft-Perhaps the least known crime committed against business is cargo theft. Cargo theft can be costly to businesses in more ways than one. A local small business owner of a swimming pool installation and supply company had their entire opening season inventory on a trailer truck that was hijacked. This caused a delay in receiving goods and a resulting loss in sales for several weeks. According to FBI crime data, reported cargo theft costs businesses more than $21 million per year, with less than 26% of merchandise recovered (Crime in the United States, 2017). The FBI is particularly interested in cargo theft as in some instances, the merchandise involved could include firearms, sensitive high-technology products, or potentially dangerous materials.

Robbery-Robbery can be considered among the more serious property crimes as in many cases a weapon or strong-arm tactics are used in the commission of the crime. The 319,356 robberies in 2017 reported an average loss of $1,373, or a total of $438 million in losses (Crime in the United States, 2017).

Cybercrime-according to Dr. Jane LeClair, Chief Operating Officer of the National Cybersecurity Institute, “Fifty percent of small to medium-sized businesses (SMB) have been the victims of cyber-attack and over 60% of those attacked go out of business.” The cost of a cyber-attack to a small business today averages $20,752 and for those businesses whose bank accounts were hacked, those losses were $19,948 (The Impact of Cybersecurity on Small Business). Fruhlinger (2018) also reports that it takes the typical organization an average of 191 days to identify data breaches and the average ransomware attack costs a company $5 million.

Egeland (2015) believes there are four ways that cybercrime can hurt your small business. First, is the loss of your business reputation and consumer confidence. A computer attack that compromises customer financial data can halt business operations and even permanently put a company out of business. The second way that a small business can be harmed is with the cost of fixing the issue. Small businesses that rely heavily on the internet to operate their business would suffer the most while their business is down and for the resulting costs associated with finding and resolving business damage. The third way that a small business can suffer is when the organization’s financial information is compromised. Money and credit can be stolen through an online incursion. Finally, a computer breach can result in substantial legal liability for a small business should customer or vendor personal or financial information be stolen.

Shoplifting and inventory shrinkage

Among the most serious problems facing retail businesses in 2019 is inventory shrinkage and shoplifting. Inventory shrinkage typically amounts to 1.33% of gross sales and costs the U.S. retail industry more than $45 billion annually (Tyree, 2019). Inventory shrinkage includes fraud, theft, shoplifting, and organized retail crime (ORC). U.S. grocery stores allocate only 0.36% of sales to reducing shrinkage (Source: National Retail Federation survey).

In fact, according to the National Retail Federation survey, ORC costs the retail industry approximately $30 billion each year and almost all retailers have been impacted by ORC. In addition to costs associated with theft of merchandise, retail crime activity places both employees and shoppers in potential danger. The average cost per shoplifting incident doubled to $559 and the average cost for return merchandise fraud is $1,766.27 (National Retail Federation survey).

TYCO integrated security reports that 40 percent of thefts involve money, ranging from five dollars to $2 million, averaging $20,000 (www.tycois.com). In addition to money, employees sometimes steal products that the company manufactures (about 20% of all employee thefts) and another 6% being equipment and supplies used by the company, ranging from pens, staples, and paper towels.

In a 2016 study by global specialist insurer Hiscox, U.S. businesses affected by employee theft lost an average of $1.13 million. Small and midsize businesses were targeted disproportionately, accounting for 68 percent of employee theft. Last year the median loss amounted to $289,864. Surprisingly, Hiscox found financial services firms reported the greatest total losses across all industries. Collectively, in 2016 they suffered losses of more than $120 million. One instance lasted for 41 years and involved $2.5 million stolen from a bank.

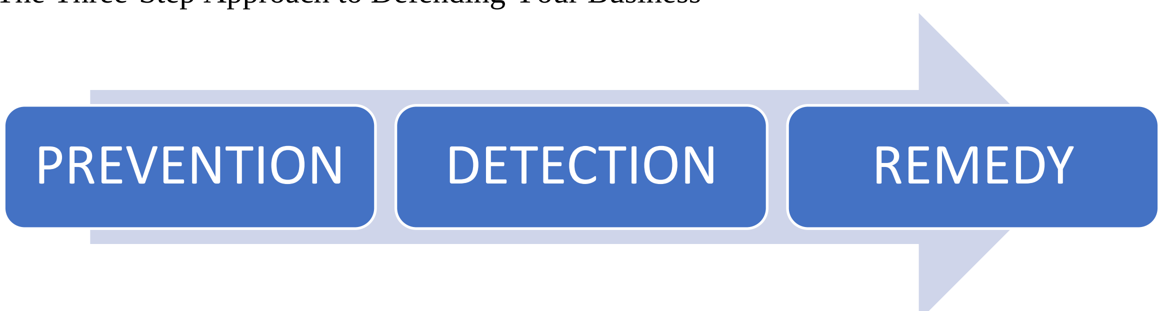
PREVENTION STRATEGIES

The Association of Certified Fraud Examiners (ACFE) indicates that in smaller businesses with 100 or less employees, organizations uncover employee fraud by receiving tips from employees or other persons in 44% percent of cases (Report to the Nations, 2018). 29.3% surveyed said they were allocating new resources to technology, while only 17.3% said they were hiring additional staff dedicated to combatting ORC (Source: NRF Survey)

Not surprisingly, technology is leading the way in protecting business against criminal activity. Experts today consider biometric surveillance technology as one of the most effective means to deter criminal activity in retail establishments Source: Center for Data Innovation 34% decrease in shoplifting reported by retailers using face recognition. 91% decrease in workplace-related injuries from violent assault by retailers using face recognition. 75 million: the number of images FACEFIRST can query in 1/10 of a second.

The figure below highlights the three-step approach to combatting crimes committed against businesses. The first, and most important step is prevention. Prevention is important because when you prevent crime, you do not need to bother with the problems and costs associated with the criminal activity. Although most businesses do not like to spend the money up-front for personnel, technology and other means to prevent crime, the investment pays off. With the average amount of money embezzled in an embezzlement case at $357,650 was the average amount of money embezzled.

The Three-Step Approach to Defending Your Business



Source: Bressler, M. & Bressler, L., 2007.

In addition to technology, prevention techniques should include instituting a review of all bank statements and cancelled checks by someone other than the bookkeeper, ensuring that more than one person sees every transaction. Companies should also perform rigorous background checks, as allowed by law, on all employees — especially those who handle money. Corporate bank statements should be delivered to an owner at their home address. In 65% of embezzlement cases, someone in the company noticed something was amiss and the scheme was uncovered (Hiscox, 2018).

Depending on the type of crime, various technologies can be helpful in preventing crime. For example, to help prevent burglary, exterior lighting, video cameras, and security systems would be the minimum equipment for prevention/detection of burglaries. For other types of criminal activity, sophisticated software programs and special monitoring equipment would help prevent crime. Because the Price Waterhouse Coopers survey (cited in Verschoor, 2018) reported that the largest cause of fraud (59%) results from weak internal controls, the report recommends investing in people, not just technology.

Some of the more basic preventive techniques include locks, key control, outsourcing payroll, secure websites, secure passwords, drug testing of applicants and/or employees, security guards/dogs, employee background checks, employee I.D. badges, and keeping a minimal amount of cash on hand.

Criminal background checks should be standard procedure for businesses and nonprofit organizations. However, according to the National Small Business Association (2017), 59% of small business employers fail to conduct background checks (https://www.nsba.biz/wp-content/uploads/2017/06/Workforce-Survey-2017.pdf). Background checks not only protect the company against liability, guard the safety of customers and customer financials, they are often required when contracting with larger companies and the federal government (https://www.nsba.biz/wp-content/uploads/2017/06/Workforce-Survey-2017.pdf).

DETECTION STRATEGIES

Technology provides organizations the means to determine who is committing criminal activity and how the activity is committed. Technology is less expensive than employing humans and technology is often able to perform tasks humans are unable to perform. Advancements in technology, such as the developments in biometric technology, provides companies and law enforcement with an important advantage over criminals.

Despite the importance of technology, employees and others play an important part in prevention and detection. HISCOX (2018) reports that someone in the company noticed something was wrong and the embezzlement was uncovered. n 65% of embezzlement cases, someone in the company noticed something was amiss and the scheme was uncovered (Hiscox, 2018).

Standard detection techniques include unscheduled audits, internal auditors, external auditors, alarm systems, financial statement analysis, monitoring employee lifestyle changes, other behavior changes.

Biometrics

Many controls could be used to protect access to a company's digital records (https://www.csoonline.com/article/2130877/data-breach/the-biggest-data-breaches-of-the-21st-century.html; Olson, 2019; Philips, et al, 2000; http://www.upsizemag.com/business-builders/fraud-recovery). Biometric security includes hand movements when working on the computer system, iris or retina scanning, capillary mapping/identification or simple recognitions such as voice or fingerprint identification (Berger, 2007; Robertson, et., al, 2015). Another biometric security which can recently be noted in the news would be Biometric patterns. Steve Jillings, CEO of TeleSign explained how biometric patterns can be identified as legitimate users of the company's system or identified as an intruder. Jillings indicates that their software called Behavior ID can read an individual's manner by which they use a mouse, screen usage, and other employee demonstrates when working on a company's system and not demonstrating the user's biometric patterns can be identified because it is virtually impossible for another person to exactly duplicate another person's biometric patterns (https://www.cnbc.com/2016/04/05/biometrics-future-of-digital-cyber-security.html).

Biometrics can be very helpful in preventing and detecting fraud in companies, but some authors indicate that unfamiliar face recognition can be prone to error (Robertson, 2015). The author give an example of a younger Asian man utilizing a hyper-realistic silicone mask and he passed by security as an older Caucasian male. In addition, face image manipulation can be purchased for Internet and cell phone users. Apps are available that not only distort a face, but fuse two different pictures into one face while keeping characteristics of both faces intact. Robertson (2015) indicated that acceptance rates for passports merged in this way were significantly higher than a forged passport and the author suggested counter-measures for this type of clever fraud should be researched and perhaps shared with the Department of Defense.

In addition, other authors note that the new security could be use expanded for negative purposes such as racialization (Berger, 2007). Some thought needs be given to protection of privacy with the use of biometric security. Our biometric data should be considered sensitive and personal and that becomes even more difficult with surveillance systems in public areas (Evans, et., al, 2015).

Maguire (2017) noted that biometrics could be expanded to racial identification or racialization and even further, racial profiling. The author noted that even simple fingerprinting can identify races; for example, Jewish persons show whirled fingerprint patterns and although now, no specific identification can be found, as the software becomes more evolved, exact racial matching techniques could be created (Lyon, 2008).

REMEDIES

Cyber Crime & Liability

When an individual, investor, or company experiences financial fraud, they may be dealing with years of recovery from a stolen identity including loss of thousands of dollars, credit ruined, and will most likely be dealing with emotional loss, frustration, fear it could happen again, fear they won't ever recover and, of course, anger toward themselves, the perpetrator, and even the police who will be doing their best to help even though it can be very difficult to help the victims to full financial recovery http://www.accounting-degree.org/scandals/; Pedneault, 2017) ; 2019 http://www.finra.org/investors/highlights/take-action-recover-financial-fraud; https://www.justice.gov/usao-wdwa/victim-witness/victim-info/financial-fraud\; Romanosky et. al., 2011)

But recovery can be possible whether the fraud was perpetrated by employees, management, fraudsters, manipulation, etc. Usually by the time the victims discover the fraud, the stolen funds, will be spent or hidden with little chance of partial or full restitution. If the assets can be identified and located, there can be a better chance of recovery. However, with real estate, the thief may have mortgaged the property to extract all available funds or luxury items may have liens attached to them (Pedneault, 2017)

There can be several ways investors can recover some of the embezzled or stolen funds. (How can investors get money back, 2019). Pedneault (2017) noted it would be a good idea to hire a lawyer not only for their professional expertise, but also to utilize privilege regarding the fraud and if there would be enough evidence, the victim can imitate criminal as well as civil proceedings at the same time. However, sometimes the only way a victim can recover funds is via insurance. Although many times investors receive only a small percentage of the lost funds, it may be worth the investors' time to investigate the various ways Congress authorized the Securities and Exchange Commission to seek remedies for investors facing fraud. Some of these remedies include receiverships whereby the SEC will file a court action asking a judge to appoint someone to safeguard recovered assets. Another could be the company utilizing Chapter 11 of the Bankruptcy code to reorganize their business rather than a Chapter 7 liquidation whereby only pennies on the dollar lost would be recovered by victims.

A third remedy could be private class action lawsuits which private individuals initiating a lawsuit without the SEC's involvement (How can investors get money back, 2019; Wilt, 2018). In the article *Take Action* (2019), a fourth remedy suggests reporting the fraud to other agencies such as the North American Securities Administrators Association, the National Futures Association or the U.S. Commodity Trading Commission. Black (2013) notes that although some successful private class action lawsuits prevailed in court, it can sometimes be difficult for plaintiff's to even have their day in court because the victims could not specify damages from the unauthorized use of their information being hacked. The author gave an example about the Third Circuit Court upholding a dismissal of charges because the court found "that indefinite risks of future harm and mitigation costs were too speculative to give the plaintiffs standing…"

There can be two schools of thought as to who is to blame when a company has experienced losses from a cybercrime. Gupta and Hassib (2019) indicate that there is the thought process that the blame lays only on the perpetrator as the company did not solicit the crime. The second school of thought deals with whether the company did their due diligence in safeguarding their assets (employees' private information as well as the company's assets including intellectual property and cash or cash equivalents). If the company dealt with cyberthreats by initiating best practices in their industry, the answer could be no, they are victims also. The authors also discussed partial blame to the company noting that there might be special circumstances whereby it was not reasonable to follow industry safeguards against cybercrime and they believed further research would be warranted on this topic because partial blame to companies enduring losses from cybercrime is a new area in digital harm and cybersecurity.

CONCLUSION

Businesses today are more likely to fall victim to more types of crime, including cyber-crimes, and by criminals using more sophisticated techniques and technologies. Smaller businesses often suffer proportionately larger losses and are less able to weather those losses. The Hiscox (Hiscox, 2018) study reports that the typical fraud or embezzlement loss to a small business averages $200,000 and the average cyber-crime loss is $80,000 (Guta, 2018). This can substantially erode profits and even cause some small businesses to close their doors.

Unfortunately, fewer remedies are available to the business owner who becomes a crime victim and those remedies are generally limited to insurance, criminal prosecution of offenders, employee dismissal, negotiations and settlements, and punitive damages. However, small business owners sometimes fail to protect their business with adequate prevention and detection systems. In addition, some businesses and non-profit organizations become part of the “prevention-paradox” when failing to prosecute criminal acts committed against their business.

Business owners might not want to file charges with the police when the criminal acts are committed by friends, relatives, or long-service employees. This is especially true among non-profit organizations. However, when the business or organization fails to prosecute, the criminal goes free to potentially commit the crime again and again. All too often, smaller businesses choose not to pay for criminal background checks but even when they do, incidents where the business or organization failed to prosecute will not appear.

The best defense is the best defense you can afford. In other words, purchase and use the best prevention and detection technologies and methods available to you. Remedies can help to mitigate losses and serve as a deterrent to help prevent future crimes. In addition, be sure to prosecute offenders rather than letting criminals escape to continue harming businesses and their employees. Finally, be sure to purchase enough insurance coverage to cover all losses and liabilities.

REFERENCES

Armerding, T. (2018). The 17 biggest data breaches of the 21st century. *CSO Online*. Retrieved 02/23/2019 from http://www.accounting-degree.org/scandals/

Berger, V. (2007). Biometrics security technology: The future now. *Security*, *44*, 10-60.

Black, J. (2013). Developments in data security breach liability. *The Business Lawyer*, *69*(1), 199-207.

Bressler, M. & Bressler, L. (Fall, 2007). A Model for Prevention and Detection of Criminal Activity Impacting Small Business. *The Entrepreneurial Executive*, *12*, (1) 23-36.

Crime in the United States, 2017. FBI Uniform Crime Report. Retrieved 02/01/2019 from https://ucr.fbi.gov/crime-in-the-u.s/2017/crime-in-the-u.s.-2017

Egeland, B. (September 4, 2015). Four Ways Cyber Crime Can Hurt Your Small Business. Retrieved 02/01/2019 from https://www.businessknowhow.com/security/cybercrime.htm

Evans, N., Marcel, S., Ross, A., & Teoh, A. B. J. (2015). Biometrics security and privacy protection [from the guest editors]. *IEEE Signal Processing Magazine*, *32*(5), 17-18.

Fraud in small business. Association of Certified Fraud Examiners. Retrieved 01/27/2019 from https://www.acfe.com/uploadedFiles/ACFE_Website/Content/rttn/2018/Fraud-in-Small-Business.pdf

Fruhlinger, J. (October 10, 2018). Top cybersecurity facts, figures, and statistics for 2018. CSOonline. Retrieved 02/02/2019 from https://www.csoonline.com/article/3153707/security/top-cybersecurity-facts-figures-and-statistics.html

Gupta and Hasib (2019). https://healthmanagement.org/c/healthmanagement/issuearticle/when-a-cybercrime-takes-place-who-s-to-blame

Guta, M. (December 3, 2018). Small Businesses Lose $80K on Average to Cybercrime Annually, Better Business Bureau Says. Small Business Trends. Retrieved 02/26/2019 from https://smallbiztrends.com/2018/12/cost-of-a-cyber-attack-small-business.html

Hiscox Embezzlement Study™ (2018). An Insider’s View of Employee Theft workplace-crime- costs-us-businesses-50-billion-a-year. Retrieved 01/25/2019 from https://www.cnbc.com/2017/09/12/workplace-crime-costs-us-businesses-50-billion-a-year.html

How can investors get money back in a fraud case involving a violation of the federal securities laws? 2019 https://www.sec.gov/fast-answers/answersrecoverfundshtm.html

Lyon, David. (Nov 2008). Biometrics, Identification and Surveillance. *Bioethics*. *22*(9). 499-508.

Maguire, Mark. (Sep 2012). Biopower, Rationalization, and New Security Technology. Social Identities. 18(5), 593-607.

National Small Business Association. (2017). Small Business Workforce and Labor Survey. Retrieved 02/19/2019 from https://www.nsba.biz/wp- content/uploads/2017/06/Workforce-Survey-2017.pdf

Olson, Jason (2019). How to prevent, detect, investigate fraud at your firm. Retrieved 02/23/2019 from http://www.upsizemag.com/business-builders/fraud-recovery

Pedneault, S. (2017). Recovering Losses from Employee Theft and Embezzlement. Retrieved 02/23/2019 from https://www.ctcpas.org/content/27648.aspx

Phillips, P. J., Martin, A., Wilson, C. L., & Przybocki, M. (2000). An introduction to evaluating biometric systems. *Computer*, (2), 56-63.

Provided by HG.org. (2019) https://www.hg.org/legal-articles/security-breach-how-businesses-may-be-liable-44358

Report to the Nations. 2018 Global Study on Occupational Fraud and Abuse, Fraud in Small Business. The Association of Certified Fraud Examiners. Retrieved 01/27/2019 from https://www.acfe.com/rttnresources/

Robertson, D. J., Noyes, E., Dowsett, A. J., Jenkins, R., & Burton, A. M. (2016). Face recognition by metropolitan police super-recognisers. *PloS one*, *11*(2), e0150036.

Romanosky, S., Telang, R., & Acquisti, A. (2011). Do data breach disclosure laws reduce identity theft? *Journal of Policy Analysis and Management*, *30*(2), 256-286.

SBA Office of Advocacy, Small Business Facts. Retrieved 01/25,2019 from https://www.sba.gov/sites/default/files/Business-Survival.pdf

SBIR/STTR The Impact of Cybersecurity on Small Business. Retrieved 02/02/2019 from https://www.sbir.gov/sites/all/themes/sbir/dawnbreaker/img/documents/Course10- Tutorial1.pdf

Simon, M. (March 3, 2016). 30% of businesses will fail because of employee theft. Hill & Hamilton Insurance Blog Retrieved 01/26, 2019 from https://www.hillandhamilton.com/ohio-insurance-blog/30-percent-of-businesses-will-fail- because-of-employee-theft

Small Businesses Can Be Hit With White Collar Crime Retrieved 01/26/2019 from http://smallbusinessdigestmag.com/content/small-businesses-can-be-hit-white-collar- crime

Take Action to Recover http://www.finra.org/investors/highlights/take-action-recover-financial-fraud

Tyree, W. (January 15, 2019). 30 Shocking Retail Loss Prevention and Violent Crime Statistics for 2019. FACEFIRST. Retrieved 01/27/2019 from https://www.facefirst.com/blog/retail-loss-prevention-and-violent-crime-statistics/.

Verschoor, C. (June 2018). Striking jump in business fraud and crime. *Strategic Finance*, 17-18.

Wagner, E. (September 22, 2013). Five Reasons 8 Out Of 10 Businesses, Forbes online. Fail Retrieved 01/26/2019 from https://www.forbes.com/sites/ericwagner/2013/09/12/five- reasons-8-out-of-10-businesses-fail/#38e7d1a16978

Wilt, J. (2018). Cancelled Credit Cards: Substantial Risk of Future Injury as a Basis for Standing in Data Breach Cases. *SMUL Rev.*, *71*, 615.

APPENDICES

Table 1

Financial	impact	of crime	activity
CRIME	Number of offenses	Total value	Cost per offense
Robbery	319,356	$438 million	$1,373
Burglary	1,401,840	$3.4 billion	$2,416
Larceny-theft	5,519,107	$5.6 billion	$1,007
-shoplifting		20% of all theft	$260
Embezzlement-fraud	1,021,226	$300-600 billion	$200,000

Source: 2018 Hiscox Embezzlement Study

Table 2

ANTI-FRAUD CONTROLS
Code of Conduct
Management Review
Management certification of financial statements
Fraud training for executives and managers
Fraud training for employees
Rewards for Whistleblowers
Job rotation/mandatory vacation
Dedicated fraud detection department
Formal fraud risk assessment
Proactive data monitoring/analysis
Surprise audits
Hotline
Independent audit committee
External audit of internal controls
Internal audit department
Anti-fraud policy
External audit of financial statements

Table 3

TOP 5 MANAGEMENT CHANGES DUE TO EMBEZZLEMENT		
1)	Employee layoffs	29%
2)	Increased spending on auditing	27%
3)	Lost customers	26%
	Time spent discussing security	26%
	Added security & audit requirements	26%
4)	Purchased or increased insurance	25%
5)	Switched auditors	24%

Source: Report to the Nations, 2018

PEACEFULNESS OF NATIONS AND THE USE OF INTERNATIONAL FINANCIAL REPORTING STANDARDS

Bairj Donabedian, Pace University
Raymond J Elson, Valdosta State University
Susanne O'Callaghan, Pace University
John P. Walker, Queens College/CUNY
Cathy Dwyer, Pace University

ABSTRACT

The purpose of this paper is to identify any correlations between the use of a standardized accounting framework such as IFRS, and the level of peacefulness of the nations in the world. Not all of the world's 163 nations use a standardized framework to capture financial information or to report with a consistent manner of transparency. However, countries that use a particular systematized reporting framework seem to enhance the economic environment and provide an adequate standard of living among their own inhabitants. To explore this hypothesis, we examined two databases: the 2018 Global Peace Index of 163 ranked countries on their peacefulness (including democracy, transparency, education and material well-being in addition to the economic value of peace and violence) and the IFRS database of countries that require domestic companies to file using IFRS. An analysis of variance (ANOVA) test was applied to the peacefulness index of countries that require IFRS, compared to those that do not. We found that countries that have adopted IFRS are significantly more peaceful compared to those that have not, and that the correlation is not by chance. Future research could study the causation of such a correlation. This research could make a case for consistent use of IFRS around the world and possibly increase the peacefulness of the world.

INTRODUCTION

The purpose of this paper is to identify any correlation between the use of a standardized accounting framework such as IFRS, and the peacefulness of our worlds' nations. Not all of our world's 163 nations require use of a standardized framework to capture financial information or to report with a consistent manner of transparency for reporting entities. Yet countries that require this systematized reporting framework seem to maintain an appropriate economic environment and provide an adequate standard of living among their own inhabitants.

This research is important because "modern economies rely on cross-border transactions and the free flow of international capital. More than a third of all financial transactions occur across borders, and that number is expected to grow. IFRS standards address this challenge by providing a high quality, internationally recognized set of accounting standards that bring transparency, accountability and efficiency to financial markets around the world." (IFRS)

IFRS is a conceptual framework for financial reporting that helps corporations, governments and other investing entities create a conscious movement towards more informed research decisions about economic transactions. Unlike U.S. GAAP, IFRS helps link world economies.

The Global Peace Index (2018) considers issues around safety and security, global conflicts and the state of militarization. Taking these two frameworks into consideration, the quality of consistent accounting reporting standards might be better able to move global neighbors to a more peaceful state of existence.

To explore our hypothesis of a relationship between good accounting and peacefulness, we examined two databases: the 2018 Global Peace Index of 163 ranked countries on their peacefulness (including democracy, transparency, education and material well-being in addition to the economic value of peace and violence) and the IFRS database of countries that require domestic companies to file financial information using IFRS. A Chi-square goodness of fit test was used to examine the strength of association between the two categorical variables: a 3 X 2 matrix represented by three peacefulness levels and a categorical (yes or no) variable of use of IFRS for domestic filings. An ANOVA test was performed to determine whether there was a difference between the peacefulness of states that mandated IFRS compared to those that had not. One hundred and thirty-nine countries have adopted IFRS, and 24 have not.

Our results indicate that there is a significant correlational relationship between peacefulness of countries and the use of IFRS for financial reporting that is not due to chance.

LITERATURE REVIEW

Beattie (2018) explains that bartering and keeping track of economic transactions started four thousand years ago. The purpose of this pre-accounting phenomena was to keep people from entering into disputes. Bookkeeping emerged from the bartering system to handle a cash and commerce economic society. It appears that accounting actually started to reduce conflicts between exchanging economic players.

Phillips & Axelrod (2004) documents the history of war and states that of 1,763 wars, 1,640 (or 90%) were caused, not by religion, but by economic factors such as access to scarce resources, imperialism and population growth. And 98% of casualties of war were also due to economic underpinnings and not religion.

Zaidi & Huerta (2014) concludes that the adoption and enforcement of rules and laws of a comprehensive accounting framework always precedes a country’s economic growth. IFRS adoption leads to improved disclosure, increased transparency (reducing agency cost, estimation of risk, information asymmetry and uncertainly while increasing comparability and credibility.) This transparency leads to more investors, better market liquidity and lower costs of capital leading to more efficient capital markets, and economic growth that ensues in the adapting country.

Fino (2007) indicates the need for accounting in the role of economic growth in developing countries. Accounting is necessary to promote a successful economic planning process. But as IFRS is introduced into developing countries, the success depends on the government’s ability to impose and enforce the standards, given the country’s particular environment or circumstances.

Kubiskova (2016) finds that the adoption of IFRS in the Czech Republic (#7 on the 2018 Global Peace Index) has “contributed to greater cultivation of the economic environment and facilitated international operations” (where foreign parents of Czech Republic companies are required to use IFRS.)

Lastly, the Global Peace Index of 2018 (“GPI”) has studied the relationship between business, peace and prosperity. It has found that in the last 70 years, per capita economic growth has been 3X higher in highly peaceful countries when compared to countries with low levels of peace. (The global impact of violence is approximately $2,000 per person or 12.4% of annual GDP globally.) In the last 10 years GDP has been 7X higher in countries that increased peacefulness. The GPI has found that interest rates and rates of inflation are more stable in peaceful countries and foreign investment is 2X higher in peaceful countries. And if corruption has any effect on economic growth, from 2005 to 2016, 101 countries out of 163 (or 60%) had worsening levels of corruption.

RESEARCH METHODS

We hypothesized a correlation between good global accounting reporting frameworks and the peacefulness of a nation. Our research methods included exploring two databases: the IFRS database of countries that require domestic companies to file using IFRS and the 2018 Global Peace Index that ranks the peacefulness of 163 countries. We wanted to examine the consistent use of a global set of generally accepted accounting principles and their association with the peacefulness of nations. A Chi-Square goodness of fit test was used to examine the strength of association between two categorical variables: a 3 X 2 matrix represented by 3 peacefulness levels (high, medium, low) and a categorical (yes or no) variable of use of IFRS for domestic filings. Table 1, Table 2 and Table 3 provide data on the contents of this 3 X 2 matrix.

Table 1 illustrates the 2018 Global Peace Index classification into a) high peacefulness [countries 1 to 54]; b) medium peacefulness [countries 55 to 108]; and c) low peacefulness [countries 109 to 163]. Peacefulness Rankings begin with #1 being the most peaceful nation and #163 the least peaceful nation.

TABLE 1
2018 Global Peace Index Rankings N = 163

2018 Global Peace Index Ranking [High]	Name of Nation	2018 Global Peace Index Ranking [Medium]	Name of Nation	2018 Global Peace Index Ranking [Low]	Name of Nation
1.	Iceland	55.	Indonesia	109.	Algeria
2.	New Zealand	56.	Qatar	110.	Cote d'Ivoire
3.	Austria	57.	United Kingdom	111.	Guatemala
4.	Portugal	58.	Montenegro	112.	China
5.	Denmark	59.	Timor-Leste	113.	Thailand
6.	Canada	60.	Vietnam	114.	Tajikistan
7.	Czech Republic	61.	France	115.	Djibouti
8.	Singapore	62.	Cyprus	116.	El Salvador
9.	Japan	63.	Liberia	117.	Guinea-Bissau
10.	Ireland	64.	Moldova	118.	Honduras
11.	Slovenia	65.	Equatorial Guinea	119.	Turkmenistan
12.	Switzerland	66.	Argentina	120.	Armenia
13.	Australia	67.	Sri Lanka	121.	United States of America
14.	Sweden	68.	Nicaragua	122.	Myanmar
15.	Finland	69.	Benin	123.	Kenya
16.	Norway	70.	Kazakhstan	124.	Zimbabwe
17.	Germany	71.	Morocco	125.	South Africa
18.	Hungary	72.	Swaziland	126.	Rep of the Congo
19.	Bhutan	73.	Oman	127.	Mauritania
20.	Mauritius	74.	Peru	128.	Niger
21.	Belgium	75.	Ecuador	129.	Saudi Arabia
22.	Slovakia	76.	The Gambia	130.	Bahrain
23.	Netherlands	77.	Paraguay	131.	Iran
24.	Romania	78.	Tunisia	132.	Azerbaijan
25.	Malaysia	79.	Greece	133.	Cameroon
26.	Bulgaria	80.	Burkina Faso	134.	Burundi
27.	Croatia	81.	Cuba	135.	Chad
28.	Chile	82.	Guyana	136.	India
29.	Botswana	83.	Angola	137.	Philippines
30.	Spain	84.	Nepal	138.	Eritrea
31.	Latvia	85.	Trinidad & Tobago	139.	Ethiopia
32.	Poland	86.	Mozambique	140.	Mexico
33.	Estonia	87.	Macedonia (FYR)	141.	Palestine
34.	Taiwan	88.	Haiti	142.	Egypt
35.	Sierra Leone	89.	Bosnia & Herzegovina	143.	Venezuela
36.	Lithuania	90.	Jamaica	144.	Mali
37.	Uruguay	91.	Dominican Republic	145.	Colombia
38.	Italy	92.	Kosovo	146.	Israel
39.	Madagascar	93.	Bangladesh	147.	Lebanon
40.	Costa Rica	94.	Bolivia	148.	Nigeria
41.	Ghana	95.	Gabon	149.	Turkey
42.	Kuwait	96.	Cambodia	150.	North Korea
43.	Namibia	97.	Guinea	151.	Pakistan
44.	Malawi	98.	Jordan	152.	Ukraine
45.	UAE	99.	Togo	153.	Sudan
46.	Laos	100.	Papua New Guinea	154.	Russia
47.	Mongolia	101.	Belarus	155	Central African Rep
48.	Zambia	102.	Georgia	156.	Dem. Rep. Congo
49.	South Korea	103.	Rwanda	157.	Libya
50.	Panama	104.	Lesotho	158.	Yemen
51.	Tanzania	105.	Uzbekistan	159.	Somalia
52.	Albania	106.	Brazil	160.	Iraq
53.	Senegal	107.	Uganda	161.	South Sudan
54.	Serbia	108.	Kyrgyz Republic	162.	Afghanistan
				163.	Syria
	n = 54		n = 54		n = 55
Total N = 163					

Table 2 illustrates the mandatory (or not) use of IFRS by these 163 countries. The IFRS database consists of 139 countries that are mandated to use IFRS for national reporting by domestic companies and 24 countries that do not mandate such use.

Table 2
International Financial Reporting Standards – Use by Country
Mandatory Use in Domestic Filings vs. Non-Mandatory Use in Domestic Filings

IFRS Mandated by Domestic Filings n = 139				IFRS NOT Mandated for Domestic Filings n = 24
Argentina	Mauritius	Angola	Lesotho	Albania
Australia	Moldova	Armenia	Liberia	Indonesia
Austria	Mongolia	Azerbaijan	Macedonia	Japan
Belgium	Montenegro	Bahrain	Mali	Madagascar
Bhutan	Morocco	Bangladesh	Mauritania	Nicaragua
Botswana	Mozambique	Belarus	Mexico	Panama
Bulgaria	Namibia	Benin	Myanmar	Paraguay
Canada	Netherlands	Bosnia and Herzegovina	Nepal	Switzerland
Chile	New Zealand	Brazil	Niger	Vietnam
Costa Rica	Norway	Burkina Faso	Palestine	Bolivia
Croatia	Oman	Burundi	Papua New Guinea	China
Cyprus	Peru	Cambodia	Philippines	Egypt
Czech Republic	Poland	Cameroon	Republic of the Congo	Guatemala
Denmark	Portugal	Chad	Rwanda	Honduras
Ecuador	Qatar	Colombia	Saudi Arabia	India
Equatorial Guinea	Romania	Cuba	South Africa	Thailand
Estonia	Senegal	Djibouti	Sri Lanka	United States
Finland	Serbia	Dominican Republic	Tajikistan	Uzbekistan
France	Sierra Leone	El Salvador	Trinidad and Tobago	Lebanon
Germany	Singapore	Eritrea	Turkmenistan	Afghanistan
Ghana	Slovakia	Ethiopia	Uganda	DPR Korea
Greece	Slovenia	Gabon	Venezuela	Libya
Hungary	Spain	Gambia	Zimbabwe	South Sudan
Iceland	Swaziland	Georgia	Central African Republic	Sudan
Ireland	Sweden	Guinea	Democratic Republic of the Congo	
Italy	Taiwan	Guinea-Bissau	Iraq	
Kazakhstan	Tanzania	Guyana	Nigeria	
Korea Republic	Timor-Leste	Haiti	Pakistan	
Kosovo	Togo	Iran	Russia	
Kuwait	Tunisia	Israel	Somalia	
Laos	United Arab Emirates	Ivory Coast	Syria	
Latvia	United Kingdom	Jamaica	Ukraine	
Lithuania	Uruguay	Jordon	Yemen	
Malawi	Zambia	Kenya	Turkey	
Malaysia	Algeria	Kyrgyzstan		
Total of 139 Countries				**Total of 24 Countries**
Total = 163 Countries				

Table 3 illustrates the three domains used by the 2018 Global Peace Index to measure peacefulness: a) safety and security; b) on-going conflict and c) militarization. It also illustrates the 23 categories underlying each of these three domains.

TABLE 3: Components of the Global Peace Index Calculation	
	a) Safety and Security
1	Perceptions of Criminality
2	Police Rate
3	Homicide Rate
4	Incarceration Rate
5	Access to Small Arms
6	Violent Demonstrations
7	Violent Crime
8	Political Instability
9	Political Terror Scale
10	Terrorism Impact
11	Refugees & IDPs
	b) Ongoing Conflict
1	Intensity of Internal Conflicts
2	Internal Conflicts Fought
3	Deaths from Internal Conflict
4	Neighboring Countries Relations
5	External Conflicts Fought
6	Deaths from External Conflicts
	c) Militarization
1	Weapons Imports
2	Military Expenditures (% GDP)
3	Armed Services Personnel Rate
4	UN Peacekeeping Funding
5	Nuclear and Heavy Weapons
6	Weapons Exports

Table 4 describes the breakdown of peacefulness compared to IFRS mandated use in all 163 countries. The countries are grouped based on their peacefulness (High Peace, Medium Peace, and Low Peace), and this is compared to IFRS mandated use.

Table 4: Countries Listed by Peacefulness Cross-tabbed With IFRS Mandate						
Global Peace Index	**Countries Mandating Use of IFRS**			**Countries Allowing Optional or No Use of IFRS**	**Total Countries**	
High Peace	49 Iceland New Zealand Austria Portugal Denmark Canada Czech Republic Singapore Ireland Slovenia Australia Sweden Finland Norway Germany Hungary	Bhutan Mauritius Belgium Slovakia Netherlands Romania Malaysia Bulgaria Croatia Chile Botswana Spain Latvia Poland Estonia Taiwan Sierra Leone	Lithuania Uruguay Italy Costa Rica Chana Kuwait Namibia Malawi UAE Laos Mongolia Zambia South Korea Tanzania Senegal Serbia	5 Japan Switzerland Madagascar Panama Albania	54	**Total Countries**
Medium Peace	48 Qatar United Kingdom Montenegro Timor-Leste France Cyprus Liberia Moldova Equatorial Guinea Argentina Sri Lanka Benin Kazakhstan Morocco Swaziland Oman Peru	Ecuador The Gambia Tunisia Greece Burkina Faso Cuba Guyana Angola Nepal Trinidad & Tobago Mozambique Macedonia (FYR) Haiti Bosnia & Herzegovina Jamaica	Dominican Republic Kosovo Bangladesh Gabon Cambodia Guinea Jordan Togo Papua New Guinea Belarus Georgia Rwanda Lesotho Brazil Uganda Kyrgyz Republic	6 Indonesia Vietnam Nicaragua Paraguay Bolivia Uzbekistan	54	**Total Countries**
Low Peace	42 Algeria Cote d'Ivoire Tajikistan Djibouti El Salvador Guinea-Bissau Turkmenistan Armenia Myanmar Kenya Zimbabwe South Africa Rep of the Congo Mauritania	Niger Saudi Arabia Bahrain Iran Azerbaijan Cameroon Burundi Chad Philippines Eritrea Ethiopia Mexico Palestine Venezuela	Mali Colombia Israel Nigeria Turkey Pakistan Ukraine Russia Central African Rep Dem. Rep. Congo Yemen Somalia Iraq Syria	13 Guatemala China Thailand Honduras United States of America India Egypt Lebanon North Korea Sudan Libya South Sudan Afghanistan	55	**Total Countries**
		139		24	163	**Total Countries**

RESULTS

ANOVA

The Global Peace Index generates a calculated value that measures the degree of peacefulness within a country. This calculated value is used to determine each country's global ranking (#1 to #163). For 2018, the country with the lowest value (most peaceful) is Iceland, with a score of 1.096. The country with the highest value (least peaceful) is South Sudan, with a value of 3.599.

We wanted to conduct an analysis that determined whether there was a difference between the peacefulness of nations that mandated IFRS compared to those that had not. One hundred thirty-nine countries have adopted IFRS, and 24 have not. The mean peacefulness value for countries that have mandated IFRS is 2.06309, while the mean for those who allow IFRS to be optional is 2.32554 (see Table 5).

Table 5:
Mean Peacefulness Index for 2018 Cross-tabbed with IFRS Requirements

IFRS Adoption	Mean	Number of Countries	Std. Deviation
Y	2.06309	139	0.487516
N	2.32554	24	0.602181
Average Mean for all Countries	2.10174	163	0.51249

An analysis of variance (ANOVA) test was applied to these two groups. The analysis resulted in an F value of 5.517 with a significance level of .02. There is a significant difference between the results for these two groups. Countries that have adopted IFRS are significantly more peaceful compared to those that have not.

Chi Square

Table 6 presents a 3 X 2 Chi-Square that looks like this:

Table 6: Chi Square Analysis

Global Peace Index Rankings of 2018	Countries Mandating Use of IFRS	Countries Allowing Optional Use of IFRS	Total Countries	
High	49	5	54	Total Countries
Medium	48	6	54	Total Countries
Low	42	13	55	Total Countries
Total Countries	139	24	163	

The results of this 3 X 2 matrix, with 2 degrees of freedom, has a Chi Square Statistic of 5.3251, and a p value of .069771, significant at the $p < .10$ level. The results of this Chi-Square goodness of fit test, along with the ANOVA test, prove our hypothesis. The use of IFRS and the peacefulness of a nation are not independent of each other and do have a significant correlational relationship. It confirms that countries that have adopted IFRS are significantly more peaceful.

DISCUSSION

The Chi Square and ANOVA results give us confidence about the association between the use of IFRS and the peacefulness of nations. It measures how well the observed distribution of data fits with the distribution that is expected, assuming the variables are independent. We certainly found that to be true.

However, the use of IFRS might not be the CAUSE of more peace and prosperity. Peacefulness in a country may be influenced by the safety of its citizens, the relationship between nation neighbors (such as India and Pakistan), or the build-up of militarization (all of which have economic impacts that need to be measured.) The use of IFRS may just be “noise” and obscuring the relationship between peacefulness and the use of IFRS. However, “there is no correlation without causation” (Kelleher 2016). According to Kelleher, if a) the use of IFRS does not increase peace and b) peace is not caused by the use of IFRS, BUT the two are correlated, then there must be some common cause of the two. “It may not be a direct cause of each of them, but it’s there somewhere “upstream” in the picture.”

Our research did not control or include hidden common causes of the two phenomena but our results lead to interesting speculation. What if good use of IFRS could and does promote a more peaceful world? The significance of this research is a challenge to continue studying the relationship between accounting and peace.

CONCLUSION

Our objective in this paper was to study the relationship between the use of a single high quality global accounting standard versus other accounting standards across the countries of the world to examine the result on peacefulness of those countries. A major finding is that there is a strong and significant correlation between countries that use IFRS and the existence of higher peacefulness in those countries. Implications of this study could include: a) policy implications; b) a move for non-peaceful nations to better accounting standards; c) the creation of more awareness of the role of accounting in creating a better world and; d) moving the United States toward an IFRS framework.

FUTURE RESEARCH

To build on our research findings, we will continue to research any basis for causation of IFRS use and peacefulness or alternatively, peacefulness causing the use of IFRS. Based on research by Zaid & Huerta (2014), a country with mandated IFRS use, but with little or no enforcement of auditing and disciplinary procedures for non-compliance, and other rules and laws -- makes reliable financial reporting doubtful. We can study countries that use IFRS but are not peaceful. What unique forces occur in these countries for them to use IFRS? We could also examine the 28 European Union countries, all of whom are mandated to use IFRS, comparing their peacefulness differences. For example, France is the most un-peaceful European Union country ranked by the 2018 Global Peace Index at #61 while Austria is ranked #3. A trend study from 2007, when the first Global Peace Index was developed, to present time, could be investigated. Another study might include the country of Russia (very un-peaceful at #154 on the Global Peace scale) and the subset of countries over which Russia has influence. An examination of the 12 countries that rank as the most un-peaceful would also be possible. We also could study countries with poor economic development and good economic development and their relationship with national vs IFRS reporting standards.

Lastly, the Global Peace Index of 2018 also produces a "Positive Peace" index that reports that the most peaceful countries in the world have better sustainable development goals such as: a) acceptance of the rights of others; b) equitable distribution of resources; c) free flow of information; d) good relations with neighbors; e) high levels of human capital; f) a low level of corruption; g) sound business environments and h) well-functioning governments. The Positive Peace Index reports robust economic development and higher GDP growth, strong domestic currencies and appreciation in exchange rates. These characteristics could be studied against the effectiveness of global accounting standards.

REFERENCES

Beattie, A. (2018), "Financial History: The Evolution of Accounting," Investopedia. https://www.investopedia.com/articles/08/accounting-history.asp

Fino, D. The Role of IFRS in Economic Growth of Developing Countries. Retrieved May 21, 2019 from http://www.academic.edu/1160057/

The Global Peace Index 2018, http://visionofhumanity.org/app/uploads/2018/06/Global-Peace-Index-2018-Snapshot.pdf

IFRS. Why Global Accounting Standards. Retrieved August, 3, 2019 from https://www.ifrs.org/use-around-the-world/why-global-accounting-standards/

IFRS. Who Uses IFRS Standards. Retrieved May 21, 2019 from https://www.ifrs.org/use-around-the-world/use-of-ifrs-standards-by-jurisdiction/

Kelleher, A., (2016), blog.godatadriven.com and adamkelleher.com/writing. Accessed on October 12, 2019.

Kubickova, D. (2016). Economics and Political Implications of International Financial Reporting Standards. Retrieved May 21, 2019 from http://www.researchgate.net/publication/315043256

Phillips, C., & Axelrod, A. (2004), "Encyclopedia of War" Infobase Publishing, New York, New York

Zaidi, S., & Huerta, E., (2014) IFRS Adoption and Enforcement as Antecedents of Economic Growth," International Journal of Accounting and Financial Reporting, 4(1).

A VALUE PERSPECTIVE: THE CASE OF WARREN BUFFET AND HIS INVESTMENT BEHAVIOR TOWARDS APPLE, WALMART AND AMAZON

Shanhong Wu, University of Arkansas-Fort Smith
Kermit Kuehn, University of Arkansas-Fort Smith
Jing Jiang, Sacred Heart University

ABSTRACT

In this paper, we use metrics of Ben Graham's value investing principle to examine the actions taken by Warren Buffet toward three prominent stocks: Amazon, Apple and Walmart. We find that decisions of investment/dis-investment and not-investment by Buffet toward the stocks are largely in line with Graham's view on value investing. This paper provides in-depth analysis of value for three stocks and relates to research on the book-to-market anomaly in the finance literature.

INTRODUCTION

Value investing is an investment strategy by which stocks are selected that trade for less than their intrinsic values. Benjamin Graham was a representative figure who pioneered the principles used in security analysis and value investing decisions. The value investment philosophies and strategies can be traced back to Graham and Dodd (1934) on security analysis. For many years, scholars and investment professionals have argued that value strategies outperform the market (Dreman, 1977). Graham's published his ideas in the 1949 classic *The Intelligent Investor*.

A central theme of Graham's thinking is that one should make an investment only when there is a margin of safety available in the security being considered. This requires the investor to "measure or quantify" the investment in terms of "what is paid to what is being offered". If a business can be acquired at a rational price, regardless of what the stock market might say to the contrary, "the ultimate result of such a conservative policy is likely to work out better than exciting adventures into the glamorous and dangerous fields of anticipated growth (Introduction xvi)."

Warren Buffett is perhaps the most prominent and successful figure alive today who practices Graham's investment philosophy. Joined by his partner Charlie Munger, Buffett has expanded on Graham's principles by focusing on "finding an outstanding company at a sensible price", as opposed to chasing a rather generic company at a bargain price.

In this paper, we present an analysis of three prominent stocks that Buffett has regularly discussed but acted toward in differing ways. They are Amazon (AMZN), Apple (AAPL), and Walmart (WMT). These investment decisions will be used to illustrate how the principles of security analysis proposed by Graham were adopted and acted on by Buffett.

In sum, the paper is a case study which examines value investing through the application of theory by a prominent practitioner.

The purpose of this study, then, is to demonstrate value investing as carried out by Buffett, as well as illustrate the shifting realities which appear to move him to invest, disinvest or never invest in what most would consider great companies. Specifically, this study (1) used several metrics to assess the relative attractiveness of each of the three companies based on principles of the value investor and (2) compared these findings with the actions taken by Buffett's Berkshire Hathaway to determine their consistency with Graham's view on investing.

The primary contribution of this research is the application of value investing principles to the investment decisions of a real and substantial market participant and celebrity, Warren Buffett. It is admittedly limited, but we believe representative. Additionally, the paper is related to one of the most researched market anomalies in finance, the book-to-market phenomenon. Notable examples of this literature include Fama and French (1992), Bartov and Kim (2004), and Daniel and Titman (2012). This paper provides this literature with concrete anecdotal evidence of the issues highlighted by this stream of literature.

ANALYSIS

Berkshire's Investment History with AMZN, AAPL and WMT

For this analysis, we selected Amazon (AMZN), Apple, Inc. (AAPL), and Walmart (WMT). These companies are prominent players in their respective industries and Buffett has taken decidedly different investment approaches to each. We begin our discussion by summarizing Berkshire's behavior toward each.

As of June 30, 2018, Warren Buffett's Berkshire Hathaway owned about 246.5 million shares, or about 5.1% of Apple (AAPL), which is worth nearly $50 billion and making it by far the most valuable slice of any company Buffett has invested in (Kim, 2018; Oyedele, 2018).
Buffett was a major shareholder in Walmart (WMT) until 2016, before he sold most of Berkshire Hathaway's stake in the retailer (Lutz, 2017). Berkshire still held roughly 1.4 million shares of Walmart at the end of June 2018, valued at roughly $140 million, but exited completely by the end of 2018 (Boyle & Kochkodin, 2018). At the same time, Buffett cited Jeff Bezos and Amazon as a threat that made retail stocks a "tough" game (Rosenbaum, 2018). Walmart has invested billions in e-commerce, yet it holds a tiny share of the online market compared to Amazon (AMZN). While still well behind Amazon, Walmart has reported online sales of $20.91 billion in 2018 compared with Amazon's $250.92 billion during the same period.

Buffett has praised Bezos effusively, stating, "Jeff Bezos has built an extraordinary economic machine from standing still, a start of zero, with competitors with lots of capital". Yet, he has not bought any Amazon stock. "I should have bought long ago, but I didn't understand the power of the model and the price always seemed more than the power of the model…", the Berkshire CEO told CNBC in 2016. As of 2018, Berkshire had not purchased any Amazon shares.

Table 1 summarizes Buffett's holdings of Apple and Walmart as recently reported by Berkshire.

Table 1
Buffett's Positions in AAPL and WMT (as of reported by Berkshire's most recent 10K)

Firm	Last Report	Percentage of Company Owned	Market Cap (Millions)	First Report	Percentage of Company Owned	Highest Percentage Owned	Highest Percentage Report	Highest Market Cap (Millions)
AAPL	12/31/2017	3.30%	28,213	12/31/2017	1.10%	5.10%	6/30/2018	51,000
WMT	12/31/2015	2.00%	3,893	12/31/2005	0.50%	2.10%	12/31/2014	5,815

Note: major investment holdings from Berkshire Hathaway annual report

Basic Company Information

Apple Inc. (AAPL) is a well-known technology company that designs, develops, and sells consumer electronics, computer software, and online services. The company's major hardware products include the iPhone smartphone, the iPad tablet computer, the Mac personal computer. Apple's key software includes the macOS, iOS operating systems. Its online services include the iTunes Store, the iOS App Store, Apple Music, iCloud, and more. On August 2, 2018, Apple became the world's first trillion-dollar public company in terms of market value.

Amazon.com, Inc. (AMZN) is an American electronic commerce and cloud computing company. The tech giant is the largest Internet retailer in the world as measured by revenue and market capitalization. The amazon.com website sells a well-diversified range of products. The company also produces consumer electronics—such as Kindle and Echo, —and is the world's largest provider of cloud infrastructure service. Amazon also sells certain low-end household products under its in-house brand AmazonBasics. On September 4, Amazon became the second trillion dollar public company.

Walmart Inc. (WMT) is an American multinational retail corporation that operates a chain of hypermarkets, discount department stores, and grocery stores.

In table 2, we present a summary of basic information for the three companies, based on each company's 2017 annual report.

While all three companies are large cap firms, as of the end of August 2018, both AMZN and AAPL market caps were around $1 trillion. The market cap of WMT, which is still one of the largest companies in the world, now only stands at around $280 billion, less than one-third of the other two companies.

Although WMT's market cap is only a fraction of the other two companies, WMT still generates sales twice those of AAPL ($496,785 million vs. $229,234 million) and about three times those of AMZN ($496,785 million vs. $177,866 million). WMT's total net earnings is more than three times that of AMZN, $9,862 million vs. $3,033 million. On the other hand, AAPL is much more profitable in terms of total earnings ($48,351 million vs. $9,862 million).

By the end of 2017 fiscal year, earnings per share (EPS) rankings place AAPL on top, followed by AMZN and WMT. Walmart has been falling out of favor with investors for some time as evidenced by its declining EPS, especially in recent years. Its average EPS during 2010-2012 was $4.58, while the average for the most recent three years is only $4.08. In contrast, both AMZN and AAPL show significant growth of EPS during the same period. Despite the declining earnings, WMT still pays $2.07 per share dividend. AMZN has yet to pay a dividend. Impressively, AAPL paid $2.40 per share dividend in the most recent fiscal year.

Table 2
Basic Information on AAPL, WMT and AMZN

A. Capitalization	AMZN	WMT	AAPL
Price of common, Aug 29, 2018	1998.10	96.08	222.98
Number of shares of common, Jun 29, 2018 (million)	485.23	2950.84	4915.14
Market cap of common, Aug 29, 2018 (million)	969532.07	283517.09	1095977.47
Fiscal year end, 2017			
Fiscal year end month	12	1	9
Number of shares (million)	484.00	2952.00	5126.20
Price of common	1169.47	106.60	154.12
Market cap of common, fiscal year 2017 (million)	566023.48	314683.20	790050.10
Long-term debt (million)	37926	36825	97207
Preferred stock	0	0	0
Total capitalization, fiscal year 2017 (milliion)	603949.48	351508.20	887257.10
B. Income Items, fiscal year end 2017			
Sales	177866	496785	229234
Net income	3033	9862	48351
EPS	6.15	3.28	9.21
EPS, ave., 2015-2017	4.10	4.08	8.91
EPS, ave., 2010-2012	1.27	4.58	4.14
EPS. Ave. 2005-2007	0.78	2.92	0.37
Current dividend	0.00	6124.00	12803
Current dividend per share	0.00	2.07	2.4
C. Balance-sheet Items, fiscal year end 2017			
Current assets	60197	59664	128645
Current liabilities	57883	78521	100814
Current assets to current liabilities	1.04	0.76	1.28
Net assets for common stock (equity)	27709	77869	134047
NWC	2314	-18857	27831
TA-LCT-DLTT	35501	89176	177298
Book value per share	57.25	26.38	26.15

Data source: fiscal year data is from Compustat. Number of shares in recent date is from CRSP.

Overall, all three companies are profitable. Though WMT's profitability has been declining in recent years, AMZN and AAPL's EPS have been growing rapidly, with AAPL even having begun to offer dividends.

For some balance sheet items, AAPL stands out as having the best current ratio of 1.28. In contrast, WMT's current ratio is below the desired level of 1, which, however, may not be a major concern given the nature of the retail business and the quick turnover of the inventory by WMT.

Valuation Ratios

Following the basic concepts of value investing, we examine the valuation ratios, especially the earnings multiples of the three companies. We investigate whether there is a contradiction between fundamentals and valuations. The results can be found in table 3.

Table 3
Valuation Ratios for AAPL, WMT and AMZN

	AMZN	WMT	AAPL
Ratios			
P/E, August, 31, 2017, TTM	159.4	54.84	22.72
Price/earnings, present price, 2017 earnings	324.89	29.29	24.21
Price/earnings,present price, avg. 2015-2017 earnings	487.34	23.57	25.02
Price/book value, present price, 2017 book value	34.90	3.64	8.53
Dividend yield, present price, 2017 dividend	0.00%	2.16%	1.08%
Price/earnings, fiscal 2017 price, 2017 earnings	190.16	32.50	16.73
Price/earnings,fiscal 2017 price, avg. 2015-2017 earnings	285.24	26.15	17.29
Price/book value, fiscal 2017 price, 2017 book value	20.43	4.04	5.89
Dividend yield, fiscal 2017 price, 2017 dividend	0.00%	1.95%	1.56%
52-week low as of Aug, 30	931.75	77.50	149.16
52-week high as of Aug, 30	2025.57	109.98	228.26

Data source: fiscal year earnings are from Compustat, 52-week range is from Yahoo Finance

AMZN’s valuation ratio, especially price earnings (PE), is much higher than those of WMT and AAPL. This clearly is a reflection of AMZN’s greater growth momentum. The question is always whether the optimism of growth is overblown, which can lead to an irrationally high valuation. Even at a modest valuation level, AMZN is only selling at 0.625% (160 PE) earnings yield. This might be one of the reasons Buffett can’t bring himself to invest in AMZN.

AAPL, on the other hand, is performing noticeably better than WMT on a number of key variables, including EPS growth, better overall earnings, a comparable level of dividends, and better current ratios. Yet, AAPL is selling at a similar earnings multiple with WMT. This may be an indication of value that Graham (and Buffett) seeks in an investment: better fundamentals coupled with similar or even cheaper valuation.

WMT’s PE, in some cases, is higher than that of AAPL. This perhaps is an indication that even with the declining earnings, the market has not counted WMT out. Walmart has actually gained following Berkshire’s 2016 sale of the stock. WMT said U.S online sales climbed 40 percent during the second quarter of fiscal year 2018, and the company is still anticipating an increase of 40 percent for the full year. Even though it is down from the 50 percent jump logged in the third quarter of fiscal year 2017, it still raises the question whether Walmart is underestimated by Buffett — again.

As of August 30, 2018, all three stocks are selling close to 52-week highs despite vastly different fundamental readings and relative valuation levels with respect to their fundamentals.
Different factors could contribute to high valuation multiples, such as PE or MB (market-to-book). First, high multiples may represent a company with a lot of intangible assets, such as R&D capital, that are not reflected in accounting book value due to being expensed. A high multiple could also describe a company with attractive growth opportunities and thus, high expected future growth. A high multiple might also indicate a company with high, but temporary, profits. Finally, a high multiple may indicate an overvalued stock based on overestimated future growth opportunities (Lakonishok, Shleifer and Vishny, 1994).

In the following sections, we examined additional fundamentals of the three companies which provides considerable support for the latter case.

Stock Return Performance

In figure 1 and table 4, we present the return performance of the three stocks since 2009. Stock performance illustrates the business growth underlying the three companies.

Figure 1
Growth of $10,000 Investment in AAPL, WMT and AMZN from 2009-2018

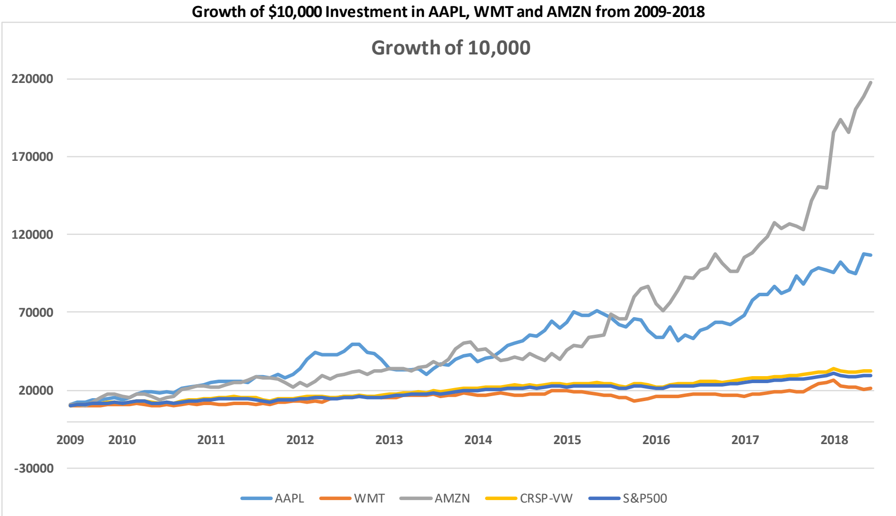


Table 4
Return Performance for AAPL, WMT and AMZN

	2013	2014	2015	2016	2017	2009-TD
AAPL	8.03%	40.43%	-3.04%	12.43%	48.44%	1881.00%
CRSP	30.45%	10.51%	98.32%	12.67%	20.64%	
S&P500	29.60%	11.39%	-0.73%	9.54%	19.42%	
ALPHA	-13.27%	34.20%	-9.43%	20.19%	4.23%	
	2013	2014	2015	2016	2017	2009-TD
WMT	18.24%	11.83%	-26.59%	16.02%	46.51%	114.00%
CRSP	30.45%	10.51%	98.32%	12.67%	20.64%	
S&P500	29.60%	11.39%	-0.73%	9.54%	19.42%	
ALPHA	3.56%	1.29%	-46.75%	25.64%	37.26%	
	2013	2014	2015	2016	2017	2009-TD
AMZN	58.96%	-22.18%	117.78%	10.95%	55.96%	3603.00%
CRSP	30.45%	10.51%	98.32%	12.67%	20.64%	
S&P500	29.60%	11.39%	-0.73%	9.54%	19.42%	
ALPHA	14.98%	-49.49%	103.28%	25.95%	4.83%	

Data source:
Return is calculated using the data from CRSP.
Alpha is calculated using four factor model and factor returns are from Ken French data library.

For a $10,000 investment in AMZN at the beginning of 2009, the value grows to $217,950 by the end of June 2018. AAPL also has tremendous growth, but the value ends up at less than half that of AMZN with the same $10,000 investment growing to $106,910 for the period. The stagnant growth of WMT in the last decade has taken a toll on WMT stock, with the same $10,000 investment worth only $21,603. The period returns and alphas for the three stocks reveal similar stories.

More Fundamentals – Key Profitability Ratios and Earnings Growth

Next, we examine more key profitability measures, which are contained in table 5.

Table 5
Profitability and Earnings Growth for AAPL, WMT and AMZN

	AMZN	WMT	AAPL
Net/sales, 2017	1.71%	1.99%	21.09%
Net per share/book value	10.95%	12.66%	36.07%
Return on invested capital	4.85%	12.25%	19.72%
Earnings growth per share			
2015-2017 vs. 2010-2012	222.83%	-10.99%	115.20%
2015-2017 vs. 2005-2007	423.40%	39.61%	2312.11%
Annual rate: 2015-2017 vs. 2010-2012	26.41%	-2.30%	16.56%
Annual rate: 2015-2017 vs. 2005-2007	18.00%	3.39%	37.48%

Note:
RIOC= (operating income-Taxes)/(LDTT+equity)
Accounting data is from Compustat

Thanks to its dominating ecosystem, AAPL has the best profit margin, return on invested capital (ROIC) and equity (ROE). For fiscal year of 2017, AAPL's profit margin was 21.1% compared to 1.7% and 2.0% for AMZN and WMT respectively. The low profit margins for AMZN and WMT are typical for the retail business sector.

Earnings per share/book value is a measure similar to ROE. AAPL is again in a commanding position, at 36.1%, while AMZN and WMT trail at 11% and 12.7% respectively.
The return on invested capital is calculated by taking the total operating income minus taxes divided by the sum of long-term debt and equity. AMZN shows the lowest ROIC with 4.9%. WMT is in the middle with 12.3%, and AAPL has the highest ROIC at 19.7%.

Taken together, AAPL has the best valuation and margin/profit combination. AMZN on the other hand shows the worst valuation and margin/profit combination. This is not surprising, as many growth firms pursue strong growth momentum at the expense of earnings. However, it may also indicate overvaluation, which can be a red flag for the value investor, assuming other indicators cannot justify the high valuation.

The earnings per share (EPS) growth further attests to the quality of AAPL and, to a certain extent, offers an explanation for the strong price momentum of AMZN and the falling favor of WMT. During the most recent five years, the cumulative EPS growth for AMZN is 222.83%, the highest among the three, with AAPL growing by 115.20% and, in stark contrast, WMT earnings per share declining by 10.99%. In the past decade, AAPL earnings per share grew by 2,312%, followed by AMZN 423%, and WMT by nearly 40%.

The annual compounding rate of earnings per share growth for AMZN is 18% for the past 10 years and 26.41% for the past five years. AMZN's EPS growth has accelerated in the most recent five years. AAPL's earnings per share growth is nearly 38% per year for the past 10 years and 16.6% for the most recent five years. AAPL's earnings per share growth continues to be high but at a slower pace compared to the first five years of the past decade. WMT earnings per share has been in decline. The 10-year annual earnings per share growth rate comes in at 3.4% and has turned negative in the most recent 5 years at -2.3%.

The accelerated EPS growth helps explain the greater price momentum of AMZN. At the same time, the high growth rate by AAPL strengthens the case of 'value' for AAPL. AMZN has the earnings multiple of seven times that of AAPL (159.41%/22.72%), while AMZN's earnings growth rate in recent years is only 1.6 times that of AAPL (26.41%/16.56%).

Due to the declines in recent years, the valuation of WMT has become more expensive than AAPL's. It seems that WMT does not have a case for undervaluation at the moment, at least relative to AAPL. The recent earnings multiple of WMT is 54.8 compared to AAPL's 22.7.

The traditional definition of value stocks is that their growth prospects are weak but they are so cheap that they deliver higher yields. In this sense, based on earnings history, WMT should be most likely a value stock candidate compared to AAPL and AMZN. However, the earnings multiples so far reveal a different story. The earnings multiple drop observed has not been enough to offset the declining growth prospects of WMT. This may explain Buffett's decision to reduce his holdings of the stock. WMT also fails the tests outlined in Graham's book in terms of earnings growth. He states that "[a] minimum increase of at least one-third in per-share earnings in the past ten-years using three-year averages at the beginning and end" is required (p. 184).

AAPL's earnings record shows that it is not a traditional value play either. Even if the earnings growth has slowed, it still shows attractive organic growth prospects. The value of AAPL comes from its relatively cheaper valuation compared with its stronger fundamental growth.

More on Value Strength of Apple

The following analysis substantiates the observation that AMZN may not be a security with an attractive price while AAPL is, based on the principles of value investing represented by Buffett.

Table 6
Earnings Forecast, Actual Earnings and Price Reaction

	Forecast 2015-2017	(Adjustment Stock Splits) Actual 2017	Forecast Error	Price Forecast Date	Price on Announcement Date	Price Advance
AAPL	$9.45	$9.21	-2.61%	$118.93	$168.11	41.35%
AMZN	$5.29	$4.56	-16.01%	$379.00	$1,390.00	266.75%
WMT	$6.01	$4.42	-35.97%	$83.52	$94.11	12.68%

Data source: forecast data is from I/B/E/S

In table 6, we report the median earnings projection for fiscal year 2017 made three years earlier for the three companies. We also report the actual earnings and price realized from the actual earnings announcements. Although most of the forecasts proved to be on the high side, the price has advanced significantly from the date when the forecast was made. However, the magnitude of the price advance varied considerably and render support to the view that AMZN may not be attractively priced relative to AAPL. The forecast error for AAPL is about -2.6% (computed by actual value minus forecasted divided by actual) and price advance is approximately 41%. It is worth noting that AAPL has actually been *under*estimated. In contrast, AMZN's forecast error is 16% (*over*estimated) and price advance was more than 266%.

Consistent with what we report in table 6, La Porta (1993) shows that contrarian strategies based directly on analysts' forecasts of future growth (i.e., buying stocks that are underestimated by analysts' forecast while selling those that are overestimated by analysts' forecast) can produce even larger returns than those based on financial ratios.

Earnings Stability

Graham emphasized that the price a defensive investor pays for a stock should not be unduly high as judged by applicable standards.

One of the standards that Graham proposed was to test earnings stability. Earnings stability is measured by taking the maximum decline in per share earnings in any one of the past ten years divided by the average of the three preceding years. No observed decline translates into 100% stability. Table 7 shows that APPL has a record of 100% earnings stability. AMZN has a disruption in 2011-2014 but shows strong momentum in recent years. AMZN's case may question the usefulness of looking at earnings, if the company is continuing to expand and make investments in potential growth areas. WMT's record again indicates the company is in a downward trend.

Table 7
Earnings Stability

	AAPL	AAPL-Stability	WMT	WMT-Stability	AMZN	AMZN-Stability
2005	0.22		2.68		0.78	
2006	0.32		2.92		0.45	
2007	0.56		3.16		1.12	
2008	0.77	0.40	3.35	0.43	1.49	0.71
2009	1.30	0.75	3.72	0.58	2.04	1.02
2010	2.16	1.29	4.18	0.77	2.53	0.98
2011	3.95	2.55	4.54	0.79	1.37	-0.65
2012	6.31	3.84	5.02	0.87	-0.09	-2.07
2013	5.68	1.54	4.85	0.27	0.59	-0.68
2014	6.45	1.14	4.99	0.19	-0.52	-1.14
2015	9.22	3.07	4.57	-0.38	1.25	1.26
2016	8.31	1.19	4.38	-0.42	4.9	4.46
2017	9.21	1.22	3.28	-1.37	6.15	4.27

Data source: EPS data is from Compustat, EPS has been adjusted for splits or stock dividend.
Stability is calculated by the current year's EPS minus the average of previous three year's EPS

In academic circles, it may still be an open question whether value strategy is fundamentally riskier than other more conventional approaches, and therefore requires higher expected returns, a case argued most forcefully by Fama and French (1992). The evidence here disputes the risk-based explanation, however, and supports the possibility of exploiting the naiveté of investors and markets. The value stock, AAPL, in this case, is on average a much better investment in "bad" states in which the marginal utility of wealth is high.

Growth companies may be popular to the public, but value investors demand more earnings and more assets per dollar of price than the popular issues allow. This is by no means the standard viewpoint of financial analysts. In fact, most analysts will insist that even conservative investors should be prepared to pay generous prices for growth stocks. The value perspective challenges the notion of growth by insisting that the margin of safety disappears when too large a portion of the price depends on ever-increasing earnings in the future. For AMZN's case, it may be too difficult to quantify the materialization of those potential areas. Graham's school opted for the inclusion of a modest requirement of growth over the *past* decade. In contrast, the popular tech stocks may only need a vision of the stock in the *future*.

According to Graham's basic recommendation, the stock, when acquired, should have an overall earnings to price ratio at least as high as the current high-grade bond rate. At the time of this publication, Moody's Aaa bond yield was still below 4%. AAPL provides 4.4% yield at 22.7 times the trailing twelve-month earnings. Therefore, APPL is a bargain opportunity, while AMZN is not.

Segment Profile

The fundamentals of the various business segments of the three companies convey additional qualitative and quantitative evidence to judge their valuation. That is, the relationship between price and indicated value differs considerably among the three.

Table 8
Segment Performance for AAPL, WMT and AMZN

AMZN Sales Share by Reportable Segments				AMAN Profit Margin by Reportable Segments				AMZN Sales Growth by Reportable Segments			
	2015	2016	2017		2015	2016	2017		North America	International	AWS
North America	59.5%	58.7%	59.7%	North America	2.24%	2.96%	2.67%	2015-2017	29.06%	23.82%	48.85%
International	33.1%	32.3%	30.5%	International	-1.99%	-2.92%	-5.64%	2010-2012	36.42%	30.22%	N/A
AWS	7.4%	9.0%	9.8%	AWS	19.12%	25.44%	24.81%				
WMT Sales Share by Reportable Segments				**WMT Profit Margin by Reportable Segments**				**WMT Sales Growth by Reportable Segments**			
					2015	2016	2017		Walmart U.S.	International	Sam's Club
Walmart U.S.	62.3%	64.0%	64.2%	Walmart U.S.	6.39%	5.76%	5.61%	2015-2017	3.31%	-2.19%	2.08%
International	25.8%	24.1%	23.8%	International	4.33%	5.00%	4.53%	2010-2012	2.70%	11.25%	6.81%
Sam's Club	11.9%	11.9%	11.9%	Sam's Club	3.20%	2.91%	1.66%				
AAPL Sales Share by Reportable Segments				**AAPL Profit Margin by Reportable Segments**				**AAPL Sales Growth by Reportable Segments**			
	2015	2016	2017		2015	2016	2017		America	Europe	Greater China
America	40.2%	40.2%	42.1%	America	33.22%	32.53%	31.76%	2015-2017	1.45%	4.47%	-12.68%
Europe	21.5%	23.2%	24.0%	Europe	32.83%	30.73%	30.06%	2010-2012	53.22%	39.40%	187.19%
Greater China	25.1%	22.5%	19.5%	Greater China	39.18%	38.84%	38.05%				

Data source: the calculation is based on the 2017 annual report from AMZN, WMT and AAPL

Let's begin with AMZN. As we see from table 8, the company's ecommerce business in North America is now the dominant part of its business, accounting for 60% of its sales. International ecommerce accounts for about 30%, but the number has declined slightly in recent years. The lucrative cloud computing business, the Amazon Web Service (AWS) segment, accounts for about 10% of the sales but the share has been increasing in recent years. AMZN's ecommerce has been a disruptive force in the retail industry. The Web Services business is a high growth area. The segment distribution is consistent with the growth profile AMZN exhibits.

Operating margins confirm that AWS is a high margin business as well. The recent fiscal year margin is about 25%, an increase over the 19% reported in 2015 but slightly lower than that of 2016. Even with the leading role in the ecommerce retail industry, it is a low margin business with operating margins consistently below 3%. The margins in the international ecommerce retail unit is actually negative and continues to deteriorate, suggesting the firm is driving for market share at the expense of short-term profit. This picture of segment profitability is likely to give value investors pause in the face of the hefty share price.

Another concern for the value investor when it comes AMZN revolves around growth. Segment growth data shows that ecommerce sales growth has been slowing when comparing the most recent three-year period with five years ago. AWS is the exception, which didn't even exist five years ago. This indicates AMZN's innovative power as it continues to enter into new growth areas, but these bets will not be particularly attractive to the value investor at this point.

WMT segment information is consistent with its stagnant and declining trajectory. Segment sales share has been pretty stable over the three-year period 2015-2017, except in the international segment which has declined slightly. The operating margin for all segments has been declining over the years even though the margin from Walmart U.S. and international are still higher than those of AMZN. Sales growth rates in all segments are generally declining relative to the same period five years ago. The only exception is in Walmart's U.S. operations, where sales growth in the most recent period was 3.31% compared to 2.71% five years ago.

The information from AAPL's segment is also consistent with AAPL's steady and solid results. Here, we only report the results for the three major segments (America, Europe, and Greater China) which account for more than 86% of the total sales in each year. AAPL America sales share have grown slightly in recent years. The sales share from Europe has also shown notable increases. In contrast, the sales share from the Greater China market has experienced significant declines.

The operating margin results for AAPL's three major segments confirm that AAPL is in a relatively higher margin business. The margin is always more than 30%, a stark contrast to the retail business for both AMZN and WMT. The margin from the greater China area is typically close to 40%. Unfortunately, AAPL's sales growth has slowed when compared to the same period five years ago. This may explain the much more modest multiples AAPL is trading at compared to AMZN.

Other Aspects of Fundamentals

Based on recent valuations, the general consensus seems to be that AMZN is a force of growth, which leads to it trading at higher multiples. However, the problem is that even though the growth has been impressive in recent years, earnings remain unstable. Supporters of its valuation would argue that the firm has sacrificed the short-term earnings for long-term growth. WMT has been the opposite with earnings slowing down and earnings growth deteriorating. As a result, its valuation has suffered. Given the general slump of its fundamentals, the price is still relatively on the high end.

AAPL is still another story. The fundamentals of earnings growth, stability and margin are all very impressive. Most importantly, it is still trading at moderate multiples. It is a natural candidate for the value investor who demands the fair price come with a margin of safety.

In the following section, we discuss the growth rates by looking at items other than earnings. Table 9 presents capital expenditures (CAPX), operating cash flows (OCF), free cash flows (FCF), cash holdings, and sales over the 10-year period for each of the companies. We then calculated the annual growth rate for the 10-year period and the most recent 5-year period.

Table 9
More Fundamentals for AAPL, WMT and AMZN

AAPL

	CAPX	OCF	Free Cash Flow	CASH	Sales	Dividend Per Share	Repurchase
2007	735	5470	4735	15386	24006	0.00	0.02%
2008	1091	9596	8505	24490	32479	0.00	0.00%
2009	1144	10159	9015	23464	42905	0.00	0.00%
2010	2005	18595	16590	25620	65225	0.00	0.00%
2011	4260	37529	33269	25952	108249	0.00	0.00%
2012	8295	50856	42561	29129	156508	0.38	0.00%
2013	8165	53666	45501	40546	170910	1.63	12.98%
2014	9571	59713	50142	25077	182795	1.81	21.74%
2015	11247	81266	70019	41601	233715	1.98	15.21%
2016	12734	65824	53090	67155	215091	2.18	10.23%
2017	12451	63598	51147	74181	229234	2.40	10.81%
10-growh	32.71%	27.80%	26.87%	17.04%	25.31%		
5-growth	8.46%	4.57%	3.74%	20.56%	7.93%		

WMT

	CAPX	OCF	Free Cash Flow	CASH	Sales	Dividend Per Share	Repurchase
2007	14937	20354	5417	5569	375376	0.88	5.09%
2008	11499	23147	11648	7275	402298	0.95	2.15%
2009	12184	26249	14065	7907	406103	1.09	4.45%
2010	12699	23643	10944	7395	420016	1.21	8.66%
2011	13510	24255	10745	6550	444948	1.46	3.49%
2012	12898	25591	12693	7781	467231	1.59	3.93%
2013	13115	23257	10142	7281	474259	1.88	3.29%
2014	12174	28564	16390	9135	483521	1.92	0.50%
2015	11477	27389	15912	8705	479962	1.96	2.02%
2016	10619	31530	20911	6867	482154	2.00	4.16%
2017	10051	28337	18286	6756	496785	2.04	4.17%
10-growth	-3.88%	3.36%	12.94%	1.95%	2.84%		
5-growth	-4.87%	2.06%	7.57%	-2.79%	1.23%		

AMZN

	CAPX	OCF	Free Cash Flow	CASH	Sales	Dividend Per Share	Repurchase
2007	224	1405	1181	3112	14835	0.00	5.68%
2008	333	1697	1364	3727	19166	0.00	1.54%
2009	373	3293	2920	6366	24509	0.00	0.00%
2010	979	3495	2516	8762	34204	0.00	0.00%
2011	1811	3903	2092	9576	48077	0.00	1.47%
2012	3785	4180	395	11448	61093	0.00	3.80%
2013	3444	5475	2031	12447	74452	0.00	0.00%
2014	4893	6842	1949	17416	88988	0.00	0.00%
2015	4589	11920	7331	19808	107006	0.00	0.00%
2016	6737	16443	9706	25981	135987	0.00	0.00%
2017	11955	18434	6479	32315	177866	0.00	0.00%
10-growth	48.84%	29.36%	18.56%	26.37%	28.20%		
5-growth	25.86%	34.55%	74.98%	23.07%	23.83%		

Data source: accounting information is from Compustat
Free Cash Flow = Operating cash flow (OCF) - Capital expenditure (CAPX)

The results provide some additional justification for AMZN's high valuation. For example, AMZN has the highest growth rate for all the above items for the 10-year period. 10-year capital expenditure growth rate for AMZN is a whopping 48.84% compared to Apple's 32.71% and -3.88% for WMT. This provides evidence that AMZN is pursuing long-term investment rather than short-term earnings. Cash holdings growth for AMZN is also striking. The growth rate for the 10-year period is 26.37%, compared to Apple's 17.04% and WMT's 1.95%. This is consistent with AMZN's expansion strategy where holding cash is critical for investment or M&A.

Other growth rates, such as OCF, FCF and Sales, for the 10-year period for AAPL and AMZN are quite similar. However, when looking at the growth rate of the most recent 5-year period, AMZN is much stronger than AAPL. This shows that AAPL may have lost some of its growth momentum relative to AMZN. In this regard, AAPL becomes a better value play than AMZN.

If WMT's price continues to decline, it has the potential to become a bargain. The growth for WMT is generally meager and even gotten worse in recent periods. However, WMT does have a stable history of dividends and decent growth of OCF and FCF.

A concern of note for AMZN is that recent five-year annual growth rates of CAPX and Sales have been lower than its own 10-year annual growth rate. This implies that growth have been slowing in recent years. The result is consistent with the finding of differences between glamor and value stocks as noted in Lakonishok et al (1994). Using similar descriptive characteristics here, they found that although glamor stocks grew substantially faster than value stocks before the portfolio formation years, the relative growth rates of fundamentals over the post formation years for glamor stocks are much less impressive. The evidence indicates there may be excessive extrapolation of expected future growth implied by the very high valuation multiples.

Capitalization Rates for Growth Stocks

In his book *The Intelligent Investor*, Graham suggests a formula for the valuation of growth stocks. The formula is Value = Current (Normal) Earnings × (8.5 plus twice the expected annual growth rate). The growth figure should be the expected rate over the next seven to ten years. It is easy to make the reverse calculation and determine what rate of growth is anticipated by the current market price, assuming the formula is valid. We back out the implied growth rate for the three stocks using his equation. The results are in table 10.

The difference between the implicit annual growth rate and the even higher actual rate for AAPL provides further evidence that it is a value candidate. On the other hand, WMT's record suggests it has not reached an attractive price level for the value investor. AMZN has not generated a stable earnings record.

Graham once pointed out this caution: "the valuations of expected high-growth stocks are necessarily on the low side, if we were to assume these growth rates will actually be realized. In fact, according to the arithmetic, if a company could be assumed to grow at a rate of 8% or more indefinitely in the future its value would be infinite, and no price would be too high to pay for the shares". What the value investor actually does in these cases is to introduce a margin of safety into his calculations. On this basis, the buyer would realize his assigned objective even if the growth rate actually realized proved substantially less than the projection.

Table 10
Projected Capitalization Rates for AAPL, WMT and AMZN

	P/E 2014	Projected Growth Rate (%) 2014	Earned Per Share 2014	Earned Per Share 2017	Actual Annual Growth (%) 2014-2017	P/E Ratio 2017	Projected Growth Rate (%) 2017
AAPL	15.62	3.56	6.45	9.21	12.61	16.73	4.12
WMT	17.03	4.27	4.99	3.28	-13.05	32.5	12.00
AMZN	N/A	N/A	-0.52	6.15	N/A	190.16	90.83

	P/E 2012	Projected Growth Rate (%) 2012	Earned Per Share 2012	Earned Per Share 2017	Actual Annual Growth (%) 2012-2017	P/E Ratio 2017	Projected Growth Rate 2017
AAPL	15.11	3.31	6.31	9.21	7.86	16.73	4.12
WMT	13.93	2.72	5.02	3.28	-8.16	32.5	12.00
AMZN	N/A	N/A	-0.09	6.15	N/A	190.16	90.83

	P/E 2007	Projected Growth Rate 2007	Earned Per Share 2007	Earned Per Share 2017	Actual Annual Growth (%) 2007-2017	P/E Ratio 2017	Projected Growth Rate 2017
AAPL	39.05	15.28	0.56	9.21	32.31	16.73	4.12
WMT	16.06	3.78	3.16	3.28	0.37	32.5	12.00
AMZN	82.71	37.11	1.12	6.15	18.57	190.16	90.83

Data source: EPS is from Compustat

RESULTS AND CONCLUSION

In this article, using Graham's value investing principles, we applied several tests to examine the valuations of AAPL, WMT and AMZN stocks with respect to their individual fundamentals. In our review, we found that the most attractive investment option of the three was AAPL. Based on our analysis, the reasons for this include AAPL's large size in an industry that is still growing. Additionally, AAPL was very strong in the metrics examined here, as well as providing a stable dividend history supported by earnings stability and a proven growth record. This impressive track record has not been fully recognized in its stock price. This is the definition of a value play.

We further noted that WMT was not a likely candidate for investment due to declining earnings trend in an industry experiencing changes unfavorable to the company. Moreover, the company does not seem to be trading cheaply enough to justify a bargain in the eyes of the value investor.

And finally, our analysis suggests that AMZN is a difficult prospect for the value investor to embrace due to its valuation hinging on the high expectation of the continuing high-growth without a proven earnings record.

Buffett, a successful practitioner of value investing, has behaved quite differently toward each. From a value investor's perspective, our analysis indicates that AAPL has superior intrinsic value, WMT is not yet cheap enough to invest and AMZN is too expensive relative the underlying value. The evidence strongly suggests that Warren Buffett would agree and has largely invested accordingly, at least through 2018.

REFERENCES

Bartov, E. & Kim. M. (2004). Risk mispricing and value investing, *Review of Quantitative Finance and Accounting*, 23(4), 353-376.

Bloomberg News (2019, August 3). *Warren Buffett sees cash pile swell to new record at Berkshire Hathaway*. Retrieved August 7, 2019 from https://www.investors.com/news/warren-buffett-berkshire-hathaway-earnings-q2-2019-cash/

Boyle, M. & Kochkodin, B. (2018, November 14). *After More Than Two Decades, Warren Buffett Sells His Last Walmart Shares*. Retrieved August 7, 2019 from https://www.bloomberg.com/news/articles/2018-11-14/buffett-bids-farewell-to-walmart-after-20-years-as-amazon-reigns

Daniel, K. & Titman, S. (2012). Testing factor-model explanations of market anomalies, *Critical Finance Review*, 1(1), 103-139.

Dreman, D. (1977). *Psychology and the Stock Market: Why the Pros Go Wrong and How to Profit*, New York: Warner Books.

Fama, E. & French, K. (1992). The cross-section of expected stock returns, *The Journal of Finance*, 46, 427-466.

Graham, B. (1949). *The Intelligent Investor*, New York: Collins Business.

Graham, B. & Dodd, D. (1934). *Security Analysis*, New York: McGraw-Hill.

Kim, T. (2018, August 1). *Warren Buffett just made more than $2 billion in Apple.* Retrieved September 17, 2018 from https://www.cnbc.com/2018/08/01/warren-buffett-just-made-more-than-2-billion-in-apple.html

Lakonishok, J., Shleifer, A. & Vishny, R. (1994). Contrarian investment, extrapolation, and risk, *The Journal of Finance*, 49(5), 1541-1578.

La Porta, R. (1996). Expectations and the cross-section of stock returns, *The Journal of Finan*ce, 51(5), pp. 1715-1742.

Lutz, A. (2017, Feb. 14). *Warren Buffett just dropped Walmart and signaled the death of retail as we know it.* Retrieved September 17, 2018 fromhttps://www.businessinsider.com/warren-buffett-drops-walmart-stock-2017-2

Oyedele, A. (2018, August 6). *Warren Buffett's Berkshire Hathaway now owns a whopping $50 billion-plus stake in Apple, its largest in any single company.* Retrieved September 17, 2018 from https://www.businessinsider.com/warren-buffett-berkshire-hathaway-apple-stake-rises-over-50-billion-2018-8

Perez, S. (2018, December). *Walmart passes Apple to become No. 3 online retailer in U.S.* Retrieved August 9, 2019 from https://techcrunch.com/2018/11/16/walmart-passes-apple-to-become-no-3-online-retailer-in-u-s/

Powell, J. (2019, February 26). *Buffett puts the final nail in the coffin of book value*. Retrieved July 31, 2019 from https://ftalphaville.ft.com/2019/02/26/1551164404000/Buffett-puts-the-final-nail-in-the-coffin-of-book-value/

Rosenbaum, E. (2018, August 16). *Warren Buffett's warning on Walmart: There are better stocks than retailers.* Retrieved September 17, 2018 from https://www.cnbc.com/2018/08/16/warren-buffetts-warning-on-walmart-better-stocks-than-retailers.html

SOCIAL MEDIA USAGE AND RELATIONSHIP TO REVENUE AMONG TECHNOLOGY FIRMS

Katherine Taken Smith, Texas A&M University-Corpus Christi
Karen A. Loveland, Texas A&M University-Corpus Christi
Lawrence Murphy Smith, Texas A&M University-Corpus Christi

ABSTRACT

Prior research indicates that a business firm benefits when it includes social media in the firm's marketing mix. Social media links a firm to consumers, investors, workers, suppliers, lenders, and other stakeholders. Social media platforms range from older platforms, such as Facebook and Twitter, to more recent platforms, such as Google+ and Instagram. Identifying the social networking sites that are most beneficial to a firm and its customers can be a challenge. The present study empirically analyzes the use of social media by major technology firms to determine which platforms the firms use and whether use varies according to company size (total revenue). Results will be of meaningful to business leaders and firm managers in the technology industry, as well as to academicians who study the effect of emerging technologies, specifically social media, on technology firms. From an ethical perspective, firms must disseminate information that is dependable and correct; social media provides an efficient means for firms to distribute information to customers, investors, and others.

INTRODUCTION

Research studies show that a business firm receives benefits when social media is part of the firm's marketing mix. Over recent years, a steady rise has occurred in blogs, posts, tweets, and other uses of social media. Social media links the firm to consumers, investors, workers, suppliers, lenders, and other stakeholders. Social media platforms used range from older platforms, such as Facebook and Twitter, to more recent platforms, such as Google+ and Instagram. Identifying the social networking sites that are most beneficial to a firm and its customers is a challenge to effective business operations. Since consumer preferences and requirements are diverse and constantly evolving, most business firms, including technology firms, make use of multiple social media platforms in firm operations.

The present study empirically analyzes the use of social media by major technology firms. The objectives of the study are (1) to identify the social media platforms used by major technology firms and (2) to determine whether that use varies according to company size (total revenue). Results will be meaningful to business leaders and firm managers in the technology industry, as well as to academicians who study the effect of emerging technologies, specifically social media, on technology firms. From an ethical perspective, firms must disseminate information that is dependable and correct; social media provides an efficient means for firms to distribute information to customers, investors, and others.

Firm managers in the technology sector should assess the extent to which customers use social media to share their views regarding firms and products. Prior research indicates that social media use has enlarged the Internet to become not only a source of information but also a source of influence (Smith et al., 2015). Over three-fourths of firms make use of social media to achieve business objectives (Alexander, 2011). This rise in social media use is projected to continue (Weinberg & Pehlivan, 2011; Barnes, 2010; Harris & Rae, 2009). In some settings, social media could become the primary way in which firms interact with customers (Baird & Parasnis, 2011).

No previous study has empirically analyzed social media usage by technology firms. This study uses the empirical methodology employed in prior academic studies, such as social media usage by energy companies (Chamberlain et al., 2019a), hospitals (cf., Smith, 2017) and professional accounting firms (Chamberlain et al., 2019b), to analyze social media usage by large, publicly-traded technology firms. Findings will contribute to the academic literature pertaining to social media usage.

The results of this study should be of interest to managers and industry leaders in the technology sector, as well as to academic researchers concerned with the effect of new technologies, specifically social media, on technology firms. A clearer grasp of the social media platforms employed by technology firms will help technology firm managers select the social media platforms that are more beneficial to their firms and will help academic researchers better understand social media usage in general and its impact on the technology sector in particular.

RESEARCH QUESTIONS

There is expanding use of social media by business firms of all types, including technology firms. Further, social media is widely used by consumers to disseminate information about technology firms and their products and services. Consequently, this study addressed the following three research questions:

RQ1: What social media platforms do technology firms currently use?
RQ2: Is there a significant difference in the use of social media platforms among technology firms?
RQ3: Is there a significant difference in total revenue between firms with higher use of social media platforms versus firms with lower use of social media platforms?

REVIEW OF PRIOR RESEARCH

Social media has become an increasingly important avenue by which business firms interact with consumers. For some firms, there is legitimate worry about the ability to control the information disseminated by consumers on social media, which may or may not always be accurate. In any case, firms should be involved with social media, given that it is an increasingly popular way in which consumers share information about firm products and services (Chamberlain et al., 2019a; Smith & Smith, 2018). Past studies indicate that social media has become a critical ingredient in a firm's marketing mix (Smith et al., 2015; Mangold & Faulds, 2009; Li & Bernoff, 2008). More and more, social media is employed as a marketing tool. Almost 70 percent of Fortune 2000 companies were making use of social media by 2010 (McCorkindale, 2010).

The most obvious reason companies use social media is to communicate with prospects and customers. Prior research has shown that social media has a positive impact on the way consumers view a company and their decision-making related to purchases (e.g., Ali et al., 2016). Firms have also recognized the value of social media for communicating with other stakeholders. Curley & Noormohamed (2013) explored the use of social media as part of a firm's corporate social responsibility (CSR) program. The authors reported a variety of ways firms use social media to communicate with suppliers and investors. Their research prompted them to state that social media, "is a natural platform for cultivating and instilling . . . corporate messages" (2014, p. 61).

Uyar and Boyar (2015) suggested that social media is an important tool for corporate reporting. Their analysis of publicly traded firms in Turkey found that many firms were underutilizing social media to communicate with stockholders. Another study of large firms in the US (Saxton, 2016) analyzed the impact of Twitter posts on corporate reputation and the nature of stakeholder-originated discussions of CSR activities on social media. He noted that corporate responses to CSR-related posts by the public are also a form of CSR that firms should consider in managing of corporate reputation. Prior research indicates that effectively managing corporate reputation can increase the firm's market value (Smith et al., 2010). In addition, advertising has been used to promote an industry's reputation (Smith et al., 2014). Given the expanding use of social media, advertising there could be increasingly important for this purpose.

Table 1 lists popular social media platforms found on technology firm websites. Twitter is a social platform that allows users to send and receive short, text-based messages known as "tweets." Limited to 140 characters, tweets can be used to send/receive news, follow celebrities and other high-profile people, or communicate with friends. Twitter has become very popular since its launch in 2006 with over 100 million daily active users.

Table 1
SOCIAL MEDIA PLATFORMS

Platform	Description
Twitter	An online social networking service and microblogging service that enables its users to send and read short text-based messages, known as "tweets".
Facebook	An online social networking service in which users may create a personal profile, add other users as friends, and exchange messages, including automatic notifications when they update their profile. Additionally, users may join common-interest user groups, organized by workplace, school or college, or other characteristics.
LinkedIn	A social networking website for people in professional occupations.
YouTube	A video-sharing website, on which users can upload, view and share videos.
Google+	A social networking service. Unlike other social networks which are generally accessed through a single website, Google has described Google+ as a "social layer" consisting of not just a single site, but rather an overarching "layer" which covers many of its online properties.
Instagram	An online photo-sharing and video-sharing service that enables its users to take pictures and short videos and share them on a variety of social networking services, including Facebook or Twitter.
Blog	A blog provides a platform for discussion or informational site.
Pinterest	A site denoted as a visual bookmarking location.

Source: Adapted from Smith et al. (2015).

Facebook is well-established as the world's most extensively used social media platform, with more than 700 million users (Alexander, 2011). More than 700,000 firms operate active pages on Facebook's social media site (Briones et al., 2011). On Facebook, a business firm can create “business pages” to push their products, services, and brands. Among Internet sites, only Google and YouTube have a higher traffic rank than Facebook (Alexa, 2019).

Facebook enables individuals to create a personal profile, designate other Facebook users as “friends”, and send-and-receive messages. Facebook allows users to share photos, short videos, and links to interesting information they found online. It also allows users to “like” and/or comment on other users’ posts. Users often join mutual-interest user groups, based on workplace, religion, school, hobbies, interests, or other characteristics.

The social networking site LinkedIn is a career-oriented site targeted at professionals. It is essentially an online networking site based on the concept of six degrees of separation. It allows users to designate other users as a contact and allows you to see how they are connected through their network to still other users. Businesses use LinkedIn for recruiting and to share company news with followers.

YouTube provides a platform for video files that users can upload, watch, and share (Smith et al., 2015). The platform has two groups: creators and viewers. Many firms act as creators posting videos related to their products and/or services. Non-affiliated creators may also post content relevant to businesses including product reviews, how-to-use videos, and unboxing videos. Google+ is defined by Google as a "social layer" consisting of not just one site, but as an all-encompassing "layer" that includes many of its online properties such as YouTube and Blogger.

Instagram is a social media site for sharing photographs and short video files. Instagram is owned by Facebook and reaches a somewhat younger demographic. The “Story” feature allows users to post content that is only available for one day making it particularly appealing to companies announcing flash sales or other instant. Blogs are social media platforms in which users can facilitate discussions or provide information. A blog is a social networking site because it enables back-and-forth communication, where visitors can leave comments. A business firm can use a blog to promote its brands (Smith et al., 2015).

Pinterest is a social media site that serves as a visual bookmarking location. The site’s name, Pinterest, is derived from the words “pin” and “interest.” The categories are diverse and extensive, such as art, the Bible, fashion, Star Wars, the American Civil War, WW 2, A.E. van Vogt, William Wallace, Tim Keller, and castles. A Pinterest user sets up “boards” on topics of personal interest, to which “pins” are made (either created new or pinned from other Pinterest boards). Other users can then follow these boards.

Determining social media’s return on investment (ROI) has proven difficult to measure. No consistently accepted performance measure has been developed. For the most part, businesses are not tracking ROI of social media (Briones et al., 2011; Fisher, 2009; Taylor & Kent, 2010; Solis & Breakenridge, 2009). The time and cost to track and analyze social media efforts is problematic. Few firms have the financial and personnel resources to devote to the task. Research by Hitt et al. (2015) indicates that the financial benefit of social media depends on a firm’s ability to obtain and make use of external data.

Each day social media is accessed by billions of people (Hansen et al., 2011). Principally used for sending and receiving information, social media is also a factor in decision-making by consumers. Online messaging can be effective in establishing diverse facets of consumer behavior, such as awareness, attitudes, and purchasing (Mangold & Faulds, 2009; Mangold & Smith, 2011). One research study found that 60 percent of consumers employed social media to create a review or disseminate a previously written review (Johnson, 2011). Another study determined that consumers seek out product reviews found on social media to lower cognitive costs in buying-related decisions (Liu et al., 2011). In this way, social media provides product and manufacturer information that streamlines the buying decision.

Among Internet websites, social media sites are among the highest trafficked. Alexa, an Amazon company, ranks websites based on a calculation that incorporates average daily visitors with pageviews. In March 2019, Google was the highest ranked website, followed by social media site, Youtube. Facebook ranked third. Twitter ranked 11 and LinkedIn ranked 25. Thus, four social media sites were among the top 25 Internet sites, including the second and third-most visited sites (Alexa, 2019).

Some business firms are making use of social media ‘mission control’ centers to measure and react to social media activity when it occurs (Weinberg & Pehlivan, 2011). The mission control centers are referred to as ‘war rooms.’ In some cases, the control centers are set up to monitor special events. For example, several advertisers associated with Super Bowl 2013, including Oreo and Coca-Cola, established war rooms for the big game to engage in ongoing social media conversations during the game (Chamberlain et al., 2019b).

METHODOLOGY AND RESULTS

The methodology employed in the present study was developed in prior research regarding social media usage (cf., Chamberlain et al., 2019a; Chamberlain et al., 2019b; Smith, 2017). A sample was selected from the major technology-related firms listed in the Fortune 500. The sample comprised 50 major technology firms, for which comprehensive financial information was accessible. While only 50 firms were included in the sample, this sample size matches to other financial-related studies, such as those concerning energy companies, sample size 28 (Chamberlain et al., 2019a); GMO products firms, sample size 30 (Martin et al., 2017); food products firms, sample size 30 (Martin et al., 2016); federal tax rates, sample size 30 (Smith et al., 2011); and multinational corruption, sample size 48 (Okafor et al., 2014). Financial information was retrieved from Yahoo Finance (2018).

Table 2 shows the number of social media platforms used by each firm, along with the firm’s total revenue in the most recent period in which data was accessible. Social media use ranged from a high of seven social media platforms to a low of none.

Table 2
TECHNOLOGY FIRM, SOCIAL MEDIA USAGE, AND TOTAL REVENUE

#	Company	Total Social Media Platforms	Total Revenue ($ Mill.)
1	Amazon	7	135,987
2	Qualcomm	7	23,554
3	Amphenol	7	6,286
4	Motorola Solutions	7	6,038
5	NetApp	7	5,546
6	Alphabet	6	90,272
7	Oracle	6	37,047
8	Texas Instruments	6	13,370

Table 2
TECHNOLOGY FIRM, SOCIAL MEDIA USAGE, AND TOTAL REVENUE

#	Company	Total Social Media Platforms	Total Revenue ($ Mill.)
9	Applied Materials	6	10,825
10	CommScopes Holding	6	4,924
11	Advanced Micro Devices	6	4,272
12	Apple	5	215,639
13	Intel	5	59,387
14	Jabil Circuit	5	18,353
15	Thermo Fisher Scientific	5	18,274
16	Broadcom	5	13,240
17	Micron Technology	5	12,399
18	Xerox	5	10,771
19	eBay	5	8,979
20	salesforce.com	5	6,667
21	NCR	5	6,543
22	Lam Research	5	5,886
23	Nvidia	5	5,010
24	Juniper Networks	5	4,990
25	Intuit	5	4,694
26	Electronic Arts	5	4,396
27	Science Applications International	5	4,315
28	Agilent Technologies	5	4,202
29	CA	5	4,025
30	On Semiconductor	5	3,907
31	IBM	4	79,919
32	Hewlett-Packard Company	4	48,238
33	CDW	4	13,982
34	Cognizant Technology Solutions	4	13,487
35	Western Digital	4	12,994
36	Priceline Group	4	10,743
37	Corning	4	9,390
38	Leidos Holdings	4	7,043
39	Sanmina	4	6,375
40	Harris	4	5,992
41	Adobe Systems	4	5,854
42	Booz Allen Hamilton Holding	4	5,406
43	Amkor Technology	4	3,894
44	Microsoft	3	85,320
45	Cisco Systems	3	49,247
46	Danaher	3	16,882

Table 2
TECHNOLOGY FIRM, SOCIAL MEDIA USAGE, AND TOTAL REVENUE

#	Company	Total Social Media Platforms	Total Revenue ($ Mill.)
47	Liberty Interactive	3	10,647
48	Expedia	1	8,774
49	Activison Blizzard	1	6,608
50	Facebook	0	27,638

Data Sources: Fortune (2017). Fortune 500. http://fortune.com and Yahoo (2018). Yahoo Finance. http://finance.yahoo.com.

Table 3 shows the percent of firms using the different social media sites. Twitter, Facebook, and LinkedIn are the most used, with 98.0 percent of firms using Twitter; 92.0 percent using Facebook; and 86.0 percent using LinkedIn. In addition to these three, other social media sites used include YouTube, Google+, Instagram, Blog, and Pinterest.

Table 3
SOCIAL MEDIA PLATFORMS USED BY TECHNOLOGY FIRMS

Social Media Platform	% Using
Twitter	98.0
Facebook	92.0
LinkedIn	86.0
YouTube	68.0
Google +	42.0
Instagram	22.0
Blog	22.0
Pinterest	6.0

Table 4 shows the results of the t-test of social media platform usage by technology firms and the assessment of the connection between total revenue and social media platform usage. The technology firms using 6 or more social media platform usage made use of significantly more platforms than firms using 5 or fewer platforms. The average number of social media platforms used by technology firms ranged from 6.5 for the higher-social-media-use firms to 4.2 for the lower-social-media-use firms. Concerning revenue, the technology firms using 6 or more social media platform usage had higher revenue than firms using 5 or fewer platforms. The average total revenue of technology firms ranged from $30.7 billion for the higher-social-media-use firms to $21.3 billion for the lower-social-media-use firms, though the difference was not significant. Facebook was omitted from the statistical analysis due to it being a social media company.

Table 4
RESULTS OF T-TEST OF TECHNOLOGY FIRM REVENUE BY SOCIAL MEDIA USE

Ranked by # Social Media Platforms	Average # Social Media Platforms*	Average Revenue ($ mill.)**
Firms with 6 or more platforms	6.5	30,738
Firms with 5 or less platforms (Excl. FB)	4.2	21.381
All Firms	4.6	23,565

*T-Test Results, Significant Difference, p<.000.
**T-Test Results, No Significant Difference, p<.263

SUMMARY AND CONCLUSIONS

This study analyzes the extent of social media platform usage by major publicly traded technology-related firms. Knowledge of which social media platforms are most often used will help technology company managers evaluate which platforms could be the optimum choices for their individual companies. Previous research indicates that firms benefit by making social media part of the firm's marketing mix. Firms are expanding use of blogs, tweets, posts, and other social media activity to interact with customers, suppliers, employees, and others. Social media are useful in promoting a firm's products and services, as well as in enhancing the image of the tech sector in general.

The study focused on three research questions. The first question addressed which social media platforms were most used by technology firms. The results indicate that the three most frequently used platforms are Twitter, Facebook, and LinkedIn. The second question addressed whether there was a significant difference among technology firms regarding use of social media platforms. Findings show that social media platform use differs significantly among firms. The average number of social media platforms used by technology firms ranged from 6.5 for the higher-social-media-use firms to 4.2 for the lower-social-media-use firms. The most social media platforms used, by any firm, was 7 and the least was none.

The third and final research question addressed whether a significant relationship exists between social media platform usage and firm size, based on total revenue. Concerning revenue, the technology firms using 6 or more social media platform usage had higher revenue (though not significantly higher) than firms using 5 or fewer platforms, $30.7 billion and $21.3 billion, respectively. Possibly, this was due to larger firms (higher revenue) serving a more diverse customer base. Consequently, firms with more diverse customers, who likely use a wider assortment of social media, would better serve customers by offering them a wider array of social media platforms.

From an ethical perspective, it is critical that firms disseminate information that is dependable and correct; social media provides an efficient means for firms to distribute information to customers, investors, and others. Since the three most widely used social media sites by technology firms are Twitter, Facebook, and LinkedIn, these are logically sites that technology firms should consider using. Use of social media is expected to grow; consequently, social media use by technology firms will likely become increasingly important.

LIMITATIONS AND FUTURE RESEARCH

Limitations of the current study include the time period used and the sample of firms included in the analysis. The current study could be extended in future studies by using a different point in time and a different sample of firms. This study offers a starting point for future longitudinal studies of use of social media by technology firms.The expanding use social media would make this an appropriate topic for future research.

REFERENCES

Alexa Internet (2019). *The top 500 sites on the web*. Retrieved 27 March 2019 from https://www.alexa.com/topsites.

Alexander, A. (2011, September 21). Does social media return a positive ROI for businesses? [Infographic]. Retrieved 27 March 2019 from http://ansonalex.com/infographics/does-social-media-return-a-positive-roi-for-businesses-infographic/.

Ali, Z., Shabbir, M. A., Rauf, M., & Hussain, A. (2016). To assess the impact of social media marketing on consumer perception. *International Journal of Academic Research in Accounting, Finance and Management Sciences*, 6(3), 69-77.

Baird, C.H. & Parasnis, G. (2011). From social media to social customer relationship management. *Strategy & Leadership*, 39(5), 30-37.

Barnes, N.G. (2010). Tweeting and blogging to the top. *Marketing Research*, 22(1), 8-13.

Briones, R.L., Kucha, B., Liua, B.F., & Jinb, Y. (2011). Keeping up with the digital age: How the American Red Cross uses social media to build relationships. *Public Relations Review*, 37(1), 37-43.

Chamberlain, D.; Rudolph, H.; Smith, K.T.; & Smith, L.M. (2019a). Analysis of social media usage and relationship to revenue among major energy companies. *Oil, Gas & Energy Quarterly*, 67(3), 525-538.

Chamberlain, D.; Rudolph, H; & Smith, L.M. (2019b). Analysis of social media usage and relationship to firm size and revenue growth among major CPA firms, *Services Marketing Quarterly*, 40(1), forthcoming. Published online 7 January 2019 at https://doi.org/10.1080/15332969.2018.1514798.

Curley, C. B., & Noormohamed, N.A. (2013). Social media marketing effects on corporate social responsibility. *Journal of Business & Economics Research*, 12(1), 61-66.

Fisher, T. (2009). ROI in social media: A look at the arguments. *Journal of Database Marketing & Customer Strategy Management*, 16(3), 189-195.

Hansen, D., Shneiderman, B. & Smith, M.A. (2011). *Analyzing social media networks with NodeXL: Insights from a connected world*. Elsevier, Boston.

Harris, L. & Rae, A. (2009). Social networks: The future of marketing for small business. *Journal of Business Strategy*, 30(5), 24-31.

Hitt, L., Jin, F., & Wu, L. (2015). Data skills and value of social media: Evidence from large-sample firm value analysis. AIS Electronic Library. Retrieved 27 March 2019 from http://aisel.aisnet.org/icis2015/proceedings/EconofIS/17.

Johnson, D. (2011, October 11). 5 Surprising social media statistics that affect your business. *CBS Money Watch*. Retrieved 27 March 2019 from http://www.cbsnews.com/8301-505143_162-28652590/5-surprising-social-media-statistics-that-affect-your-business/.

Li, C. & Bernoff, J. (2008). *Groundswell: Winning in a world transformed by social technologies.* Boston: Harvard Business Press.

Liu, Q., Karahanna, E., & Watson, R.T. (2011). Unveiling user-generated content: Designing websites to best present customer reviews. *Business Horizons*, 54(3), 231-240.

Mangold, W.G. & Faulds, D.J. (2009). Social media: The new hybrid element of the promotion mix. *Business Horizons*, 52(4), 357-365.

Mangold, W.G. & Smith, K.T. (2011). Selling to Millennials with online reviews. *Business Horizons*, 55(2), 141-153.

Martin, H.M., Durr, D, Smith, L.M., Finke, R. a& Cherry, A. (2017). Analysis of GMO food products companies: Financial risks and opportunities in the agriculture industry. *African Journal of Economic and Sustainable Development*, 6(1): 1-17.

Martin, H., Smith, K.T., & Smith, L.M.. (2016). A financial and public policy analysis of the meat industry. *International Journal of Economics and Accounting*, 7(1): 74-88.
McCorkindale, T.C. (2010). Can you see the writing on my wall? A content analysis of the Fortune 50’s Facebook social networking sites. *Public Relations Journal*, 4(3). Retrieved 27 March 2019 from http://www.prsa.org/Intelligence/PRJournal/Vol4/No3/.
Okafor, C.; Smith, L.; & Ujah, N. (2014). Kleptocracy, nepotism, kakistocracy: Impact of corruption in sub-Saharan African countries. *International Journal of Economics and Accounting*, 5(2): 97-115.
Saxton, G. D. (2016). CSR, big data, and accounting: Firms' use of social media for CSR-focused reporting, accountability, and reputation gain. York University. Working Paper.
Solis, B. & Breakenridge, D. (2009). *Putting the Public Back in Public Relations: How Social Media is Reinventing the Aging Business of PR*. FT Press, Upper Saddle River, NJ.
Smith, K.T. (2017). Hospital marketing and communications via social media. *Services Marketing Quarterly*, 38(3), 187-201.
Smith, K.T., Blazovich, J., & Smith, L.M. (2015). Social media adoption by corporations: An examination by platform, industry, size, and financial performance. *Academy of Marketing Studies Journal*, 19(2), 127-143.
Smith, K.T. & Smith, L.M. (2018). Social media usage by CPA firms according to firm services and size. *Journal of Accounting & Finance*, 18(10), 112-126.
Smith, K.T., Smith, L.M., and Dunbar, S. (2014). Using corporate advertising to improve public perception of energy companies. *Journal of Strategic Marketing*, 22(4): 347-56.
Smith, K.T., Smith, L.M., and Wang, K. (2010). Does brand management of corporate reputation translate into higher market value? *Journal of Strategic Marketing*, Vol. 18, No. 3 (June): 201-221.
Smith, L.C., Smith, L.M., and William C. Gruben. (2011). A multinational analysis of tax rates and economic activity. *Journal of International Business Research*, Vol. 10, Special Issue No. 1: 95-113.
Taylor, M. & Kent, M. (2010). Anticipatory socialization in the use of social media in public relations: A content analysis of PRSA’s *Public Relations Tactics*. *Public Relations Review*, 36, 207-214.
Uyar, A., & Boyar, E. (2015). An investigation into social media usage of publicly traded companies. *Journal of Corporate Accounting & Finance*, 27(1), 71-78.
Weinberg, B.D. & Pehlivan, E. (2011). Social spending: Managing the social mix. *Business Horizons*, 54, 275-282.
Yahoo Finance (2018). Financial data for the sample of technology companies. Yahoo. Retrieved 5 January 2018 from finance.yahoo.com.

U.S. REIT FIRMS AND U.S. C-CORPORATIONS IN THE HOSPITALITY INDUSTRY: A RETURN ANALYSIS

James Stotler, North Carolina Central University

ABSTRACT

This study examines the return performance of U.S. firms in the hospitality industry by comparing C-Corporation and REIT return measures. These returns are then broken down based on their component parts using a 3-factor DuPont identity approach. Each return component is then tested to determine any significant difference between C-Corp and REIT groups. Results indicate no significant difference in the component return measures of profit margin, asset turnover and equity multiplier for the two types of firms in the same industry suggesting a firms asset type is a more significant factor than C-Corp versus REIT status in determining a firms return.

INTRODUCTION

REITs were originally created and defined as "an unincorporated association with multiple trustees as managers and having transferable shares of beneficial interest" in the 1960's. They have evolved significantly since that inception causing the number of REITs to grow from 2 in 1962 to 221 in 2019 and total capitalization over that same time period to grow from $42 million to approximately $1 trillion. A real estate investment trust (REIT) is a closed-end investment company that owns assets related to real estate such as buildings, land and real estate securities. REITs sell on the major stock market exchanges just like common stock.

REITs as they are currently operating began in the early 1990's. Ironically, the first REITs were regional retail mall REITs and now many of the "brick and mortar" retail businesses are closing down and doing more of their sales online. Many of these retail mall REITs are closing or being repurposed. Other types of REITs rapidly emerged. In the late 1990's hotel REIT acquisition activity lead to the consolidation of the U.S. hospitality industry which has resulted in a larger number of hotel rooms being controlled by fewer companies. As hospitality REITs purchased properties aggressively hotel C-corporations also began to expand into operation of hotel properties that were under the ownership of REITs which allowed the non-REIT hotel corporations to expand the number of hotels they operate without the cost of property acquisition.

This study examines the relative return performance of REIT and non-REIT firms in the hospitality industry. Return measures and related factors examined are return on equity, return on assets, profit margin, asset turnover and leverage.

COMPARISON OF REITS AND C-CORPORATIONS

In many ways REITs and C-Corporations are similar, but there some significant ways in which they differ. One possible difference between the two could be the type of assets they hold. REITs are required to hold a very large percentage of their assets in the form of real estate while C-Corporations are not subject to such a restriction. This study uses a data set comprised of equity REITs and C-Corporations in the U.S. hospitality industry so the nature of their real estate assets is very similar which mitigates the possibility of a significantly different asset base. The essential elements for a firm to qualify as a REIT are the following.

- Be an entity that would be taxable as a corporation but for its REIT status
- Be managed by a board of directors or trustees
- Have shares that are fully transferrable
- Have a minimum of 100 shareholders after its first year as a REIT
- Have no more than 50% of its shares held by five or fewer individuals during the last half of the taxable year
- Invest at least 75% of its total assets in real estate assets and cash
- Derive at least 75% of its gross income from real estate related sources, including rents from real property and interest on mortgages financing real property
- Derive at least 95% of its gross income from such real estate sources and dividends or interest from any source
- Have no more than 25% of its assets consist of non-qualifying securities or stock in taxable REIT subsidiaries
- Pay out dividends of at least 90 percent of taxable earnings.

LITERATURE REVIEW

Prior research has been done which evaluates REIT performance and REIT versus non-REIT investment. Oak and Dalbor (2008) evaluated the impact of dividend policy on institutional holdings for REIT versus non-REIT hotel corporations and found that institutions tend to prefer REIT's over non-REITS for their portfolio holdings of hotel REIT's. Institutional holdings were found to be larger for hotel REIT's than for non-REIT hotel corporations. Additionally, they found that there is a significant difference between hotel REIT's paying out more than 90 percent of their earnings as dividends versus those paying out only 90 percent

Hotel corporations commonly use acquisitions as a means of expansion. Such acquisitions could increase or decrease firm value. Bebchuk, Cohen and Ferell (2006) noted that this change in value may depend of the CEO's motivations. Another common method of expansion is to use a franchising model. Dogru (2017a) reviewed the two primary reasons that hotel corporations have expanded through franchising: capital scarcity and agency theory. The capital scarcity theory is straightforward. The hotel corporation does not need a large capital expenditure to grow when they just franchise their name and brand recognition to the franchisee. The agency theory explanation suggests that firms may choose to franchise rather than own the expansion hotel due to the high monitoring costs for general managers of the firm when the corporation owns the hotel expansion hotel. This monitoring dilemma is not as critical today due to the technology that enables the immediate access to performance data as well as customer feedback through email and social media platforms.

When analyzing hotel REITs versus hotel C-corporations Dogru (2017b) found significant differences with respect to cash, capital expenditures, acquisition expenditures and total assets with all being higher for REITs than for non-REITs except capital expenditures which was higher for non-REIT's. There was no significant difference found by Dogru (2017b) between REITs and non-REIT's with respect to leverage or market value. A significant difference was found between REITs and C-corporations with respect to EBITDA. Although non-REITs may have an incentive to use more debt due the tax-deductibility of the interest cost, REITs have very limited ability to retain any earnings due to the legal requirement that most earnings must be paid as dividends and therefore debt is used by REITs to acquire capital despite the deductibility of interest.

The relationship between REIT ownership and property level performance has also been examined. Howton, Howton, Lee and Luo (2012) found that REIT ownership has a positive impact on performance at the property level using operating margin as the performance measure. Their findings indicate a 3.1 percent higher operating margin for REIT hotels than for non-REIT hotels analyzed. Analyzing lagged operating margin they also find that REIT ownership has a positive impact on future property level performance of hotel properties.

A study by Gentry, Kemsley and Mayer (2003) found that investors capitalize the impact of substantial taxes into the share price of REIT stocks. This study used data from a time period when the required distribution rate for REITs was 95 percent. The REIT Modernization Act of 1999 reduced this distribution requirement to 90 percent of taxable income and allowed REITs to own taxable subsidiaries that conduct some previously prohibited activities.

METHODS

The return data for this study come from the S&P Capital IQ database and include 10 years of quarterly return data for 18 U.S. Hospitality firms from 2008 through 2017 including 9 REITs and 9 C-corporations. The limited size of this set is due to the fact that there are relatively few firms of significant size that own the majority of hotel and lodging properties. This includes both REIT and C-Corporation data for firms in the industry. This study uses a data set comprised of equity REITs and C-Corporations in the U.S. hospitality industry so the nature of their assets is very similar which mitigates the possibility of a significantly different asset base. Since the primary purpose is to examine REIT and Non-REIT firms in the hospitality industry with respect to return measures the first two variables examined are Return on Equity and Return on Assets.

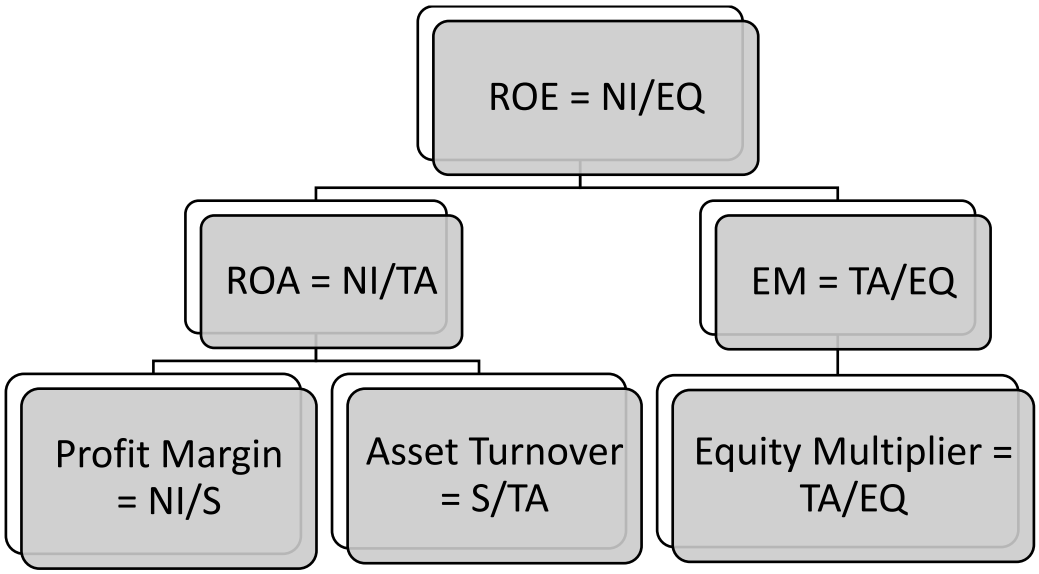
Further, these returns are analyzed using a DuPont analysis approach to compare cost control effectiveness, asset use efficiency and leverage between REITs and C-corporations. Returns are evaluated using the individual components of the DuPont identity. Profit Margin is used as a measure of cost control effectiveness, Asset Turnover is used a measure of asset use efficiency and the Equity Multiplier is used as a measure of leverage. Dogru (2017b) evaluated differences between REITs and C-corporations but did not specifically address the cost control, asset use efficiency and leverage components of the DuPont Identity.

The factors examined are return on assets (ROA), return on equity (ROE), profit margin (PM), asset turnover (AT) and equity multiplier (EM).

ROE = PM x AT x EM

and

ROA = PM X AT



These return measures and their component ratios are evaluated for both the REIT and Non-REIT firms in the hospitality industry. First, the two types of firms are evaluated with respect to ROE and ROA to determine if firm type impacts these return measures. Then, the return measures for each group are broken down into their component parts. The ROA and leverage components of ROE are separated and compared. The ROA is then broken down into profit margin and asset turnover and these two components are compared for the two samples.

RESULTS

Table 1 below reports the summary statistics for the variables analyzed in this study. The mean, variance and standard deviation is shown for each of the 5 variables. Each of these measures is examined to determine if there is a significant difference between hotel REITs and non-REIT hotel firms for each measure.

TABLE 1
Summary Statistics for the REIT and C-Corp sample

		C-Corp	REIT
ROE (Return on Equity)	Mean	6.153	1.482
	Variance	84.95	93.775
	Std. Deviation	9.217	9.684
ROA (Return on Assets)	Mean	2.62	2.393
	Variance	3.137	2.277
	Std. Deviation	1.771	1.509
Profit Margin (NI/S)	Mean	42.541	36.279
	Variance	364.729	267.188
	Std. Deviation	19.099	16.349
Asset Turnover (S/TA)	Mean	.310	.270
	Variance	.027	.014
	Std. Deviation	.164	.118
Equity Multiplier (TA/EQ)	Mean	3.342	13.793
	Variance	10.187	701.867
	Std. Deviation	3.192	26.493

The five variables in the table above are analyzed to determine if they are significantly different for C-Corporations and Real Estate Investment Trusts in the hospitality industry. The following tables report the results for the return measures (Table 2) and their component parts (Table 3).

TABLE 2
Evaluation of Return Measures

Return on Equity and Return on Assets

	ROE-C	ROE-R	ROA-C	ROA-R
Mean	6.153	1.482	2.620	3.393
Variance	84.95	93.775	3.137	2.277
N	9	9	9	9
P(T<=t)	.3101		.7734	
T	2.120		2.120	
α	.05		.05	

The ROE for the C-Corp and RIET sample had means of 6.153 and 1.482, respectively. The results indicate that there is no significant difference (with $\alpha = .05$) in the ROE for the C-Corp and REIT firms in the sample. With respect to ROA for the two types of firms there was a mean ROE of 2.620 for the C-Corp and 3.393 for the REIT which indicates no significant difference at $\alpha = .05$. Together these results indicate no significant difference in the mean return measures for these two groups of firms.

Further analysis in Table 3 below will break down each return measure into its component parts based on a DuPont identity approach.

TABLE 3
Breakdown of Return Measures into Components

Profit Margin, Asset Turnover and Leverage

	PM-C	**PM-R**	**AT-C**	**AT-R**	**EM-C**	**EM-R**
Mean	42.541	36.279	.310	.270	3.342	13.793
Variance	364.729	267.188	.027	.014	10.187	701.867
N	9	9	9	9	9	9
P(T<=t)	.233		.284		.2738	
T	1.746		1.753		2.306	
α	.05				.05	

Each return measure is broken down into its component parts where ROA is composed of profit margin (PM) and asset turnover (AT) while ROE is composed of PM, AT and the equity multiplier (EM). The results indicate that with respect to profit margin C-Corps with a mean of 42.541 and REITs with a mean of 36.279 do not have significantly different profit margins at α = .05. This suggests that both C-Corps and REIT's are similar with respect to cost management and control.

The mean asset turnover is .310 for C-Corps and .270 for REIT's which indicates that there is no significant difference in the asset turnover for the two firm types at α = .05. This result suggests that C-Corps and REITs do not differ significantly with respect to their asset use efficiency. The mean equity multiplier is 3.342 for C-Corps and 13.793 for REITs which indicates that there is no significant difference in the equity multiplier for the two firm types at α - .05. This suggests that C-Corps and REIT's do not differ significantly with respect to their utilization of leverage.

CONCLUSION

Return performance of firms in the hospitality industry has been compared based on C-Corporation and REIT return measures. These returns were then broken down based on their component parts using a 3-factor DuPont identity approach. Each return component was then tested to determine any significant difference between C-Corp and REIT groups. Results indicate no significant difference in the component return measures of profit margin, asset turnover and equity multiplier for the two types of firms in the same industry suggesting REIT status alone is not a significant factor in determining a firms return based on these three measures. These results further suggest that further research with a more detailed breakdown of the return components to analyze such factors as tax burden, interest burden and EBIT margin could potentially provide additional insight into the tax and interest implications associated with a C-Corp versus a REIT structure in the hospitality industry.

REFERENCES

Beals, P. and Singh, A.J., The Evolution and Development of REITS: The Securitization of Equity Structures for Financing the U.S. Lodging Industry, Journal of Hospitality Financial Management, 2002, Volume 10, Issue 1.

Bebchuck, L., and Ferrell, A., What Matters in Corporate Governance?, Review of Financial Studies, 22(2) 2006.

Chan, S.U., Erickson, J., and Wang, K., Real Estate Investment Trusts: Structure, Performance, and Investment Opportunities, Financial Management Association Survey and Synthesis Series, Oxford University Press, 2003.

Dogru, Tarik, C-corporation Hotels vs. Hotel REITs: A Theoretical and Practical Comparison, Boston Hospitality Review, Winter 2017a, Volume 5, Issue 1.

Dogru, T., Under- vs. Over-investment: Hotel Firms Value Around Acquisitions, International Journal of Contemporary Hospitality Management, 29(8), 2017b.

Gentry, W., Kemsley, D., and Mayer, C., Dividend Taxes and Share Prices: Evidence from Real Estate Investment Trusts, The Journal of Finance, Volume 58, No. 1 (February 2003, pp. 261-282.

Howton, S., Howton, S., Lee, J.,and Luo, M., REIT Ownership and Property Performance: Evidence from the Lodging Industry, Journal of Real Estate Portfolio Management, May-Aug. 2012.

Oak, Seonghee and Dalbor, Michael, The Impact of Dividend Policy on Institutional Holdings: Hotel REITs and Non-REIT Hotel Corporations, Journal of Hospitality Financial Management: The Professional Refereed Journal of the Association of Hospitality Financial Management Educators, 2008, Volume 16, Issue 1.

Pellika, John Richard Cane, Comparing Lodging REITs using DuPont Analysis: Evaluating Shareholder Equity, 2009, UNLV Theses, Dissertations, Professional Papers and Capstones, 559. http://digitalscholarship.unlv.edu/thesesdissertations/559.

MARKET BREAKDOWN OF THE REACTION OF INITIAL ADR ISSUERS TO SUBSEQUENT ADRS

C. Alan Blaylock, Henderson State University

ABSTRACT

Previous research has shown that new ADR programs affect the market from which the program originates as well as the initial ADR issuer from the market. While previous research analyzed the effect of each subsequent ADR issuance on the initial ADR issuer, this paper focuses on the effect on the initial ADR issuer for specific markets. Mixed but significant results are found for six of the nine markets studied. Results are reported for various event windows using listing and announcement dates.

INTRODUCTION AND LITERATURE REVIEW

The purpose of this study is to assess the reaction of the first firm offering an ADR program to subsequent ADR programs in the same country. Blaylock (2014b) reports that, in aggregate, the initial ADR is both positively and negatively affected by subsequent ADR issuances. This study is similar but reports reactions at the country level for nine emerging markets.

ADRs offer benefits to investors seeking international diversification as well as for the issuing companies. According to Jiang (1998) benefits to investors include fewer complications and costs of directly investing in the foreign market. Specifically, there are no custodian safekeeping charges, they provide greater liquidity, are easily executed, U.S. clearing systems are used for trading, clearing, and settlement, and currency is converted at wholesale rates. Companies issuing ADRs benefit by using them to facilitate U.S. investment, raise capital, make acquisitions, and improve name recognition. ADRs also broaden the shareholder base, may increase demand for shares, and potentially lower the cost of financing in the U.S. See Sundaram and Logue (1996) and Foerster and Karolyi (1993, 1999) for additional benefits for investors and companies.

The benefits of international diversification are clear. Early studies demonstrate that the variance of a purely domestic portfolio is reduced when indices of international equity markets are added (Grubel, 1968; Levy and Sarnat, 1970; and Speidell and Sappenfield, 1992) and later studies confirm the benefits of diversifying internationally (Fouquau, Kharoubi, and Spieser, 2018; Rim and Setaputra, 2012). However, international markets may become segmented due to investment barriers resulting in higher risk premiums in the more restricted markets (Errunza and Losq, 1985; Foerster and Karolyi, 1993). The barriers between securities markets restrict information flow and asset pricing to within distinct and separate markets so that the same level of risk in the segmented markets may not be compensated by the same level of returns. In other words, two assets with the same level of risk in different markets offer different risk premiums. Direct and indirect barriers to international investment include regulatory barriers to capital flows such as ownership restrictions (Miller, 1999; Foerster and Karolyi, 1993; Domowitz, Glen, and Madhavan, 1997; Bailey, Chung, and Kang 1999; Sundaram and Logue, 1996), transactions cost (Foerster and Karolyi, 1993; Sundaram and Logue, 1996), information availability and costs (Miller, 1999; Foerster and Karolyi, 1993; Sundaram and Logue, 1996), poor liquidity (Miller, 1999), different tax rules (Miller, 1999; Foerster and Karolyi, 1993; Sundaram and Logue, 1996), different accounting standards (Miller, 1999), and fear of expropriation (Adler and Dumas, 1983).

Removing international investment barriers, a process called market liberalization, would reduce the cost of capital in formerly segmented markets due to increased market integration. Since market segmentation and the resulting heterogeneous risk premiums result from investment barriers, bypassing or removal of those barriers such as dual-listing a company's shares (Stapleton and Subrahmanyam, 1977) or regulatory change (Henry, 2000) would tend to integrate international markets resulting in risk premiums that are more homogeneous. Risk premiums and the cost of capital in the restricted markets would tend to fall (Bekaert and Harvey, 2000). Indicators listed by Bekaert and Harvey are the introduction of depositary receipts and country funds, regulatory changes, and breakpoints in capital flows. Regulatory changes are official liberalizations that reduce direct barriers to investment such as foreign ownership restrictions. Breakpoints in capital flows would indicate when the presence of foreign investors is significantly increased. However, despite market liberalizations, Bekaert, Hodrick, and Zhang (2009) do not find a significant increase in market correlations during the 1980-2005 period. Correlations seem to increase during market downturns (Longin and Solnik, 2001; Ang and Bekaert, 2002; Ang and Chen, 2002).

Depository receipts, specifically American Depository Receipts (ADRs), are addressed in this study. Yuan, Gupta, and Roca (2016) find ADRs are beneficial diversifying vehicles. Miller (1999) and Blaylock and Duett (2004) find that ADR issuers experience positive abnormal returns around the time of ADR issuance. They interpret this reaction as a reduction in the cost of capital (i.e., risk premiums) due to the liberalizing event of issuing ADRs. Chakraborty and Holani (2011) find ADR issuers experience positive returns on the ADR listing day but experience an adverse reaction during the post listing period.

Liberalization and cost of capital reductions happen gradually. As markets are integrated the reductions in the cost of capital decrease in magnitude with each additional liberalization (Bekaert and Urias, 1999; Bekaert and Harvey, 1997). Cho and Rhee (1999) imply that marginal gains of international diversification are small after markets have liberalized. Madura and Whyte (1991) find that international diversification benefits may have decreased through time due to increased correlations between credit risk premiums. More integrated markets characterized by a greater number of ADRs and country funds have a lower average cost of capital (Bekaert, 1995). However, market segmentation and diversification gains still exist. Christoffersen, Errunza, Jacobs, and Langlios (2012) find correlations have increased in the 1973-2009 period, especially among developed markets, but emerging markets sill provide diversification benefits (see also, Boamah, 2017). According to Switzer and Tahaoglu (2015) investors can benefit from diversification by investing in portfolios with both developed and emerging markets.

The diminishing marginal effects of liberalizations are notably addressed in Bekaert and Harvy (2000) and Blaylock and Duett (2004). The cost of capital in liberalizing emerging markets decrease at a decreasing rate for each marginal liberalization (Bekaert and Harvey, 2000). Initiating an ADR program is one of the market liberalizations they studied. The key to Bekaert and Harvey's study is that such reductions in the cost of capital decrease with subsequent liberalizations. Similarly, Blaylock and Duett (2004) find that the abnormal returns decrease for each subsequent ADR issuer in the same market. In other words, the abnormal returns experienced by the fifth ADR issuer are smaller than the abnormal returns experienced by the fourth ADR issuer. Blaylock (2007) isolates the first ten ADR issuances in the South Korean market and find that ADR issuances both positively and negatively affect the cost of capital of previous ADR issuances.

Blaylock (2014b) focuses on the reaction of the first ADR issuance to the subsequent five ADR issuances in the same country. The paper reports that initial ADR issuers are affected by subsequent ADR programs from the same market. However, the results are aggregated across countries. Blaylock finds that the initial ADR issuer for a country predominately experiences negative returns when subsequent ADRs are issued from the same country. His findings are examined more closely in the Empirical Results and Analysis section. This paper seeks to build on Blaylock (2014b) by analyzing by country the effects subsequent ADR issuances have on the country's initial ADR.

DATA AND METHODOLOGY

This study seeks to expand on Blaylock (2014b) by measuring by country the reaction to the market's first ADR issuer to subsequent ADRs from the same market. From the nine emerging markets in Blaylock (2014b) 37 ADR programs have listing dates, and 39 ADR programs have announcement dates. The nine countries are Chile, Colombia, Greece, India, Korea, Portugal, Taiwan, and Venezuela. This final sample results from an initial sample of emerging markets studied in Bekaert and Harvey (2000).

ADR programs are identified from directories from the Bank of New York, Citibank, and J.P. Morgan. The Citibank directory is the most comprehensive of the three and is used as the primary directory in selecting the list of ADRs for this study. NYSE and NASDAQ also provide a directory of foreign securities traded on their respective exchanges. A country must have more than one ADR program to be included in the study. As in Blaylock (2014b) only the first six ADR programs in a country are examined. Daily returns are computed from underlying stock and index prices obtained from Datastream International. In instances where data is not available from Datastream, data from foreign exchanges are used.

Both announcement dates and listing dates are used as event dates. Announcement dates from Lexis/Nexis are used, and SEC filing dates are used in cases where dates from Lexis/Nexis cannot be found. The listing dates are those dates reported by NASDAQ, NYSE, AMEX, and the Citibank directory. Given the difficulties experienced by Blaylock (2014a) with privately placed ADRs, these ADRs are not used. Also, as Blaylock (2014a), given the ambiguity of listing dates provided by the exchanges, announcement dates are used as listing dates when the announcement date occurs after the reported listing date.

The event windows around each of the announcement and listings dates need to be large enough to capture the cost of capital effect yet small enough so as not to include other effects. Henry (2000) notes that an initial market reaction may accompany a liberalization announcement followed by a gradual price appreciation as the imminence of the actual risk sharing draws closer as well as information and the certainty of the liberalization becomes public knowledge.

Foerster and Karolyi (1999) report a mean difference between the announcement and listing dates of 70 days. They find, using the common residual approach, average daily abnormal returns at the 5 percent significance level from 100 to 10 days before the date of announcement as well as before the date of listing. Finding similar results in their dummy variable regression approach, they define a pre-announcement period of 52 weeks and a post-announcement period of 52 weeks with an event window around the announcement date of one week. Miller (1999), finding the time between the announcement date and the listing date to be 77 days, uses a pre-announcement period of 125 days, an announcement period of 51 days, and a post-announcement period of 125 days. Lau, Diltz, and Apilado (1994) use an eleven-day event window around each of the three event days they study.

Multiple event windows are used in this study to better assess the market reaction. As in Miller (1999) and Blaylock (2014a, 2014b) a 51-day event window is used for both announcement dates and listing dates. The 51-day window incorporates days -25 to +25. An 11-day window is also used. The 11-day window is divided into two smaller windows: a 6-day window from 5 days before the event up to the event day itself, and a 5-day window from the first day after the event to 5 days after the event. Miller (1999) finds significant results immediately around the event date only. For the first ADR issuer only the 51-day window is also segmented into two smaller windows: a 25-day window from day -25 to -1 and a 25-day window from day +1 to +25. An estimation window of 100 days is used prior to and following the event windows. For example, the 51-day window uses return data from 126 days before the event to 126 days after the event.

The following hypothesis is tested:

H_0: The first firm to list an ADR is not affected by subsequent ADR listings/announcements by other firms in the same country.

H_1: The first firm to list an ADR in a country experiences positive abnormal returns during subsequent listings/announcements of ADRs by other firms in the same country.

A multivariate regression model (MVRM) using dummy variables is used. The dummy variables capture the abnormal returns. This is the model used in Foerster and Karolyi (1999), Henry (2000), Blaylock and Duett (2004), Blaylock (2014a), and Blaylock (2014b). Returns of market indices are used to control for systematic risks.

The equation estimated using the 51-day event window is

$$R_t = \alpha_i + \gamma_k^{ADR}ADR_{kt} + \beta_1^{a}R_M^{a} + \beta_1^{US}R_M^{US} + \varepsilon_{1t}$$

and the equation estimated for the 11-day event window is

$$R_t = \alpha_i + \gamma_k^{PRE}PRE_{kt} + \gamma_k^{POST}POST_{kt} + \beta_1^{a}R_M^{a} + \beta_1^{US}R_M^{US} + \varepsilon_{it}$$

where

- R_t is the daily return for time t of the first ADR issuer,
- ADR_{kt} is a dummy variable that equals 1 during the 51-day event window (-25 to +25) for the kth ADR,
- PRE_{kt} is a dummy variable that equals 1 during the 6-day event window leading up to the event (-5 to 0) for the Kth ADR,
- $POST_{kt}$ is a dummy variable that equals 1 during the 5-day event window after the event (+1 to +5) for the Kth ADR,
- R_M^{US} is the daily return of the S&P 500,
- R_M^a is the daily return of the home (foreign) market index.

Each equation is estimated across all subsequent ADR events separately by country. The criterion for testing is the coefficient γ for the event parameters in the panel regressions. The coefficient γ measures the average daily abnormal returns for the first ADR issuer over the event window due to subsequent ADR events. The null hypothesis is rejected in favor of the alternative hypothesis if γ has a value that is significantly positive.

EMPIRICAL RESULTS AND ANALYSIS

Results are presented in Table 1. For listing dates, six of the nine countries show negative average abnormal daily returns over the 51-day event window. None of these are significant. Six of the nine show negative returns in the 6-day pre-listing window, but only two show negative returns in the post-listing window. Of those with negative returns in the pre-listing window only two, Chile and Colombia, are significant. Only one of the two showing negative returns in the post-listing window, Colombia, is significant. Interestingly, Venezuela shows significant positive returns in the post-listing window.

For announcement dates, six of the nine countries show negative average abnormal daily returns over the 51-day event window, but no returns are significant. Six of the nine show negative abnormal returns in the 6-day pre-announcement window, but only three show negative returns in the post-announcement window. Only Colombia and Greece show significant negative abnormal returns in the pre-announcement window while only Portugal shows significant negative returns in the post-announcement window. Another interesting market is Korea that shows significant positive abnormal returns in the post-announcement window.

Five of the nine countries show significant abnormal returns across event types and event windows. Note the consistency in the sign of the returns across event windows. For both listing dates and announcement dates, the 51-day and 6-day pre-event windows have more countries containing negative returns than positive. In fact, in each of the windows, there are only three out of nine countries containing positive returns although the signs for each country are not consistent across windows. Colombia is unique in that significant negative abnormal returns are shown for both listing and announcement dates. The signs of the returns are predominately positive in the 5-day post event window. For listing dates, seven of the nine returns are positive compared to six for the returns for announcement dates.

Table 1
RESULTS

The coefficient γ_k^{ADR} from equation $R_t = \alpha_i + \gamma_k^{ADR} ADR_{kt} + \beta_1^a R_M^a + \beta_1^{US} R_M^{US} + \varepsilon_{1t}$ is reported in panel A, and the coefficients γ_k^{PRE} and γ_k^{POST} from equation $R_t = \alpha_i + \gamma_k^{PRE} PRE_{kt} + \gamma_k^{POST} POST_{kt} + \beta_1^a R_M^a + \beta_1^{US} R_M^{US} + \varepsilon_{it}$ are reported in panel B. R_t is the daily returns at time t for the first firm to issue an ADR, and ADR_{kt} is a dummy variable that equals 1 during the event window (-25 to +25) around the k[th] ADR event after the initial ADR issuance. γ_k^{ADR} measures the average daily abnormal return of the first ADR issuer due to a subsequent event actuated by another firm. PRE_{kt} is a dummy variable that equals 1 during the 6-day window leading up to the event (-5 to 0), and POST is a dummy variable that equals 1 during the 5-day window after the event (+1 to +5), γ_k^{PRE} measures the average daily abnormal return for the five days leading up to and including the event and γ_k^{POST} measures the average daily abnormal return for the five days after the event.

	Listing Dates			Announcement Dates		
	A	B		A	B	
	51-Day	11-Day		51-Day	11-Day	
	-25, +25	-5, 0	+1, +5	-25, +25	-5, 0	+1, +5
Chile	-0.00042	-0.00361	0.00155	0.00078	0.00305	0.00284
	0.5888	0.0059***	0.4695	0.3133	0.1215	0.2084
Colombia	-0.00258	-0.00658	-0.00902	-0.00140	-0.00693	0.00601
	0.1069	0.0903*	0.0676*	0.7242	0.0397**	0.2405
Greece	0.00198	0.00605	0.01191	0.00544	-0.01771	0.00131
	0.6508	0.5382	0.1412	0.3565	0.0716*	0.8740
India	0.00083	-0.00853	0.00454	-0.00202	-0.00120	-0.00345
	0.7629	0.1146	0.3185	0.4037	0.7498	0.6159
Korea	-0.00182	-0.00160	0.00366	-0.00000	0.00446	0.00543
	0.2289	0.6212	0.4630	0.9992	0.2312	0.0682*
Portugal	0.00031	-0.00358	0.00137	-0.00008	0.00103	-0.00325
	0.6316	0.1773	0.3915	0.8890	0.2715	0.0071***
Taiwan	-0.00070	0.00474	-0.00332	-0.00021	-0.00210	0.00109
	0.7498	0.2643	0.5954	0.9024	0.7239	0.8223
Turkey	-0.00033	0.00148	0.01269	0.00095	-0.00238	0.00185
	0.9205	0.8477	0.2993	0.8000	0.7433	0.8327
Venezuela	-0.00131	-0.00141	0.00876	-0.00138	-0.00180	-0.01085
	0.5513	0.7116	0.0296**	0.6193	0.8145	0.3696

Note: p-values are located underneath the coefficients with *, **, *** indicating significance at the 10%, 5%, and 1% levels, respectively.

Of the seven significant return measures only one is positive, for Venezuela in the post listing period. The negative returns are surprising in that positive abnormal returns would be expected given ADRs are considered liberalizing events. However, the results are not surprising since they agree with the findings of Blaylock (2014b). Blaylock finds that initial ADR issuers are predominately negatively impacted by subsequent ADR listings in the 51-day listing period and the 6-day pre-listing period. He partially attributes the negative reactions to the time-varying degrees of market segmentation described in Bekaert and Harvey (1995) and Francis, Hasan, and Hunter (2002).

SUMMARY

This study adds to the findings of Blaylock (2014b) by examining at the country level the reaction of a country's first ADR issuer to subsequent ADRs. This was also examined by Blaylock (2007) but only for Korea. Negative returns dominate the 51-day window and the 6-day pre-event window. Significant negative returns are found in the pre-listing window. This indicates the cost of capital predominately increases for the initial ADR-issuing firm in a country leading up to subsequent ADR listings.

REFERENCES

Adler, M., & Dumas, B. (1983). International Portfolio Choice and Corporation Finance: A Synthesis. *Journal of Finance*, 38(3), 925-984.

Ang, A., & Bekaert, G. (2002). International Asset Allocation With Regime Shifts. *The Review of Financial Studies*. 15(4), 1137–1187.

Ang, A., & Chen, J. (2002). Asymmetric correlations of equity portfolios. *Journal of Financial Economics*. 63(3), 443-494.

Bailey, W., Chung, Y.P., & Kang, J. (1999). Foreign Ownership Restrictions and Equity Price Premiums: What Drives the Demand for Cross-Border Investments? *Journal of Financial and Quantitative Analysis*, 34(4), 489-511.

Bekaert, G. (1995). Market integration and investment barriers in emerging equity markets. *The World Bank Economic Review*. 9, 75-107.

Bekaert, G. & Harvey, C.R. (1995). Time-varying World Market Integration. *Journal of Finance*. 50(2), 403-444.

Bekaert, G. & Harvey, C.R. (1997). Foreign Speculators and Emerging Equity Markets. *NBER, Working Paper*. No. W6312.

Bekaert, G. & Harvey, C.R. (2000). Foreign Speculators and Emerging Equity Markets" *The Journal of Finance*. 55(2), 565-613.

Bekaert, G., Hodrick, R.J., & Zhang, X. (2009). International Stock Return Comovements. *The Journal of Finance*. 64(6). 2591-2626.

Bekaert, G. & Urias, M.S. (1999). Is there a free lunch in emerging market equities? *The Journal of Portfolio Management*. 25, 83-95.

Blaylock, A. (2007). Reaction of Korean ADR Issuers to New Korean ADRs. *International Journal of Business Disciplines*, 18(3), 35-39.

Blaylock, C.A. (2014a). Market Breakdown of the Declining Marginal Reaction to ADR Issuers. *Academy of Accounting and Financial Studies Journal*. 18(2), 39-49.

Blaylock, C.A. (2014b). Reaction of Initial ADR Issuers to Subsequent ADRs. *Academy of Accounting and Financial Studies Journal*. 18(3), 21-28.

Blaylock, A. & Duett, E.H. (2004). The Declining Market Reaction to ADR Issuers in Emerging Markets. *Global Business and Finance Review*. 9(2), 1-13.

Boamah, N.A. (2017). The global financial market integration of selected emerging markets. *International Journal of Emerging Markets*. 12(4), 683-707.

Chakraborty, A., & Holani, U. (2011). International Listing and Stock Returns: Evidence from Emerging Economies. *International Journal of Financial Management*. 1(2), 61-73.

Cho, Y.J. & Rhee, C. (1999). The Gains From International Investment Diversification: The Korean Case. *Journal of Economic Theory and Econometrics*. 5(1), 23-41.

Christoffersen, P., Errunza, V., Jacobs, K., & Langlois, H. (2012). Is the Potential for International Diversification Disappearing? A Dynamic Copula Approach. *The Review of Financial Studies*. 25(2), 3711-3751.

Domowitz, I., Glen, J., & Madhavan, A. (1997). Market Segmentation and Stock Prices: Evidence From an Emerging Market. *Journal of Finance*. 52(3), 1059-1085.

Errunza, V. & Losq, E. (1985). International Asset Pricing Under Mild Segmentation: Theory and Test. *The Journal of Finance*. 40(1), 105-124.

Foerster, S.R., & Karolyi, A.G. (1993). International Listings of Stocks: The Case of Canada and the U.S. *Journal of International Business Studies*. 24(4), 763-784.

Foerster, S.R. & Karolyi, A.G. (1999). The Effects of Market Segmentation and Investor Recognition on Asset Prices: Evidence from Foreign Stocks Listing in the United States. *The Journal of Finance.* 54(3), 981-1013.

Fouquau, J., Kharoubi, C., & Spieser, P. (2018). International and temporal diversifications: the best of both worlds? *Journal of Risk*. 20(4), 27-54.

Francis, B., Hasan, I., & Hunter, D. (2002). Emerging Market Liberalization and the Impact on Uncovered Interest Rate Parity. *Journal of International Money and Finance*. 21, 931-956.

Grubel, H.G. (1968). Internationally diversified portfolios: Welfare Gains and Capital Flows. *The American Economic Review.* 58(5), 1299-1314.

Henry, P.B. (2000). Stock Market Liberalization, Economic Reform, and Emerging Market Equity Prices. *The Journal of Finance*. 55(2), 529-564.

Jiang, C.X. (1998) "Diversification with American depository receipts: The dynamics and the pricing factors. *Journal of Business Finance and Accounting.* 25, 683-699.

Lau, S.T., Diltz, D.J., & Apilado, V.P. (1994). Valuation Effects of International Stock Exchange Listings. *Journal of Banking and Finance.* 18(4), 743-755.

Levy, H., & Sarnat, M. (1970). International Diversification of Investment Portfolios. *The American Economic Review.* 60(4), 668-675.

Longin, F., & Solnik, B. (2001). Extreme Correlation of International Equity Markets. *The Journal of Finance*. 56(2), 649-676.

Madura, J., & Whyte, A.M. (1991). International Linkage of Credit Risk Among Countries. *Rivista Internazionale di Scienze Economiche e Commeriali.* 38(3), 255-265.

Miller, D.P. (1999). The Market Reaction to International Cross-listings: Evidence from Depositary Receipts. *Journal of Financial Economics*. 51(1), 103-123.

Rim, H., & Setaputra, R. (2012). Studies on the International Diversification. *International Journal of the Academic Business World*. 6(1), 105-110.

Speidell, L.S., & Sappenfield, R. (1992). Global Diversification in a Shrinking World *Journal of Portfolio Management*. 19(1), 57-67.

Stapleton, R.C., & Subrahmanyam, M.G. (1977). Market Imperfections, Capital Market Equilibrium and Corporation Finance. *Journal of Finance*. 32(2), 307-319.

Sundaram, A.K., & Logue, D.E. (1996). Valuation Effects of Foreign Company Listings on U.S. exchanges. *Journal of International Business Studies*. 67-88.

Switzer, L.N., & Tahaoglu, C. (2015). The benefits of international diversification: market development, corporate governance, market cap, and structural change effects. *International Review of Financial Analysis*. 42, 76-97.

Yuan, T., Gupta, R., & Roca, E. (2016). Why Not Diversify into Emerging Equity Markets via ADRs? *Journal of Investing*. 25(2), 18-27.