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Empirical Investigation of the Impact of Multilateral Trade on Income Convergence Across Countries

By LEI ZHOU, BASUDEB BISWAS, CHRIS FAWSON, AND PETER J. SAUNDERS*

This paper investigates empirically the effects of established country-to-country trade on income convergence across countries. Using the β-convergence criterion we demonstrate that poorer economies grow faster than richer economies with international trade. Consequently, we find empirical evidence of a convergence in per capita income among richer and poorer countries. Monte Carlo models are estimated to simulate the characterization of β-convergence in randomly created trading groups of 8 to 23 member countries' economies. Our results indicate that income convergence is less likely to occur in our randomly created trading partnerships than in those that are formed as part of existing trade relationships. This result reaffirms the argument that countries that have established trade relationships are more likely to experience income convergence than countries that lack such trade relationships. Additionally, our research provides new empirical evidence on the impact of international trade on economic growth in general. This information is particularly valuable for the current analyses of the costs and benefits of restricting international trade in the U.S. and elsewhere.

Keywords: Multilateral Trade, Income Convergence

JEL Classification: F63, 010

I. Introduction

Although globalization is clearly occurring throughout most economies, there has recently been a strong trade protectionist movement in numerous countries, including the U.S., that emphasizes the harmful impact of free trade on some sectors of their economies, while at the same time denying the macro benefits from international trade.[1] The movement's origins can be traced to the mercantilists' trade doctrine, which denies the benefits from international trade that occur to countries that participate in such trade. Consequently, there appears to be doubts about the benefits of unrestricted international trade in particular, and of globalization in general. In addition to the current anti-free trade climate concerning the impact of such trade on economic growth, there is

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[1] This movement resulted, among other outcomes, in the 2016 U.K. exit from the European Union and the U.S. November 2016 Presidential election of Donald Trump whose campaign relied heavily on anti-free trade policies.

also no consensus on the impact of globalization on income distribution in trading countries. Critics of globalization and multilateral trade claim that trade is an exploitive mechanism that concentrates wealth and income and leads to increasing disparities in the well-being of rich and poor countries. In a closed economy context, economists have argued that the stocks of physical capital, human capital, technology, and infrastructure represent the primary determinants of the level of per capita output and thus, per capita income. In an open economy context, once countries are allowed to trade, the pursuit of comparative advantage allows countries to move beyond the constraints imposed by the in-country resource endowment. Therefore, the countries that participate in international trade can increase their productive capacity and their per capita incomes.

International trade can also impact factor prices and incomes in trading countries (Samuelson, 1948; Jones, 1965). According to conventional trade theory, which is based on the Heckscher-Ohlin model (Ohlin, 1933) and the Stolper-Samuelson (1941) theorem, increasing trade has had some effect on wage rate inequality in countries that trade. Empirical investigations of this issue include contributions by Krugman (1995), Feenstra and Hanson (1999), Ghosh *et al*. (2000 and 2002), Edwards and Lawrence (2010), and Liu and Trefler (2008), among others. Recent theoretical investigations of this issue include the work of Oladi and Beladi (2008), who developed a general equilibrium model to investigate the impact of technological change on wages of skilled and unskilled workers. According to their model, unskilled workers' wages are negatively affected by technological advances while the skilled workers' wages can also be reduced in some instances. Additionally, in their 2009 article, the two authors find that the elasticity of import demand can explain a wage gap between skilled and unskilled workers.

Furthermore, as mentioned previously, the standard free trade view of the beneficial impact of international trade on countries that participate in such trade has been challenged recently in the U.S. and elsewhere. In particular, in the U.S. a significant part of President Trump's economic plan directly contradicts the free trade paradigm by reviving the mercantilists' protectionist arguments against free trade. The proposed plan calls for imposing tariffs on a number of imports into the U.S. while subsidizing U.S. exports. This "border adjustment tax" economic policy is aimed at promoting economic growth in the U.S. Therefore, the current protectionist climate makes it imperative to provide further empirical evidence on the impact of international trade on economic growth. One way to accomplish this objective is to analyze the effects of free trade on the per capita income growth in countries that engage in such trade. Our paper makes such a contribution by analyzing the impact of trade on income convergence across 23 trading countries.

International trade promotes economic growth in numerous ways. According to Grossman and Helpman (1991), trade can affect long-run growth through several different channels. First, commodity exchange facilitates the transmission of new technology and technical information. Second, international competition provides incentives for firms in each country to adopt new ideas and innovations. Third, the size of the market that each country faces is enlarged by global integration. Van Den Berg (2001) also demonstrates that the introduction of learning-by-doing, human capital accumulation, and research and development (R&D) in an open country trade model may induce permanent economic growth.

However, because of power asymmetries that govern most trade relationships, the gains from trade may be allocated across the trading group in such a way that some of its members may be relatively disadvantaged in comparison to the relative advantage captured by others within it. It is in this context that our research proposes to add to the existing and expanding body of the literature on this issue. Our present paper analyzes the impact of multilateral trade on income distribution among trading countries. In particular, our study provides empirical evidence on whether countries that trade within an established trade framework experience increased capacity for income convergence, or if this multilateral trade leads to an increasing gap between rich and poor countries. In other words, can the existing differences in technology, knowledge, and infrastructure for countries within a trading network be reduced through trade? Furthermore, does international trade result in a convergence of per capita income among the countries that engage in such trade?

The main objective of our research is to provide answers to the above mentioned issues. Since the convergence of per capita income among rich and poor countries is more likely to occur under the conditions of rapid economic growth, such as was the case in the late 1990s and early 2000s, we focus our empirical investigation on this period of time. Additionally, the results of our present research provide timely empirical evidence on the broader benefits of free trade.

II. Methodological Framework

Barro and Sala-i-Martin (1992 and 2003) and Sala-i-Martin (1996) introduce the two types of convergence that reflect the standard used in empirical studies of cross-country income convergence. These two different measures of convergence are termed β-convergence and σ-convergence. β-convergence refers to the situation where poorer economies experience a faster growth rate in per capita income than rich economies and σ-convergence refers to the situation where the dispersion of per capita income across a selected group of economies decreases over time.

We focus on β-convergence as the chosen method for exploring income convergence in this paper because β-convergence remains the primary focus for exploring income convergence in the literature of growth empirics and because it is a necessary condition for σ-convergence. In this study, we propose a comparison approach in which identical regression equations are estimated for both established trading groups and randomly selected countries assigned to a hypothetical trading group that has the same network size as the established trading group. The results for the actual trading groups are then compared to the properties of randomly assigned trading groups so that the effect of the trade group is identifiable. The method we employ is similar to that used by Ben-David (1996) to study the convergence among trading partners. We depart from Ben-David (1996) in two ways. First, while Ben-David took the σ-convergence approach, our study uses the β-convergence approach. Second, the present research includes larger trading groups than those used by Ben-David (1996). For example, our trading group size ranges from 8 to 23, whereas Ben-David's (1996) trading group sizes were 3 to 9.

III. The Empirical Model

Neoclassical growth models generate convergence with a set of exogenous and constant economic parameters, such as the constant saving rate. However, the assumption of an exogenous saving rate could introduce problems like dynamic inefficiency or excessive saving. This type of problem was resolved by the Ramsey (1928) model, and refined by Cass (1965) and Koopmans (1965). This approach relaxes the exogenous assumption of the saving rate by allowing consumers to make savings decisions based on the optimal intertemporal allocation of resources. In the Ramsey model, consumers behave optimally, and the saving rate rises or falls as the economy develops. The Ramsey model generates a pair of differential equations by using a log-linear approximation of the growth rate of capital per labor and the law of motion of consumption per labor around the steady state. The solution gives the time path of the log of per capita income. Barro and Sala-i-Martin (2003) introduce the following parameterization of the Ramsey model:

$$(1/T)\cdot\log\left(y_{i,t_0+T}/y_{i,t_0}\right)=[(1-e^{-\beta T})/T]\cdot\log\left(\hat{y}^*\right)-[(1-e^{-\beta T})/T]\cdot\log(y_{i,t_0})+\varepsilon_{i,t_0,t_0+T}, \tag{1}$$

where $y_{i,t}$ is the real per capita GDP of the i^{th} economy at time t; T is the number of years of the time span; β is the parameter to be estimated; and $\varepsilon_{i,t_0,t_0+T}$ is the effect of the error terms between time t_0 and t_{0+T}. Again, Barro and Sala-i-Martin (2003) identify the coefficient β as a measure of the speed of convergence. If β is positive, $(1-e^{-\beta T})/T$ will be positive, hence the coefficient for the initial level of the log of real per capita GDP $\log(y_{i,t_0})$ will be negative. The negative relationship between the growth rate and the initial level of income is referred to as the β-convergence criterion.

The first term of the right-hand side is an expression of the steady-state income value $\hat{y}^*$. By assuming that all economies have the same value for the steady-state income, the following regression equation can be estimated by using an ordinary least squares (OLS) method.

$$(1/T)\cdot\log\left(y_{i,t_0+T}/y_{i,t_0}\right)=\beta_0+\beta_1\cdot\log(y_{i,t_0})+\varepsilon_{i,t_0,t_0+T}, \tag{2}$$

where β_0 and β_1 are parameters to be estimated. The dependent variable of the model is the average growth rate of the real per capita GDP of one economy during a certain period of time. The explanatory variable is the initial level of the log of real per capital GDP of the economy. If β-convergence exists in this group of economies, the coefficient for $\log(y_{i,t_0})$ should be negative, which means that the growth rate of real per capita GDP is inversely related to the initial level of the log of real per capita GDP. If the coefficient is positive, divergence occurs and poorer economies will never catch up with richer economies. In the next section, β in Equation (1) and β_0 and β_1 in Equation (2) are estimated.

IV. Data and Estimation Methodology

As explained previously, the focus of our paper is on the late 1990s and the early 2000s. Therefore, the data used in this study are obtained from the Penn World Table Version 6.0 (Heston *et al*., 2001), World Trade Organization (1998), and International Monetary Fund (1998). The Penn World data provide y_{i,t_0}, per capita income of the i^{th} economy in 1960, and y_{i,t_0+T}, per capita income of the i^{th} economy in 1997.

Membership in the trading network group is determined by using the following methodology. First, leader economies are selected from the top 25 exporters and the top 25 importers in world trade of merchandise and commercial services in 1997 (World Trade Organization, 1998). As a considerable overlap exists in the leading exporters and importers for both merchandise trade and commercial services, only 30 leader economies are selected from the leading traders.[2] Among the 30 economies selected, Germany and the Russian Federation are excluded because the per capita incomes in 1960 are not available; Taiwan is also excluded because of the lack of data on bilateral trade with other economies.

In the next step, member economies of trading groups are defined for each of the 27 leader economies. For each of the 27 leader economies, membership in the trade network group is

[2] Trading network groups are identified by the leader economy; e.g., Group France refers to the trading network group based on the pattern of trade relative to exports to and imports from France.

established as follows. Consider the leader country *A* and another country *B*. If country *B* received more than 1% of country *A*'s total exports in 1997, or if more than 1% of economy *A*'s total imports in 1997 were from country *B*, country *B* is included in country *A*'s trading group (data are from the International Monetary Fund, 1998). Within a trading network group, Middle East countries and formerly communist countries are excluded.[3] There are other economies that are excluded due to lack of data on income growth, e.g., Libya (should be assigned to Group Italy). There is not an *a priori* reason that 1% is used as the cutoff point; however it generates a group size between 8 to 23 economies, and this gives us a broad range of group sizes to explore the nature of the convergence criteria. If the group size of the trading network is too small, the regression results might not be robust and if the sample size is too large, economies in one group might be so heterogeneous that they will not converge to a same steady-state level of per capita income. Based on this grouping, there are 27 trading groups and 45 countries/economies involved in this study. The names of the countries/economies included in the study are listed in Appendix A.

In addition to the 27 groups, we also study another three additional "special case" trading groups. We call these three additional "special case" groups the Industrial Countries Group, Group India (1960-97), and Group China (1980-97). The Industrial Countries Group is formed in the same way as the other trading groups, but is limited to inclusion of countries on the list of industrial countries provided by the International Monetary Fund (1998). Our inclusion of India is due to India's growing importance to global trade flows even though India was not identified as a leading exporter or importer in 1997. Economic reform started in China in 1979 when the process of economic liberalization began. The inclusion of China in our analyses can provide information on the impact of trade liberalization on China's income convergence.

V. Empirical Results

The 27 trading groups and regression results for Equations (1) and (2) are given in Table 1. $\hat{\beta}$ is the estimator of convergence speed in Equation (1), which is estimated by the Gauss-Newton nonlinear least squares method. An estimate of the coefficient on the log of initial income per capita in Equation (2), $\hat{\beta}_1$, is estimated using a linear least squares method. Calculated *t*-values for each estimator are listed in parentheses.

With few exceptions, the estimates of β in Equation (1) and β_1 in Equation (2) reflect interpretive consistency in the sense that they reinforce each other with appropriate signs and magnitudes. The estimated coefficient $\hat{\beta}_1$ indicates that among these 27 trading groups, 24 of them have statistically significant coefficients, and all of the significant coefficients have the expected negative sign. This means the growth rate of per capita income is negatively related to the starting value of per capita income, i.e., poorer economies grow faster than richer ones. Twenty-four trading groups show strong evidence that trading partners converge in per capita income. Ben-David (1996) measures the standard deviation of log real per capita GDP and gets 17 converging groups out of 25 using the Summers-Heston data (Heston *et al*., 2001) from 1960 to 1985. In Ben-David's study, the groups whose leader economies are the United Kingdom (U.K.), Ireland, Spain, United States (U.S.), Uruguay, Mexico, Argentina, and Chile show significant divergence.

[3] China is an exception to the communist country exclusion and enters into our analysis as one of the special case leader countries.

Table 1: Twenty-Seven Trading Groups and Coefficients Estimates

	Leader Economy	Trade Partners	$\hat{\beta}$ (Eq. 1)	$\hat{\beta}_1$ (Eq. 2)
1	U.S. (21)	Bel-Lux, Switzerland, Singapore, H.K., Japan, Canada, France, Netherlands, Australia, U.K., Italy, Korea, Malaysia, Mexico, Thailand, Brazil, Venezuela, Philippines, Taiwan, Indonesia	0.0169* (2.600)	-0.0126* (-3.439)
2	Japan (17)	U.S., Singapore, H.K., Canada, France, Netherlands, Australia, U.K., Korea, Malaysia, Thailand, Brazil, Panama, Philippines, Taiwan, Indonesia	0.0161* (2.240)	-0.0121* (-2.874)
3	Canada (10)	U.S., Norway, Japan, France, U.K., Italy, Korea, Mexico, Taiwan	0.0344* (2.758)	-0.0194* (-4.979)
4	France (15)	U.S., Bel-Lux, Switzerland, Norway, H.K., Austria, Japan, Netherlands, U.K., Sweden, Italy, Ireland, Spain, Portugal	0.0279* (3.085)	-0.0174* (-5.033)
5	U.K. (21)	U.S., Bel-Lux, Switzerland, Norway, Singapore, Denmark, Japan, Canada, France, Netherlands, Australia, Finland, Sweden, Italy, Ireland, Spain, Korea, Malaysia, Turkey, Taiwan	0.0283* (4.035)	-0.0175* (-6.796)
6	Italy (19)	U.S., Bel-Lux, Switzerland, H.K., Austria, Japan, France, Netherlands, U.K., Sweden, Ireland, Spain, Greece, Portugal, South Africa, Turkey, Brazil, Algeria	0.0089 (1.536)	-0.0076 (-1.721)
7	Netherlands (16)	U.S., Bel-Lux, Switzerland, Norway, Denmark, Austria, Japan, France, U.K., Sweden, Italy, Ireland, Spain, Malaysia, Taiwan	0.0241* (4.150)	-0.0160* (-6.270)
8	H.K. (16)	U.S., Singapore, Japan, Canada, France, Netherlands, Australia, U.K., Italy, Korea, Malaysia, Thailand, Philippines, Taiwan, India	0.0148 (2.010)	-0.0114* (-2.502)
9	Bel-Lux (13)	U.S., Switzerland, Austria, Japan, France, Netherlands, U.K., Sweden, Italy, Ireland, Spain, India	0.0049 (1.378)	-0.0045 (-1.389)
10	Korea (21)	U.S., Switzerland, Singapore, H.K., Japan, Canada, France, Netherlands, Australia, U.K., Italy, Malaysia, Mexico, South Africa, Thailand, Brazil, Panama, Philippines, Taiwan, Indonesia	0.0182* (2.574)	-0.0133* (-3.496)

Table 1: Twenty-Seven Trading Groups and Coefficients Estimates: Continues

	Leader Economy	Trade Partners	$\hat{\beta}$ (Eq. 1)	$\hat{\beta}_1$ (Eq. 2)
11	Singapore (17)	U.S., Switzerland, H.K., Japan, France, Netherlands, Australia, U.K., Italy, Ireland, Korea, Malaysia, Thailand, Philippines, Taiwan, India	0.0163* (2.202)	-0.0122* (-2.836)
12	Mexico (8)	U.S., Japan, Canada, France, Italy, Malaysia, Taiwan	0.0251 (2.154)	-0.0164* (-3.077)
13	Spain (18)	U.S., Bel-Lux, Switzerland, Austria, Japan, France, Netherlands, U.K., Sweden, Italy, Ireland, Portugal, Argentina, Turkey, Brazil, Algeria, Nigeria	-0.0011 (-0.0034)	0.0011 (0.2821)
14	Sweden (18)	U.S., Bel-Lux, Norway, Denmark, H.K., Austria, Switzerland, Japan, Canada, France, Netherlands, Australia, Finland, U.K., Italy, Ireland, Spain	0.0329* (3.108)	-0.0190* (-5.724)
15	Malaysia (18)	U.S., Bel-Lux, Singapore, H.K., Switzerland, Japan, France, Netherlands, Australia, U.K., Italy, Korea, Thailand, Philippines, Taiwan, Indonesia, India	0.0126* (2.312)	-0.0101* (-2.780)
16	Switzerland (16)	U.S., Bel-Lux, Singapore, H.K., Austria, Japan, France, Netherlands, U.K., Sweden, Italy, Ireland, Spain, Korea, Turkey	0.0312* (2.853)	-0.0185* (-5.025)
17	Australia (23)	U.S., Bel-Lux, Switzerland, Singapore, H.K., Japan, Canada, France, Netherlands, U.K., Sweden, Italy, New Zealand, Korea, Malaysia, South Africa, Thailand, Philippines, Taiwan, Indonesia, PNG, India	0.0131* (2.394)	-0.0104* (-2.943)
18	Austria (11)	U.S., Bel-Lux, Switzerland, Japan, France, Netherlands, U.K., Sweden, Italy, Spain	0.0185* (2.232)	-0.0134* (-2.898)
19	Thailand (18)	U.S., Bel-Lux, Switzerland, Singapore, H.K., Japan, Canada, France, Netherlands, Australia, U.K., Italy, Korea, Malaysia, Philippines, Taiwan, Indonesia	0.0173* (2.854)	-0.0128* (-3.768)
20	Brazil (22)	U.S., Bel-Lux, Switzerland, Japan, Canada, France, Netherlands, U.K., Sweden, Italy, Spain, Korea, Argentina, Chile, Uruguay, Mexico, Venezuela, Algeria, Paraguay, Taiwan, Bolivia	0.0117 (1.812)	-0.0095* (-2.161)
21	Indonesia (19)	U.S., Bel-Lux, Singapore, H.K., Japan, Canada, France, Netherlands, Australia, U.K., Italy, Spain, Korea, Malaysia, Thailand, Philippines, Taiwan, India	0.0115* (2.242)	-0.0093* (-2.642)
22	Ireland (17)	U.S., Bel-Lux, Switzerland, Norway, Singapore, Denmark, Japan, France, Netherlands, U.K., Sweden, Italy, Spain, Korea, Malaysia, Taiwan	0.0319* (4.027)	-0.0188* (-7.223)

Table 1: Twenty-Seven Trading Groups and Coefficients Estimates: Continues

	Leader Economy	Trade Partners	$\hat{\beta}$ (Eq. 1)	$\hat{\beta}_1$ (Eq. 2)
23	Turkey (19)	U.S., Bel-Lux, Switzerland, Singapore, Austria, Japan, France, Netherlands, U.K., Sweden, Italy, Spain, Greece, Korea, Portugal, Romania, Algeria, Taiwan	0.0189* (2.699)	-0.0136* (-3.698)
24	Denmark (14)	U.S., Bel-Lux, Switzerland, Japan, France, Netherlands, Finland, U.K., Sweden, Italy, Spain, Portugal, Norway	0.0188* (2.992)	-0.0136* (-4.003)
25	Philippines (14)	U.S., Singapore, H.K., Japan, Canada, France, Netherlands, Australia, U.K., Korea, Malaysia, Thailand, Taiwan	0.0233* (2.293)	-0.0156* (-3.369)
26	Norway (17)	U.S., Bel-Lux, Switzerland, Denmark, Austria, Japan, Canada, France, Netherlands, Finland, U.K., Sweden, Italy, Ireland, Spain, Korea	0.0276* (4.339)	-0.0173* (-7.093)
27	China (17)	U.S., Singapore, H.K., Japan, Canada, France, Netherlands, Australia, U.K., Italy, Korea, Malaysia, Thailand, Brazil, Taiwan, Indonesia	0.0154* (2.907)	-0.0117* (-3.681)

Note: Leader economies are selected from the top 25 exporters and the top 25 importers in world trade of merchandise and commercial services in 1997, considering also the availability of income and trade data. For each leader economy A, if more than 1% of economy A's total exports in 1997 were to economy B, or if more than 1% of economy A's total imports in 1997 were from economy B, B is a trading partner of A. In the second column, the numbers in the parentheses are group sizes. The numbers in parentheses of the last two columns are *t*-values for the corresponding estimates.
* Indicates significantly different from zero at the 5% level.

In this study, Uruguay, Argentina, and Chile are not selected as leader economies, but the U.K., Ireland, U.S., and Mexico groups show significant convergence. Group Spain is still not significantly converging. In addition to Group Spain, Group Italy and Group Belgium-Luxemburg (Bel-Lux) also have insignificant $\hat{\beta}_1$, although they have the desired negative sign.

The nonlinear least squares estimation in Equation (1) indicates slightly different results. There are 21 significant estimates out of 27. The coefficients that are significant have the expected positive signs. Except for the three non-converging groups estimated by Equation (1), Group Hong Kong (H.K.), Group Mexico, and Group Brazil are also non-converging in Equation (1). The value of $\hat{\beta}$, i.e., the estimated convergence speed, ranges from 0.0115 (Group Indonesia) to 0.0344 (Group Canada), which indicates a half life from 20 to 60 years approximately. In other words, it will take 20 to 60 years for an economy to halve the distance from the current per capita income to the steady state. Although the convergence speed is somewhat slow, our results give support to the claim that for trading partners poorer economies grow faster than richer ones. Therefore, our present research indicates that convergence takes place among trading partners.

The estimation results for our "special case" trading groups are reported in Table 2. Not surprisingly, these results show that the Industrialized Countries Group and Group China (1980-97) are converging. The converging speed for Group China (1980-97) is greater than that for Group India (1960-97). However, for Group India during 1960-97, the estimated coefficient is not significant.

In contrast to the six non-converging trading groups in Table 1, including Group India in Table 2, most of these groups consist of either several developing economies or poor economies. It is important to differentiate between developed and developing economies. In particular, the assumption that all economies have the same characteristics is clearly incorrect. Furthermore, developing economies have to grow faster to catch up with more developed economies.

There are 45 economies in total analyzed in the present study. The number of economies in a trading group varies from 8 to 23. In most of the trading groups, poorer economies grow faster than richer ones. In order to highlight the role of trade, it is natural to investigate whether a similar result will happen in a group of economies that do not engage heavily in international trade.

Table 2: Four Trading Groups and Coefficients

Leader Economy	Trade Partners	$\hat{\beta}$ (Eq. 1)	$\hat{\beta}_1$ (Eq. 2)
Industrial Countries (1960-97)	U.S., Bel-Lux, Switzerland, Norway, Austria, Japan, Canada, France, Netherlands, Australia, U.K., Sweden, Italy, Ireland, Spain	0.0213* (2.816)	-0.0147* (-3.989)
China (1960-97)	U.S., Singapore, H.K., Japan, Canada, France, Netherlands, Australia, U.K., Italy, Korea, Malaysia, Thailand, Brazil, Taiwan, Indonesia	0.0154* (2.907)	-0.0117* (-3.681)
China (1980-97)	U.S., Singapore, H.K., Japan, Canada, France, Netherlands, Australia, U.K., Italy, Korea, Malaysia, Thailand, Brazil, Taiwan, Indonesia	0.0223* (2.395)	-0.0152* (-3.499)
India (1960-97)	U.S., Bel-Lux, Singapore, H.K., Switzerland, Japan, Canada, France, Netherlands, Australia, U.K., Italy, Spain, Korea, Malaysia, South Africa, Thailand, Taiwan, Morocco, Sri Lanka, Indonesia, Bangladesh, Nigeria	0.0060 (1.367)	-0.0053 (-1.465)

* Indicates significantly different from zero at the 5% level.

Our study addresses this possibility by randomly selecting 8 to 23 economies out of the 45 economies, and then estimating the regression coefficients for each group. For groups with 8 economies, there are $C_{45}^{8} = 215{,}553{,}195$ different combinations out of 45 economies; for groups with 23, there are $C_{45}^{23} = 4.117 \times 10^{12}$ different combinations. Since each of the different-sized groups consists of such a large number of possibilities, 10,000 combinations are randomly drawn from the pool of each group size.

Given the 10,000 regressions for each group, the mean is calculated from the set of only those groups with the statistically significant coefficients. Table 3 summarizes the results of these estimates. The means of $\hat{\beta}_1$'s are still negative but with a scale of 10^{-3} for all groups. Compared to the values of the significant $\hat{\beta}_1$'s in Table 1, these means are very small numbers although they are significantly different from zero.

Table 3: Coefficients for Random Groups with Different Sizes

Group Size	Mean of $\hat{\beta}_1$	Standard Deviation of $\hat{\beta}_1$
8	-0.0070	0.0069
10	-0.0069	0.0058
11	-0.0069	0.0052
13	-0.0069	0.0046
14	-0.0068	0.0044
15	-0.0068	0.0040
16	-0.0069	0.0038
17	-0.0068	0.0036
18	-0.0068	0.0035
19	-0.0068	0.0033
20	-0.0068	0.0031
21	-0.0068	0.0030
22	-0.0068	0.0028
23	-0.0068	0.0027

Note: For each group size, 10,000 regressions are estimated among randomly selected economies. The means and the standard deviations are for the significant (at 5% level) estimates only.

The distribution of $\hat{\beta}_1$ for each sample size is normal. Therefore, we can use this distribution to generate the probability of observing the coefficient estimate for a trading group. For most of the groups, that is 20 out of 27, the probability of observing $\hat{\beta}_1$ is less than 5% or 10% (Table 4). Given these results, it is fair to conclude that these $\hat{\beta}_1$ distributions do not occur accidentally. Therefore, it appears that convergence is less likely to happen in the randomly selected groups than in the trading groups.

In this study, an indirect method is used to analyze the role of trade in convergence. The results indicate that trade contributes to convergence in per capita income among trading partners. However, this conclusion does not hold for all the trading groups studied, especially for the groups that include both developed economies and the poorest economies. However, in general, it is reasonable to conclude that globalization or integration of the countries of the world may raise the per capita income of all countries.

Table 4: Probability of Observing the Results of Trading Groups

Leader Economy	$\hat{\beta}_1$ (Eq. 2)	Prob(observing $\hat{\beta}_1$)
Canada (10)	-0.0194*	0.0154
Sweden (18)	-0.0190*	0.0002
Ireland (17)	-0.0188*	0.0004
Switzerland (16)	-0.0185*	0.0011
U.K. (22)	-0.0175*	<0.0001
France (15)	-0.0174*	0.0040
Norway (17)	-0.0173*	0.0018
Mexico (8)	-0.0164*	0.0869
Netherlands (16)	-0.0160*	0.0084
Philippines (14)	-0.0156*	0.0228
Turkey (19)	-0.0136*	0.0197
Denmark (14)	-0.0136*	0.0606
Austria (11)	-0.0134*	0.1056
Korea (21)	-0.0133*	0.0150
Thailand (18)	-0.0128*	0.0436
U.S. (21)	-0.0126*	0.0268
Singapore (17)	-0.0122*	0.0668
Japan (17)	-0.0121*	0.0708
China (17)	-0.0117*	0.0869
H.K. (16)	-0.0114*	0.1190
Australia (23)	-0.0104*	0.0918
Malaysia (18)	-0.0101*	0.1736
Brazil (22)	-0.0095*	0.1685
Indonesia (19)	-0.0093*	0.2236
Italy (20)	-0.0076	0.3974
Bel-Lux (13)	-0.0045	0.3015
Spain (18)	0.0011	0.0119

Note: Based on the distribution of $\hat{\beta}_1$ for randomly selected economies for each group size, this table shows the probability of observing the $\hat{\beta}_1$ for trading partners. Fourteen are less than 5% and 20 are less than 10%.
* Indicates significantly different from zero at the 5% level.

VI. Conclusion

This paper makes three contributions to the literature regarding per capita income convergence among countries/economies that are members of established trading groups. First, empirical evidence suggests that trade within a trade group increases per capita income of poorer countries in such a group at a faster rate than richer countries in that group. Second, when estimated income convergence parameters are compared between established trading groups and randomly assigned trading groups of identical size, there is no evidence of income convergence within the randomly assigned trading groupings. This result strengthens the case that international trade does exert influence in characterizing β-convergence among countries/economies within an established trading group. Third, our research provides new empirical evidence on the Ben-David (1996) research. Ben-David compared change in the dispersion of incomes between trading partners and non-trading partners and found that it is more likely for trading partners to have σ-convergence. It is possible that dispersion in real per capita income is affected by random shocks that are not related to income. Consequently, even if an increasing dispersion in per capita income is observed among a group of economies, they still could have β-convergence. Restricting one's focus to σ-convergence limits the exploration of another important aspect of convergence. As a complement to Ben-David's work, our paper provides further, and more complete, empirical evidence of the effects of trade on income convergence within trading groups.

Our research indicates that if countries are able to enter into a pattern of trade within a trading group, then it is likely that trade liberalization will benefit these countries. Furthermore, the test results of the present study indicate that trade will eventually help developing countries catch up with the per capita income levels enjoyed by their developed countries trading partners. Additionally, the results of our study provide further empirical evidence in the current discussion of the costs and benefits of free trade in general. It is reasonable to conclude that trade increases the per capita income in all countries that engage in it. Therefore, restricting international trade may perhaps benefit some sectors of domestic economies, but it will harm their overall economic growth.

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Appendix A: List of Economies

27 Leader Economies	45 Economies Involved in This Study
Canada	Argentina
Sweden	Australia
Ireland	Austria
Switzerland	Belgium-Luxemburg
U.K.	Bolivia
France	Brazil
Norway	Canada
Mexico	Switzerland
Netherlands	Chile
Philippines	China
Turkey	Denmark
Denmark	Algeria
Austria	Spain
Korea	Finland
Thailand	France
U.S.	U.K.
Singapore	Greece
Japan	H.K.
China	Indonesia
H.K.	India
Australia	Ireland
Malaysia	Italy
Brazil	Japan
Indonesia	South Korea
Italy	Mexico
Belgium-Luxemburg	Malaysia
Spain	Nigeria
	Netherlands
	Norway
	New Zealand
	Panama
	Philippines
	Papua New Guinea
	Portugal
	Paraguay
	Romania
	Singapore
	Sweden
	Thailand
	Turkey
	Taiwan
	Uruguay
	U.S.
	Venezuela
	South Africa

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Intangibles and the Market Value of Biopharmaceutical Startups

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This paper investigates the relationship between various measures of intangible capital and the market valuation of young biopharmaceutical firms. We employ a non-linear model to measure the impact of R&D, patents, alliances, organizational capital, and mergers on the value of 349 newly-incorporated firms between 1980 and 2006. We find that, with the exception of mergers, our measures of intangible capital have positive and significant effects on market values; the impact of R&D declines as firms mature; and the omission of either alliances or organizational capital leads to a significant overstatement of the influence of R&D.

Keywords: Innovation, R&D, Intangible Assets, Market Valuation, Biopharmaceuticals

JEL Classification: O32, L65, E22, G32

I. Introduction

The valuation of firms in technology-based industries is among the most challenging tasks in finance. Despite considerable research efforts over the last three decades,[1] a substantial unexplained differential remains between book and market values (Amir and Lev, 1996). Various studies point to a failure to account for intangible assets, rather than "mismeasurement of conventional equity or the vicissitudes of the stock market," (Hulten and Hao, 2008, p. 1) as the primary source of this differential. Valuing intangible assets of young technology-based firms, which typically derive the bulk of their value from such assets, is "notoriously difficult" (Guo *et al.*, 2005, p. 3). Prime examples of this, and the focus of our study, are newly-incorporated biopharmaceutical firms, which invest heavily in intangibles[2] and have impressive track records with respect to innovation. We analyze the relationship between R&D-based intangibles and the value of young firms[3] where information asymmetries are particularly acute and financial information is of limited value.[4]

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[1] Numerous studies have explored this relationship. Examples include Griliches (1981), Cockburn and Griliches (1988), Hall (1993), Lev (2001), Chan *et al*. (2001), and Hall *et al*. (2005), among others.

[2] The biopharmaceutical sector is one of the most R&D-intensive in the United States, with companies investing over 12 times the amount of R&D per employee than manufacturing industries overall; see Phrma.org, 2017 State of the Industry (http://phrma.org/industryprofile/).

[3] During the first 12 years after their incorporation.

[4] Although prior studies have investigated the impact of various intangibles on firm value, we consider the impact of several intangibles simultaneously with the goal of parsing out the different effects. Related works include:

We use a market value function based on hedonic Tobin's Q equations first introduced by Griliches (1981).[5] This is the standard approach used in the literature to test the influence of various measures of intangible assets on firm performance using stock market data. We expand the standard version of the value function to include additional terms, capturing several intangibles that are unique to the biopharmaceutical industry and for which data are publicly available. In selecting our intangible asset measures, we work under the premise that any outlay intended to increase future rather than current revenues should be considered a capital investment (as in Corrado *et al.*, 2006). Therefore, spending on R&D, new patents, and even improved organizational structures should, in principle, be counted as investment.

A general consensus exists in the literature that R&D conducted by firms is an input in the production process whose output is an intangible asset.[6] R&D is especially critical in the biopharmaceutical industry according to Filson *et al.* (2015). To measure the R&D output, most studies have used the number of patent applications a firm has filed, weighted by the number of citations those patents receive to adjust for their quality, and thus economic value.[7] Patent information has limitations however—it measures knowledge output at the end of the discovery stage and at the beginning of a potential product development. In a great majority of cases, however, patented inventions do not even enter the product development stage, and of those that do, relatively few are developed into final marketable products.[8] For this reason, it is important to test the impact of another measure of R&D success, namely the clinical pipeline[9] that tracks pharmaceutical product development through a number of well-defined stages and which is a

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Trajtenberg (1990), who demonstrates that patents are important for optical scanners; Megna and Mueller (1991), who find that advertising is an important source of intangible capital in the distilled beverage and cosmetic industries; Megna and Klock (1993) and Shane and Klock (1997), who show that R&D expenditures and citation-weighted patent metrics measure intangible capital in the semiconductor industry, respectively; Chan *et al.* (1997) and Filson and Oweis (2010), who show that alliance formation has a positive impact on the value of biotech firms; Klock and Megna (2000), who demonstrate that spectrum license data can be used as a metric of intangible capital of cell phone companies; Rzakhanov (2004), who shows that advertising and clinical trials are important in the biotech industry; Darby *et al.*(2004), who study the value of R&D, citations, and human capital in biotech; Filson (2004), who examines the impacts of advertising and promotional alliances on the value of young e-commerce firms; Gleason and Klock (2006), who show that advertising is also important in the pharmaceutical and chemical industry; Hulten and Hao (2008), who study the impact of organizational development on the market value of a sample of pharmaceutical firms; and Gupta *et al*. (2017), who analyze the relationship between market value and firm investments in customer acquisitions and customer service.

[5] Other examples of this approach can be found in: Cockburn and Griliches (1988), Megna and Klock (1993), Klock *et al.* (1996), Shane and Klock (1997), Klock and Megna (2000), Hall *et al*. (2000), and Hall *et al.* (2005).

[6] Numerous studies have shown that R&D expenditures have a large impact on the market value of firms (Hall *et al*., 2005 and others).

[7] The large-scale use of patent data in economic research goes back to Scherer (1965), Schmookler (1966), and Griliches (1984). Prior literature shows that quality-adjusted patents do seem to add information above and beyond that obtained from R&D input measures (see Trajtenberg, 1990; and Hall *et al*., 2000 and 2005).

[8] An average of four years from beginning discovery research to beginning human clinical trials involving thousands of rejected compounds, and an average of eight years from beginning human clinical trials to introducing a new approved drug with an approximately one-in-five chance of success (Filson *et al*., 2015).

[9] In order for a company to market a product, it has to be approved by the Federal Drug Administration (FDA). The process involves different phases: The first one is the Pre-Clinical studies. Then, it files an Investigational New Drug Application with the FDA (IND). If approved, then it goes to clinical trials. There are three clinical trials: Phase I, Phase II, and Phase III. If a drug passes all of the three clinical trials, then a firm files a New Drug Application (NDA). If the application is approved by the Board of Review, then it can commercialize the drug.

strong indicator of a firm's future cash flows[10] (see Sharma and Lacey, 2004; McNamara and Baden-Fuller, 2007).

Given the significance of R&D expenditures in the biopharmaceutical industry, an important question concerns the relationship between a firm's age and the value of its R&D investment. In the fast-changing technology-based industries, the fit between a firm's innovative infrastructure and the current technological environment is critical to the success of the firm. In principle, the impact of age on R&D quality can be either positive or negative. Older firms have more experience and might benefit from economies of scale and/or scope, for example. At the same time, the more mature firms may suffer from overinvestment[11] and also from having more entrenched R&D programs, both of which increase the likelihood that their innovative output becomes mismatched with current market demands. In the latter case, age, experience, and accumulated competencies can be a burden for firms as they try to adapt to, or develop, new technologies (Henderson and Clark, 1990; Henderson, 1993). Furthermore, in recent decades there has been a tight link between scientific discovery and new products—new firms have often been spinouts from universities formed by star scientists to exploit the latest scientific discoveries. This has tended to provide an edge for young/small firms.[12]

Despite large investments in R&D, numerous observers have pointed to dwindling prospects for new drug discoveries and a wave of pending patent expirations as a major concern for the biopharmaceutical industry. This has forced firms to supplement their internal R&D with external sources of innovation, such as strategic technology alliances, and to gain R&D synergies through acquisitions (see Higgins and Rodriguez, 2006; Danzon *et al.*, 2007; Grabowski and Kyle, 2008). Both alliances and acquisitions enable companies to quickly access technological assets (Lerner *et al.*, 2003), to expand their knowledge base, and to exploit their existing technological edge (Hagedoorn and Duysters, 2002). Unlike acquisitions, however, in an industry where projects are particularly uncertain, risky, long, and expensive, alliances provide flexibility and are relatively cheap to set up (Filson and Morales, 2006). Firms can experiment by creating alliances with different partners and disband them quickly if warranted by changes in the market conditions. If a firm instead chooses the acquisition route, then it "is able to grow quickly, but it shrinks with great difficulty as resources come under managerial control" (Chan *et al.*, 1997, p. 203). A misevaluation of the target firm by an acquirer can therefore be very costly for the firm. Given the importance of alliances and M&As in the biopharmaceutical industry, we test for their respective impacts on market value.[13]

Our final intangible metric tracks investments in organizational capital. Similar to R&D and other intangibles, spending on a new management system, employee training, marketing and/or sales teams seeks to improve the financial performance of a firm and should therefore be

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[10] Besides increasing the likelihood of increased future sales, successful clinical trials also create positive externalities that are valuable to the firm. The firm's experience with product development, and its familiarization with a myriad of regulations that govern it, can create positive spillovers to the development of other products and further future sales. These spillovers increase the firm's capabilities in product development which at the same time raises the likelihood of profiting from more products in the market (Danzon *et al*., 2005).

[11] This according to the life-cycle hypothesis (see Grabowski and Mueller, 1975).

[12] Darby *et al.* (1999) analyze the role of star scientists on the market value of biotechnology firms.

[13] Several papers have looked at post-merger firm performance including Filson *et al.* (2015) find that post-merger R&D intensity varies across a sample of pharmaceutical firms; Danzon *et al.* (2007) show that merging firms experience a slower growth and lower operating profits. In an authoritative study, Chan *et al*. (1997) conclude that firms that enter into an alliance improve their operating performance (in the five-year period surrounding the event), and that technical alliances trigger a stronger, positive response from equity investors.

considered an investment.[14] We use firms' selling, general, and administrative (SG&A) expenses as a proxy for their investment in organizational capital.[15] According to Hulten and Hao (2008), "at least a fraction of such expenditures should be treated as capital for accounting purposes" (p. 13). The difficulty in measuring this variable has led economists to typically account for it by using fixed effects. However, the more recent literature (including Corrado *et al.*, 2006; Hulten and Hao, 2008; Peters and Taylor, 2017) provides guidance on the measurement issues.

Our main findings indicate that a host of intangible assets—R&D, the patent portfolio, technology alliances, and organizational capital—have a positive and significant influence on the market value of young biopharmaceutical firms. R&D investments display diminishing returns: as firms age, they get less bang for their R&D buck. We find that the M&A activity mostly has an insignificant influence on the market value of the acquirers' shares. Lastly, our results show that the omission of either technology alliances or organizational capital leads to a substantial overstatement of the importance of R&D. These findings demonstrate the merit of investigating this topic at a granular level—the results otherwise may be seriously misleading due to omitted variables.

The rest of the paper is organized as follows: Section II presents the econometric specification; in Section III we construct the different measures of intangible capital and describe the data sources; Section IV discusses the results of the model; finally, Section V summarizes the main conclusions.

II. Methodology and Estimation

In the market value model, the firm is treated as a set of tangible and intangible assets where the marginal shadow value of its assets is measured by the hedonic price of the firm. The value function is:

$$V_{it} = q_{it}\, f(X_{i1t}, X_{i2t}, X_{i3t}, \dots X_{int}), \tag{1}$$

where V_{it} represents the value of firm *i* at time *t*. X_{i1t},X_{i2t}, and X_{int} denote the various tangible and intangible assets of firm *i* at time *t*. q_{it} is the current market value coefficient of the firm:

$$q_{it} = exp(b_i + c_t + u_{it}), \tag{2}$$

where b_i is the firm-specific effect, c_t is the time effect, and u_{it} is an individual disturbance term. To estimate the econometric model, we assume that the firm's assets are additively separable (as in Hall, 1990):

$$V_{it} = q_{it}\, [A_{it} + (\beta)K_{it}]^{\sigma}, \tag{3}$$

[14] Brynjolfsson *et al.* (2002) and Brynjolfsson and Hitt (2005) illustrate the case of corporations' investments in information technology during the 1990s, which were intended to increase the effectiveness of their management. Bloom and Van Reenen (2007) provide evidence that these investments increased the value of a company. Black and Lynch (2005) report similar results for investments in worker training.

[15] Lev and Radhakrishnan (2005) argue that the SG&A expense includes most of the expenditures that generate organization capital.

where A_{it} represents tangible assets of the firm, β is the relative shadow price of intangible assets, and K_{it} is a measure of intangible assets. After assuming constant returns to scale ($\sigma = 1$), and dividing by A_{it}, we have:

$$\frac{V_{it}}{A_{it}} = q_{it} \left[1 + \beta \left(\frac{K_{it}}{A_{it}}\right)\right]. \tag{4}$$

Lastly, defining Tobin's Q as $Q_{it} = V_{it}/A_{it}$ and taking logs, we get:

$$\log Q_{it} = \log \frac{V_{it}}{A_{it}} = b_i + c_t + u_{it} + \log\left[1 + \beta \left(\frac{K_{it}}{A_{it}}\right)\right]. \tag{5}$$

Hall *et al.* (2005) explain that theory is not clear about: (i) the way intangibles (K_{it}) should be specified, and (ii) the effects of intangibles on market value. The process of value creation in the biopharmaceutical industry is complex as it depends on intangibles that allow a firm to signal success, to appropriate its returns, and to enable them to carry out a successful innovation process. We assume that the innovation process occurs when firms combine their tangible assets with multiple knowledge assets. Each intangible influences market value differently, however. R&D expenses, for instance, have an effect on value by signaling commitment to the core activities of biopharmaceutical firms. Patent portfolio size and quality, on the other hand, influence the performance of a firm's shares by providing information to investors on the status of knowledge production and the synergies and economies of scale created by that knowledge. The number of drug candidates going through clinical trials indicates a firm's success in moving from discovery to development and closer to a possible product. Alliances and M&As have an effect on value by signaling that a firm is enhancing or expanding its technological capabilities and exploiting possible synergies through external technology. And lastly, a firm's investments in the development of its management systems and its employees will likely lead to a better-run, and thus more valuable, organization. We assume the investors take into account these pieces of information as they assign a value to a firm. With this in mind, we estimate the following equation using a non-linear least squares model:

$$\begin{aligned}\log Q_{it} = b_i + c_t + \log\Big(1 + \alpha_1 \frac{R\&D_{it}}{A_{it}} + \alpha_2 \frac{PAT_{it}}{R\&D_{it-1}} + \alpha_3 \frac{CITES_{it}}{PAT_{it}} + \\ \alpha_4 \frac{ORG.CAP_{it\cdot}}{A_{it}} + \alpha_5 \frac{CLIN.TRIAL_{it}}{R\&D_{it}} + \alpha_6 \frac{ALLIANCES_{it}}{A_{it}} + \alpha_7 \frac{M\&A_{it}}{A_{it}}\Big) + u_{it}.\end{aligned} \tag{6}$$

In Equation (6), $R\&D_{it}/A_{it}$, $ALLIANCES_{it}/A_{it}$, and $M\&A_{it}/A_{it}$ represent measures of knowledge and network stocks, namely stocks of R&D, technology alliances, and M&As, weighted by assets. $PAT_{it}/R\&D_{it-1}$ and $CLIN.TRIAL_{it}/R\&D_{it}$ are stocks of patents and drug candidates in clinical trials weighted by the $R\&D$ stock.[16] $CITES_{it}/PAT_{it}$ is a measure of patent portfolio quality. Finally, $ORG.CAP_{it}/A_{it}$ represents our measure of a firm's investment in organizational capital.

[16] To construct the patent yield, we divide the patent stock by the first lag of R&D stock because most of the effect of R&D on patenting occurs in the first year (see Hall *et al.*, 1986).

III. Data and Measures

Our sample consists of all firms incorporated between 1980 and 2006 whose primary 4-digit Standard Industrial Code (SIC) involves the biopharmaceutical industry (SIC 2834 and 2836). The sample of firms and the financial statement data for the first 12 years after their initial public offering (IPO) is collected from Compustat. The first available fiscal year in Compustat is assumed to be the year of the IPO. We collect information on patents, including application year, and year of citations, from the 2006 edition of the National Bureau of Economic Research (NBER) database described by Hall *et al.* (2001)[17] and the United States Patent and Trademark Office (USPTO). Alliance and clinical trials data are obtained by searching the Thomson Reuters Recap IQ Deal Builder and Development Optimizer databases, which track biopharma deals and drug development progress, respectively.

To ensure that we are focusing on the right firms, we further refine the sample by keeping only those firms that S&P's Global Industry Classification Standard (GICS) places in the Pharmaceuticals & Biotechnology & Life Sciences industry. Because of our interest in the value of clinical trials, we drop firms whose business description mentions animal health. Our next refinement drops those firms that have no Thomson Reuters Recap IQ Deal Builder record. To keep our focus in small firms, we drop the firms whose annual revenue exceeds $100 million in the first three years after incorporation. Lastly, we drop those observations where R&D or employee information is missing. The final sample is an unbalanced panel of 349 firms. Basic statistics for the main variables used in the study are reported in Table 1.

Our dependent variable is the Tobin's Q ratio, which is defined as the ratio of the market value of a firm's financial claims to the replacement cost of its assets. To construct the Q ratio, we follow Erickson and Whited (2006) and calculate the market value of the firm as the sum of total assets and market value of equity[18] minus the sum of the book value of equity and deferred taxes, all adjusted for inflation.[19] We use the book value of total assets as a proxy for the replacement cost of assets.[20] The average Q in our sample is 6.04, indicating a more significant presence of intangibles in this industry compared to the overall economy (Hall *et al.*, 2001 estimate the economy-wide Q to be 2).[21]

We use the R&D expenditure history of each firm to compute its stock of R&D. The R&D stock is constructed using the perpetual inventory method described by Hall (1990). We assume a depreciation rate (d) of 15 percent and a growth rate (g) of 8 percent.[22] Our initial value for R&D stock was calculated, using the first available (post-1979) R&D observation, as $R\&D\ stock_0 = R\&D_0/(d+g)$. The average value of R&D intensity (*R&D stock/Assets*) is 2.55, which is substantially higher than 0.35 calculated for a cross-industry sample by Hall *et al.* (2005). This illustrates just how significant R&D expenditures are for the firms in our sample.

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[17] The database contains information for more than 3 million patents granted from 1976 to 2006; this dictated the choice of our sample period.
[18] The data for the market value of equity was obtained from Compustat. Firm's market value of equity is calculated as the price multiplied by the number of shares outstanding at the end of the fiscal year.
[19] We adjust all the variables measured in dollars for inflation using the 2015 Consumer Price Index.
[20] Alternative measures are not materially different. Chung and Pruitt (1994) show that the book value of assets has a 98 percent correlation with alternative measures that have been proposed.
[21] Gleason and Klock (2006) report an average value for Q ratio of 3.6 for the chemicals industry, while Klock and Megna (2000) note that the average Q for the wireless communications industry is 10.8.
[22] Hall (1990, p. 39) shows that the exact choice of depreciation rate does not significantly change the production function estimates. Our choice of 15 percent is common in the literature.

Table 1: Summary Statistics for U.S.-Based Biopharmaceutical Firms Incorporated Between 1980-2006

	N	Mean	Std. Dev.	Min.	Max.
Market Value ($mil.)	2,182	446.66	1,125	0.05	17,352
Book Value of Assets ($mil.)	2,182	136.00	305.39	0.11	4,696
Tobin's *Q* Ratio	2,182	6.04	9.96	0.21	218.25
R&D Stock ($mil.)	2,182	117.83	149.78	0.20	1,675
Patent Stock	2,182	15.29	32.94	0	511.16
Citation Stock	2,182	117.10	155.42	0	1,138
Organizational Capital Stock ($mil.)	2,182	11.83	31.42	0	489.05
Technology Alliances Stock	2,182	6.18	7.16	0	52.32
Mergers Stock	2,182	0.39	0.94	0	13.50
Clinical Trials Stock	483	7.78	7.69	0	47.77
R&D Stock/Assets	2,182	2.55	5.10	0.01	62.20
Patents/R&D Stock	2,182	0.22	0.50	0	9.26
Citations/Patents	2,182	13.18	22.23	0	275.96
Organizational Capital/Assets	2,182	0.40	2.22	0	46.98
Technology Alliances/Assets	2,182	0.22	0.94	0	24.50
M&A/Assets	2,182	0.04	0.87	0	33.28
Clinical Trials/ R&D Stock	483	0.06	0.06	0	0.33

Notes: Calculations for all variables, except clinical trials, are based on 349 public biopharmaceutical firms in the sample. The numbers reported for clinical trials are derived using observations from 64 firms. The dollar amounts are in 2015 dollars.

By matching the NBER patent data to the firm-level Compustat data, we construct patent and citations stock values using the same perpetual inventory method with the same depreciation and growth rates used to obtain the R&D stock. If any two firms in the sample merged during the target period, we combine the information under the surviving firm's name.

Patent citations suffer from several potential sources of bias, the most obvious of which is truncation. The number of citations for any patent is truncated in time because only citations received until the end of the dataset are observed. This concern is more pronounced for more recent patents which may be too new to be cited at all. To minimize this truncation problem, we have collected additional data from the USPTO and updated the NBER dataset to include all citations received through 2016.[23] Given that our sample period ends in 2006, we have at least ten years' worth of citation information for each patent in our sample. The ten-year citation profile is reasonable considering that most of the citation activity in biopharmaceuticals occurs between the fourth and the eighth year of the patient's life (Hall *et al.*, 2005). Nonetheless, we use the estimated parameters for the pharmaceutical industry from Hall *et al.* (2007) to further correct the observed citation rates. Table A1 in the Appendix reports these parameters. Once we correct the truncation

[23] Previous methods to solve truncation problems related to patent citations are found in Hall *et al*. (2001) and Hall *et al*. (2005).

problem, we follow the same method used to construct the R&D and patent stock values to construct the citation series.

The firms in our sample are involved in diverse alliances; however, in this study we focus only on technology alliances as those are the most significant alliances for the innovation process (see Chan *et al.,* 1997). To construct the stock of alliances we count the number of alliances that a firm entered into in a given year and used the perpetual inventory method as before. We use the same method to construct the M&A stock. Thomson Reuters Recap IQ Deal Builder treats M&A activity as one type of alliance. Table A2 in the Appendix reports the number of new alliances, M&As, patent applications, and new firms incorporated in each year during our sample period.

For the clinical trials data, unfortunately, the Thomson Reuters Recap IQ Development Optimizer database provides data for only a small subsample of firms (64 firms). We collect information on the number of Phase I, Phase II, Phase III and Phase IV interventional studies per year for each of the firms in this subsample. We count the total number of clinical trials initiated in a given year and construct the clinical trial stock by applying the same method as with the other intangible stocks.

Lastly, following Hulten and Hao (2008), we construct a measure for the organizational capital stock by applying the perpetual inventory method to a fraction (30 percent) of past SG&A expenses.[24] Although it is not clear what the appropriate depreciation rates are for this intangible asset, for the sake of consistency and for ease of comparison with the other measures, we use a depreciation rate of 15 percent.

Our control variables include a firm's number of employees, its age, a dummy for patenting firms, and year dummies. Because many young biopharmaceutical firms have no revenues to report and because their assets are usually intangible, the best measure of firm size in this industry is headcount (Powell *et al.*, 1996). We define a firm's age as the year of the observation minus the year of the IPO plus one. An interaction variable between R&D intensity and age is also constructed to measure the impact of R&D intensity on the firm value over time.

IV. Results

Table 2 reports the results from the estimation of various specifications of the market value equation, with year dummies, number of employees, firm age, and a dummy for patenting firms used as controls. Column 1 displays the baseline estimates for R&D intensity, patent yield, citation intensity, and R&D over time, Column 2 incorporates the intangible measures that we construct (organizational capital, technological alliances, and M&As), Column 3 investigates the impact of intangibles on the very young firms (in the first six years after their IPO), and lastly, Column 4 reports the results of the model when we control for firm-specific fixed effects.

The results presented in the first column confirm the importance of R&D, patents, and citations in explaining some of the variation in Tobin's *Q*. The reported coefficients for these three intangibles are statistically significant at the 1 percent, 10 percent, and 5 percent level, respectively. The regression results in Column 1 also indicate that R&D intensity displays diminishing returns: as firms get older, they gain less value from their R&D investments. The interaction term (R&D intensity * firm age) is negative and significant at the 5 percent level.[25] The regressors of this model explain 24.1 percent of the variation in the *Q* ratio, which is in line with that of many studies

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[24] Hulten and Hao (2008) provide the calculations that justify the 30 percent fraction. Eisfeldt and Papanikolaou (2013 and 2014) and Peters and Taylor (2017) use a similar approach to estimate the stock of organizational capital.

[25] This result is consistent with the findings of Gleason and Klock (2006).

on this topic (for example, the r-squared ranges between 0.222 and 0.260 for different specifications of the same model in Hall *et al.*, 2005).[26]

Table 2: Market Value as a Function of R&D, Patents, Citations, Stocks, Alliances, Organizational Capital, and M&As, 1980-2006. Non-linear Model with Dependent Variable: log Tobin's *Q*

	(1)	(2)	(3)	(4)
R&D / Assets	0.264^{***}	0.155^{***}	0.190^{***}	0.136^{***}
	(0.064)	(0.052)	(0.071)	(0.052)
Patents / R&D	0.301^{*}	0.250^{*}	0.304^{**}	0.353
	(0.155)	(0.142)	(0.148)	(0.248)
Citations / Patents	0.005^{**}	0.004^{**}	0.004^{*}	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Org. capital / Assets		1.079^{***}	1.494^{***}	0.586^{**}
		(0.249)	(0.343)	(0.274)
Tech. alliances / Assets				
		0.714^{**}	0.557^{*}	1.156^{**}
		(0.302)	(0.296)	(0.463)
M&A / Assets		-0.274	-0.164	-1.242^{***}
		(0.754)	(1.083)	(0.382)
(R&D / Assets) * Age	-0.002^{**}	-0.002^{**}	-0.005^{***}	-0.001
	(0.001)	(0.001)	(0.002)	(0.001)
Employees	-0.150^{*}	-0.131^{*}	-0.502^{***}	0.354^{***}
	(0.079)	(0.077)	(0.176)	(0.137)
Firm age	-0.012	-0.007	-0.013	-0.036^{***}
	(0.011)	(0.011)	(0.019)	(0.012)
D (Patents=0)	-0.138	0.012	-0.043	-0.950^{***}
	(0.086)	(0.084)	(0.093)	(0.246)
N	2,182	2,182	1,220	2,182
R^2	0.241	0.300	0.375	0.638

Note: The estimated coefficients on the fixed and time effects are not reported, but are jointly statistically significant at the 0.01 level. Robust standard errors clustered by firm are shown in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

In the second variant of our model, we add the additional intangible measures that we constructed. The results indicate that in addition to R&D, patents, and citations, both alliance stock and organizational capital stock (relative to assets) have positive and highly significant impacts on the values of sample firms' *Q*. The coefficient for the M&A stock relative to assets, however, is statistically insignificant at conventional levels.[27] The additional regressors improve the

[26] Other studies report comparable values for r-squared. Examples include: Baum and Thies (1999) report r-squared ranges between 0.125 and 0.225; the r-squared in Gleason and Klock (2006) ranges between 0.117 and 0.281.

[27] This result is in line with much empirical research on mergers, which finds that gains from mergers accrue entirely to target firm shareholders. For the acquiring-firm shareholders, the gains are either negative or not significantly different from zero. For a summary of empirical evidence see Jensen and Ruback (1983), Jarrell *et al.* (1988), and Andrade *et al*. (2001).

performance of the model substantially (explaining 30 percent of the variation in Tobin's *Q*) and indicate potential misspecification in the first variant of the model. This conclusion is supported by the fact that the coefficient for R&D intensity drops significantly (from 0.264 to 0.155) when we move from the simpler specification to the complete model (Column 2). The coefficient for R&D intensity remains fairly stable across the various samples and model specifications for which results are presented in columns 2 through 4.

Given the acute information asymmetries that are naturally present for *very young* firms, we investigate whether the relationship between Tobin's *Q* and our various intangibles holds for firms in the first six years after incorporation.[28] The results of this specification (reported in Column 3 of Table 2) reveal that these intangibles explain even more of the variation in Tobin's *Q* (r-squared = 0.375). This indicates that the market value of firms early in their life is more reliant on changes in these intangible assets as compared to later, in their more mature, years.

Although Column 4 in Table 2 reports the estimates obtained from the model that includes firm-specific fixed effects, as Hall *et al*. (2005) argue, employing fixed firm effects in this context is problematic.[29] The primary concern comes from the fact that a firm's various intangible measures will be highly correlated with its individual effect since intangible stocks are part of a firm's long-term strategy and, as such, they change very slowly over time. Additionally, in an industry where strategic competition between firms is the norm, "the assumption that differences across them are 'fixed' or permanent is not a particularly good one." (Hall *et al*., 2005, p. 26). Thus, it should be noted that the results in Column 4 are not very reliable.

Comparing the estimated coefficients reported in columns 2 and 4 of Table 2, we observe that patent-related intangibles and our interaction variable (R&D intensity * firm age) are no longer statistically significant. Although not reported here, the same outcome is obtained when fixed effects are employed in the baseline model (Column 1). The stocks of R&D, organizational capital, and technology alliances capital (relative to assets) are all positive and statistically significant at the 5 percent level (R&D is significant at the 1 percent level). The coefficient for M&A/Assets is negative and significant at the 1 percent level. It is worth noting that the magnitude of the coefficient for organizational capital in Column 4 deviates substantially from the estimates reported in columns 2 and 3. This is likely a result of the overcorrection we introduce by using fixed firm effects.

Considering the importance of clinical trials in the biopharmaceutical industry, we also estimate the model for a subsample of 64 biotechnology firms for which we were able to find clinical trials data in the Thomson Reuters Recap IQ Development Optimizer database. Although we do not report the results of the regression for this subsample (483 observations), all the estimated coefficients have the expected sign but they are statistically insignificant at conventional levels.[30] This is likely due to the small size and the potential selection bias in the sample.[31] The fact that this subsample is comprised of only "leading" biotech firms makes comparisons with the other sample specifications invalid.

The coefficients for the different control variables have the expected signs. For example, in the first three specifications of the model, the size of the firm (measured through the number of

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[28] The choice of six years is somewhat arbitrary (half of the 12 years); however, the results are very similar to choosing other thresholds (four, five, or seven years).

[29] In fact, controlling for unobserved firm-specific fixed effects is very uncommon in this strand of literature. Blundell *et al*. (1999), Bloom and Van Reenen (2002) are prominent exceptions.

[30] The positive influence of clinical trials on the market value is also reported by Rzakhanov (2004).

[31] The Thomson Reuters Recap IQ Development Optimizer offers clinical trial data on "leading biotech companies" according to Recap IQ Factsheet (http://recap.com/sites/rc/files/pdf/recap-iq-factsheet.pdf).

employees) has a negative influence on its Q value, indicating that, on average, smaller firms have a higher Q. This result is statistically significant in all variants of the model and the sign of its coefficient in columns 1 to 3 is consistent with the findings of Gleason and Klock (2006) who note that firm "size is likely to be inversely related to expected growth opportunities" (p. 308). When controlling for fixed firm effects, the coefficient for firm size becomes positive (and significant at the 1 percent level), implying that within any given firm an increase in firm size is associated with a higher Q, on average. The coefficient on firm age is negative but only statistically significant (at the 1 percent level) in the last variation of the model (Column 4). This negative relationship is likely due to organizational rigidities and rent-seeking according to Loderer and Waelchli (2010).[32] Lastly, the coefficient on the binary variable that identifies patenting firms is not statistically significant in models 1 through 3.

To get an indication of the economic magnitude of the estimated effects, we use the coefficients of models 1 and 2 in Table 2 to calculate the quantitative impact of each of the main variables on market value. The average values of semi-elasticities and robust standard errors clustered by firm are reported in Table 3.

Table 3: Computing the Impact of Knowledge Stocks on Market Value

	(1)	**(2)**
Ratios		
R&D / Assets	2.549	2.549
Patents / R&D	0.216	0.216
Citations / Patents	13.18	13.18
Organizational Capital / Assets		0.398
Technology Alliances / Assets		0.217
M&A / Assets		0.041
Marginal Effects (Semi-Elasticities)		
$\frac{\partial \log Q}{\partial (R\&D \;/\; Assets)}$	0.105^{***}	0.050^{***}
	(0.014)	(0.013)
$\frac{\partial \log Q}{\partial (Patents \;/\; R\&D)}$	0.120^{**}	0.081^{*}
	0.056	(0.042)
$\frac{\partial \log Q}{\partial (Citations \;/\; Patents)}$	0.002^{**}	0.0012^{**}
	(0.001)	(0.0005)
$\frac{\partial \log Q}{\partial (Org.Cap. \;/\; Assets)}$		0.348^{***}
		(0.056)
$\frac{\partial \log Q}{\partial (Alliances \;/\; Assets)}$		0.231^{**}
		(0.091)
$\frac{\partial \log Q}{\partial (M\&A \;/\; Assets)}$		-0.089
		(0.244)

Note: Computed using the estimated coefficients in columns 1 and 2 of Table 2 evaluated at the mean. Robust standard errors clustered by firm are shown in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

[32] Loderer and Waelchli (2010) report a highly significant (and robust) negative relationship between firm age and profitability for a large sample of cross-industry firms.

Considering that the average R&D intensity value is 2.55 with a standard deviation of 5.1, using Model 2 estimates, we can state that firms that are one standard deviation above the mean have a market value that is almost 26 percent higher than the average firm. The average semi-elasticity for the patents yield is even more economically significant: one additional patent per million dollars of R&D increases market value by approximately 8 percent. Citations per patent, on the other hand, have a much smaller impact on the market value of the firms in our sample (semi-elasticity = 0.0012). Indicating just how important investing in organizational capital is for the young biopharmaceutical firms, an increase of 10 percentage points in the organizational capital stock to assets ratio is associated with an almost 3.5 percent increase in market value. One extra technology alliance per ten million dollars of assets increases market value by approximately 2.3 percent. Lastly, the marginal effect of additional M&As is not significant at the conventional levels of significance.

Several observations are notable from the results in Table 3. First, the quantitative impact of R&D in Model 2 is half as big as in Model 1, indicating the lesser importance of R&D when other variables are added. Second, the quantitative impact of patent yield is stronger than the impact of R&D on Tobin's *Q*. The semi-elasticity for the patent yield is also significantly higher than the ones reported by Hall *et al.* (2005 and 2007). This could be because our sample is comprised of only young firms, which are likely to have an unproven record of valuable R&D output; therefore, early success of R&D for these firms is of utmost importance. Third, the largest impacts on Tobin's *Q* come from a firm's investments in organizational capital and the number of technology alliances they create.

V. Conclusion

This paper adds to the literature on market valuation of intangibles by analyzing how the innovation process is transformed into value. We report new estimates of the economic value of several intangibles, tested jointly, in a sample of young biopharmaceutical firms. Our results suggest that in addition to R&D and patents, financial markets recognize the importance of alliances and organizational capital. We also provide some evidence on the established result that firms typically overpay for acquisitions, which naturally reduces their market value. The inclusion of the additional intangibles greatly improves the explanatory power of the model, and changes the magnitude of the R&D coefficient, lowering it drastically. Our results also indicate that the highest R&D investment returns accrue to firms in their early years, declining as they get older. The multiple specifications of the functional form of the valuation equation we consider demonstrate the robustness of these results.

We know high-technology firms generally have poor access to capital since a large fraction of their investment is intangible, which serves little or no collateral value (Berger and Udell, 1998). The situation is even worse for young firms, which rely more heavily on external funding and seldom have any revenue. The estimates reported here serve as quantitative indicators of success for these firms, which is key to securing financing. Firms can also use our findings to decide where to commit their limited resources, which is an important task in highly competitive environments. Estimates of the value of intangibles may also affect competition dynamics at the industry level and potentially lead to reshuffling in the form of M&As. Finally, these estimates may serve as a guide to policymakers in their assessments of future policy changes as they relate to intangibles.

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Appendix A

Table A1: Weights Implied by Estimated Cumulative Lag Distribution for U.S. Patents

Patent Application Year	Lag Year	Citation Factor
2006	10	2.587
2005	11	2.35
2004	12	2.155
2003	13	1.991
2002	14	1.852
2001	15	1.732
2000	16	1.627
1999	17	1.535
1998	18	1.454
1997	19	1.382
1996	20	1.317
1995	21	1.258
1994	22	1.205
1993	23	1.157
1992	24	1.112
1991	25	1.072
1990	26	1.035
≤ 1989	≥ 27	1

Table A2: Firm Activity by Year

Fiscal Year	Number of IPOs	Number of New Patent Applications	Number of New Alliances	Number of Mergers Announced
1980	3	7	12	0
1981	2	18	21	0
1982	5	45	23	0
1983	7	64	32	0
1984	9	112	28	0
1985	14	101	35	0
1986	9	141	43	0
1987	9	174	53	0
1988	16	184	72	0
1989	11	226	88	2
1990	27	281	140	4
1991	22	286	159	7
1992	22	354	208	9
1993	15	468	208	8
1994	16	636	237	15
1995	34	1,328	225	19
1996	10	765	292	12
1997	8	1030	271	23
1998	38	1,047	270	25
1999	16	1,129	293	39
2000	13	1,168	317	40
2001	15	979	352	27
2002	11	558	261	24
2003	12	270	180	29
2004	3	117	208	21
2005	2	24	167	29
2006	0	2	183	21

Note: These figures are based on a sample of 349 firms used for the estimation of the effects of various intangible assets on the value of Tobin's *Q*, in the first 12 years after incorporation.

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Relationships Between Entrepreneurial Attitudes and Intentions in an Experiential Education

By VANCE GOUGH*

The aim of entrepreneurship education is to promote entrepreneurial behavior. Governments encourage universities to teach entrepreneurship to promote entrepreneurial behavior to launch new ventures, to create jobs, and to promote economic growth. Entrepreneurial attitude, intention, and behavior are different entities. While one's intention may be followed by a behavior, one's behavior more predictably follows one's attitude. This paper seeks to demonstrate the relationship between entrepreneurial attitude and entrepreneurial intent to better predict one's entrepreneurial behavior. These findings have potential implications for Entrepreneurship Education, particularly in the design and implementation of androgogy with regards to outcomes-based learning.

Keywords: Entrepreneurship, Entrepreneurial Attitude Orientation (EAO) Scale, Entrepreneurial Intention, Entrepreneurship Education, Entrepreneurship Attitude, Currency Returns, Siegel Hypothesis

JEL Classification: D81

I. Introduction

A principal goal of entrepreneurship research has been to identify elements that predict positive entrepreneurial behavior (Shane and Venkataraman, 2000). Two of these elements are entrepreneurial intent (EI) and entrepreneurial attitude (EA). An ever-present question asked of entrepreneurship faculty and university entrepreneurship programs is whether entrepreneurship can be taught. The existence of entrepreneurship education is premised on the answer that indeed it can. There is a body of knowledge (Pittaway and Cope, 2007; Martin *et al.*, 2013; Souitaris *et al.*, 2007) that has shown a link between entrepreneurship education in universities and the EI of entrepreneurship students. There is evidence that entrepreneurship education programs and courses are able to "build awareness of entrepreneurship as a career option and to encourage favorable attitudes (EA) towards entrepreneurship" (Gorman *et al.*, 1997, p. 13). While entrepreneurial behavior is the goal, there needs to be a clearer understanding of EI and EA and the relationship between these two elements in order to facilitate stronger pedagogies/andragogies in entrepreneurship education to achieve that goal.

This study focused on determining if there is a positive correlation between EI and EA for university entrepreneurship students. Data was collected at Utah Valley University between Fall 2015 and Spring 2017. Students completed surveys using a pre-test/post-test during entrepreneurship courses. Influence from self-selection for entrepreneurship was minimized by testing first time entrepreneurship students and MBA students who were not entrepreneurship majors.

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This research is built upon the Theory of Planned Behavior (TPB) (Fishbein and Ajzen, 1975). TPB is a well-established framework that provides a conceptual and theoretical link between behavior and intentions. The central concept of the TPB is the "individual's intention to perform a certain behavior" (Autio *et al.*, 2001, p. 147). Researchers in entrepreneurship have used the TPB as a foundation for exploring the formation of EI (Hisrich *et al.*, 2013; Koe, 2016).

This research examines the correlation of EA with EI. It builds on the concept of EI being an attitude with the specific object of "starting a business." EA will be seen as a conceptual and theoretical foundation for EI. This will help us to determine if we can trust in EI assessments to measure potential entrepreneurial outcomes.

The rest of the article proceeds as follows. First, we review the literature on entrepreneurial intent, attitude, and education. The following sections will illustrate the research methodology, describe the data and measures, and then present the empirical results. The concluding sections discuss the implications of the findings and the limitations of the analysis.

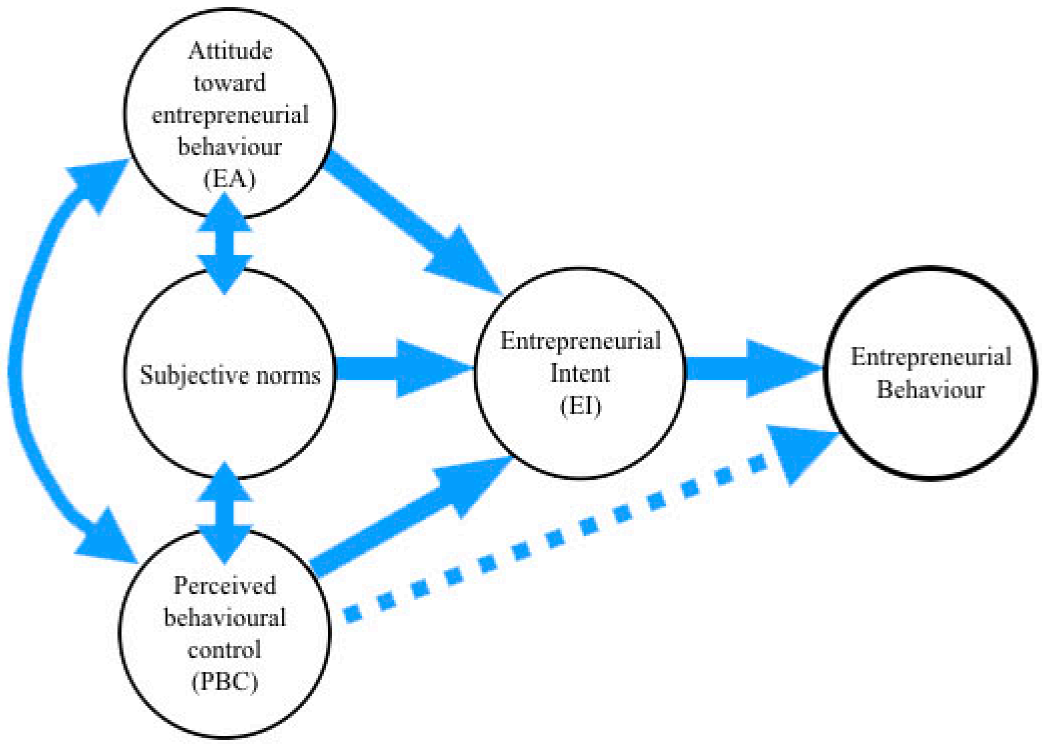
II. Review of Literature

A. Entrepreneurial Intent

Thompson (2009, p. 676) defined entrepreneurial intention as "a self-acknowledged conviction by a person that they intend to set up a new business venture and consciously plan to do so at some point in the future." It has been found that EI measurements are vague (Thompson 2009, p. 670) and lack a theoretical foundation or conceptual framework. Entrepreneurial intentions do not account for prior behaviors and their influence on present behavior (Ajzen and Madden, 1986). They are based on one merely stating that they are interested in starting a business in the future (Kolvereid and Bullvag, 1996). Ajzen postulated (1985, p. 21) that "the very act of stating an intention may induce heightened commitment to one's behavior." Yet intentions inherently have no compulsion, accountability, or responsibility for one to follow through (Thompson, 2009, p. 671). Ajzen (1985, p. 29) even admitted that "intentions can only be expected to predict a person's attempt to perform a behavior, not necessarily its actual performance." Further, most of those who convey entrepreneurial intent fail to start businesses (Aldrich and Ruef, 2006, p. 66). EI measurements also have been shown to discount the influence of social norms and peer influence (Krueger *et al*., 2000, p. 426; Bagozzi *et al*., 1992). Nevertheless, EI is currently accepted as "the single best predictor of any planned behavior, including entrepreneurship" (Krueger *et al*., 2000, p. 413). But Krueger (2000, p. 430) admitted that alternative competing models, specifically noting the Entrepreneurship Attitude Orientation (EAO) measurement of attitude, may be better suited to explain problems of the intention measurement, such as social norms issues inherent with EI.

The Theory of Planned Behavior (TPB) by Ajzen (1991, 2011) has been widely used to describe and support the measurement of entrepreneurial intention. TPB is based on the premise that actions are controlled by intentions, but it also realizes that not all intentions are fulfilled by actions (Ajzen 1985, p. 11). The TPB attempts to predict and explain volitional behavior by addressing the intention-behavior relationship (Ajzen 1985, p. 18). The theory is built upon the relationship between intentions and three precursors: attitude towards a behavior, subjective norms, and perceived behavioral control (PBC) (Ajzen 2002, p. 1). (See Figure 1.)

Figure 1: Illustration of Ajzen's Theory of Planned Behaviour (Ajzen, 1991)



The subjective norms referenced in the TPB relate to issues such as perceived social pressures to perform a certain behavior (Autio *et al*., 2001, p. 147). PBC is the combined perception of one's ease or difficulty in performing a behavior and one's perceptions of their individual control during that behavior (Ajzen 1991, p. 183). PBC is different than Rotter's (1966) concept of a perceived locus of control (LOC). One's LOC is generalized to remain stable across situations, while one's PBC is able to, and even expected to, vary in different situations (Ajzen 1991, p. 183).

Many researchers have used the TPB in attempting to explain and understand the entrepreneurial intentions of post-secondary students (Fayolle and Gailly, 2015; Autio *et al*., 2001; Fayolle and Lassas-Clerc, 2006; Liñán, 2004; Kolvereid and Moen, 1997). The TPB has also been used to predict EI (Kolvereid and Bullvag, 1996; Tkachev and Kolvereid, 1999; Krueger *et al*., 2000, Autio *et al*., 2001, Engle *et al*., 2010). It has been the "most commonly used theoretical framework in this stream of research" (Schlaegel and Koenig, 2012, p. 655). That being said, there is no uniform approach to measure individual EI (Thompson, 2009, p. 669) within the TPB. Shapero (1975) and Shapero and Sokol (1982) presented expectancy-driven frameworks. These models were built upon by Bird (1988) and Krueger (1993). Krueger (1993, pp. 6-7) used expectancy-driven models to measure the effects of prior exposure to entrepreneurial experience. He specifically looked at feasibility and desirability with regards to intention (Krueger, 1993, p. 8). Davidsson used an economic-psychological model of factors to address the factors that influence EI and coined the term 'entrepreneurial conviction,' which resembles the TPB's attitude toward behavior belief (Davidsson, 1995, pp. 5-6). Bagozzi *et al*. (1992, p. 506) suggested that the "relative effects of attitudes and subjective norms on intentions vary with personal characteristics." Autio *et al*. (2001) found "the measurement of an individual's entrepreneurial intent has only been described by disparate metrics, with no carefully developed and psychometrically validated measurement scale." Ajzen (1985, p. 28) himself specified "intentions can only be expected to predict a person's attempt to perform a behavior, not necessarily its actual performance." While scholars continue to look at different approaches to measure EI within the TPB, there are a number of methods within the literature that have been accepted. The one used in this paper is the Kolvereid (1996], Kolvereid and Bullvag (1996), and Kolvereid and Moen (1997) method.

According to the TPB, intention is strongly influenced by an individual's attitudes, subjective norms, and perceived behavioral control with regard to the object of the intention, which is entrepreneurial activity. These precursors are in turn influenced by experience-based factors. Building on Ajzen's work, there are those who have asserted that "in its simplest form, intentions predict behavior, while in turn, certain specific attitudes predict intention" (Krueger *et al*., 2000, p. 413). An increase in entrepreneurial intention has been shown to be influenced by a number of personal and environmental factors. These include education and training in entrepreneurship; a student's prior entrepreneurial experience (and/or exposure); and demographic characteristics (Fayolle and Gailly, 2015, p. 77). Some claim that these intentions may change over time, and this has created skepticism whether the constancy of intention has been proven (Fayolle and Gailly, 2015; Goode *et al*., 2010, Moreau and Raveleau, 2006). While intentions may change, a meta-analysis of 10 meta-analyses in the entrepreneurship literature by Kautonen *et al*. (2015, p. 657) found that intention explains 28% of variance in behavior (Sheeran, 2002, p. 3), and Armitage and Conner's (2001, p. 484) work found a mean explained variance of 23% in their meta-analysis of 185 independent tests of the TPB across multiple domains. Clearly, while intention may not be 100% predictive, it has indeed been shown to influence behavior.

B. Entrepreneurial Attitude

Empirical studies have found that attitudes, in general, "have been shown to explain approximately 50% of the variance in intentions, and that intentions explain approximately 30% of the variance in behavior" (Autio *et al*., 2001, p. 148). When analyzing how management education may influence attitudes, Schein (1967) identified an issue concerning the longevity of attitude change. He questioned "if a school is able to influence attitudes and values, it is likely that a company (future employer) can also influence them" (Schein, 1967, p. 619). Some say "attitudes are temporary constructions rather than memory-based entities" (Schwarz, 2008, p. 22). But Petty (2006, p. 24), using a metacognitive model on attitudes, showed that attitudes instead create evaluative predispositions that influence behavior over a longer period of time. It has further been shown that individuals who "form their attitudes through direct experience held those attitudes more confidently and behaved more consistently with those attitudes, than did subjects who formed their attitudes through indirect experience" (Fazio and Zanna, 1978b, p. 228). So, attitudes may change, but depending on the educational experiences that create these attitudes, there is a greater chance for longevity of the attitude towards a given object.

Many have found that one's attitudes have direct effects on behavior (Bagozzi *et al*., 1992, p. 505; Fazio and Zanna, 1978b). The term "attitude" refers to the inclination to assess an attitude object in a favorable or unfavorable manner (Schwarz, 2008, p. 41). The concept of EA, building on the foundation of attitude theory (Allport, 1935), has been used in entrepreneurship research since the early 1990s. In the 1960s and early 1970s, some social psychologists had abandoned the concept of attitude as a predictor of behavior (Fazio and Zanna, 1978b, p. 229). Then, later in the 1970s, there was a "challenge by others in their field, with methodological and conceptual refinements which indicated that attitudes can sometimes he relatively good predictors of behavior" (Fazio and Zanna, 1978b, p. 229). The earlier problem with attitude as a predictor of behavior was based on testing and parameters around general objects. Later research showed that attitude "can only be measured in relation to a specific object; for example, a person, thing, or action" (Hatten and Ruhland, 1995, p. 224; Robinson 1987).

The specific topic of entrepreneurial attitude (EA) looks beyond a stated intention, and instead towards the actual predisposition to behave in a generally favorable or unfavorable way with respect to a specific attitude object of starting a business (Rosenberg and Hovland, 1960; Ajzen, 1987; Shaver and Scott, 1991). Social psychologists have found that there are certain variables that influence the strength of the association between attitudes and behaviors (Fazio and Zanna, 1978b, p. 229). They found, beyond specific situational limitations or competing attitudes, that the individual is more likely to behave consistently with their declared attitudes towards a specific object (Fazio and Zanna, 1978b, p. 229; Heberlein and Black, 1976, pp. 477-8; Staub, 2013, pp. 218-9). Schein (1967, p. 619) also identified that key to attitude is "the identification of those individual and organizational variables that will determine the pattern of maintaining or abandoning the changes produced." Heberlein and Black(1976) further found that:

> Including only specific beliefs in a study is likely to give high attitude-behavior correlations but will not show how the belief and action relate to other similar attitudes and behavior. Including only general attitudes is likely to be disappointing because not much of the variance in behavior can be predicted. By including both, one can better predict behavior from attitudes, yet show how the beliefs and actions are part of a larger cognitive configuration. (Heberlein and Black, 1976, p. 479)

Once testing of attitudes is based on specific objects, the results theoretically would be better predictors of future behavior. Building on the concept that focusing on specific situational attitude objects common among entrepreneurs will strengthen the ability to predict one's actual predisposition to act as an entrepreneur, the Entrepreneurial Attitude Orientation (EAO) tool was created as a "multidimensional self-reporting measure of one's (entrepreneurial) attitudes" (Miao, 2012, p. 503). Building on the early theoretical foundation of Alport's (1935) attitude theory, the EAO instrument (Robinson, 1987; Robinson *et al.*, 1991) measures an individual's specific attitude toward four business-related attitudes that are consistently held by entrepreneurs. The EAO does not measure one's attitude toward entrepreneurship; it measures one's attitude toward specific objects related to doing business. The attitude objects measured by the EAO consist of these four subscales: achieving in business (ACH), innovating in business (INN), personal control in business (PC), and self-esteem in business (SE). The EAO compares the attitudinal components of an individual and their attitudes in interacting within a business setting to those that are consistently held by entrepreneurs. It was built based on a tripartite model of attitude components that vary on a common evaluative continuum (Breckler, 1984, p. 1191; Allport, 1935).

The EAO tool has been validated and confirmed in multiple studies using Cronbach's alpha to support internal consistency and Pearson's correlation coefficients to show that all four subscale factors are statistically significant (Miao, 2012, p. 506; Shariff and Saud, 2009, p. 132). The EAO considers attitude to be "a dynamic interactional way that an individual relates to the attitude object, changing across time and from situation to situation" (Robinson *et al.*, 1991). Specific attitudinal qualities, including "whether or not an attitude was based on a direct experience with an attitude object" (Fazio and Zanna, 1978a) have been shown to increase attitude-behavior consistency (Fazio and Zanna, 1978b). Miao (2012, p. 503) found that "the superiority of the attitudinal approach is its focus on a specific domain, which reduces unexplained variability and improves the prediction of real activity."

Allport (1935) theorized and demonstrated that attitudes consist of three specific types of reaction towards an attitude object: affect, cognition, and behavior. Building upon Allport's model, Robinson *et al*. (1991, p. 17) defined entrepreneurial attitude, where:

a) The affect component consists of positive or negative feelings toward the attitude object;
b) The cognitive component consists of the beliefs and thought about the attitude object; and
c) The behavioral component consists of behavioral intentions and predisposition with regard to the attitude object.

Robinson *et al.*'s (1991) attitude model has been cited in over 1,100 studies and has been used to examine both theoretical and practical approaches to entrepreneurial attitudes (Krueger *et al*., 2000; Busenitz and Barney, 1997; Chen *et al*., 1998, Mueller and Thomas, 2001; Peterman and Kennedy, 2003; Souitaris *et al*., 2007; Fayolle and Gailly, 2015; Shane, 2003; Zhao and Seibert, 2006; Harris *et al*., 2015; Do Paço *et al*., 2015; Fayolle and Lassas-Clerc, 2006).

C. Entrepreneurship Education

Entrepreneurship education is a growing academic field, especially in the United States (Etzkowitz *et al*., 2000; Fiet, 2001; Solomon *et al*., 2002; Katz, 2003; Matlay *et al*., 2014). Entrepreneurship education programs range "from highly intensive multiple week formats, to entire semester courses, to one- or two-year entrepreneurship programs" (Chrisman *et al*., 2012; McMullan and Gough, 2002). There are many approaches being used to teach entrepreneurship. It is not a monolithic discipline (Piperopoulos and Dimov, 2015). The growth of entrepreneurship programs has been encouraged by governments, which want more new ventures with their resulting creation of jobs (Kirby, 2004; Birch, 1987). However, Pittaway and Cope (2007) observed that "entrepreneurship education programs developed in response to government policy initiatives tend to be narrow in focus and do not necessarily benefit from an evaluation of their effectiveness." There is also a "lag between taking an entrepreneurship course, typically in a university or college, and starting a business…that may take months, years, or even decades" (Chrisman *et al*., 2012). There is little evidence on the extent to which entrepreneurship programs developed by universities lead to the creation of new enterprise or the development of new entrepreneurs. It has been found that Entrepreneurship Education has a statistically significant, yet small, positive relationship with entrepreneurial intentions (Bae *et al*., 2014, p. 234 and 238). The same study found the relationship between Entrepreneurship Education and EI is greater than that between business education and EI (Bae *et al*., 2014, p. 238). The entrepreneurship education and EI relationship has been researched by many, yet there are still theoretical and empirical disagreements. Some explain this through the orientation frame of how the course is delivered. Some courses are theory oriented while others have a more practical orientation. Piperopoulos and Dimov (2015) argue that the teaching orientation of an entrepreneurship course creates a distinct motivational frame for its students. They found that the relationship between the course orientation (theoretical vs. practical) and the student is contextually sensitive, depending on the motivational disposition of the student (Piperopoulos and Dimov, 2015). Entrepreneurship education has been "largely disconnected from the field of education...and (it) needs to clearly and accurately combine knowledge from both the fields of entrepreneurship and education"(Fayolle, 2013, p. 698). Entrepreneurship courses have typically been taught using a combination of theoretical and practical teaching methods. There is a current trend to use more experiential teaching methods in the field (Neck *et al*., 2014, p. 1; Gough, 2016, p. 111; Fayolle, 2013, p. 696).

There are dominant theoretical perspectives about the nature of learning processes in entrepreneurship education. These are based on how to help students learn and gain the aptitudes and attitudes to perform entrepreneurial tasks (von Graevenitz *et al*., 2010, p. 93). Human capital theory (HCT) and entrepreneurial self-efficacy are two unique primary theoretical perspectives that are used to teach/assist students in gaining identified attitudes/aptitudes. These perspectives also serve as a link to understanding the relationship between entrepreneurship education, entrepreneurial attitudes, and entrepreneurial intentions (Bae *et al*., 2014, p. 219).

C.1 Human Capital

Human capital, which includes attributes such as formal education, training, employment, prior start-up experience, owner experience, family business experience, skills, industry knowledge, etc., has been traditionally linked to higher potential success for nascent entrepreneurs (Unger *et al*., 2011, p. 3 42). Human capital is the investment of a student in schooling, on-the-job training, and other experiences to attain these attributes (Becker, 1994, pp. 17-8).

A meta-analysis on Human Capital Theory and entrepreneurship education (Martin *et al*., 2013, p. 220) found that entrepreneurship education is associated with higher levels of:

- Total entrepreneurship-related human capital assets
- Entrepreneurship-related knowledge and skills
- Positive perceptions of entrepreneurship
- Intentions to become an entrepreneur

The experiences gained in developing human capital assist in the creation of an entrepreneurial mindset, which has been defined as “a way of thinking about business that focuses on and captures the benefits of uncertainty” (Ireland *et al.*, 2003, p. 968). The entrepreneurial mindset involves the ability to (Ireland *et al.*, 2003, pp. 969-70):

- Recognize entrepreneurial opportunities
- Have entrepreneurial alertness
- Use real options logic
- Create one’s own entrepreneurial framework.

Some see human capital as a determinant of EI (Davidsson and Honig, 2003). Findings “suggest that while human capital increases the probability of becoming a nascent entrepreneur, it may not reliably differentiate successful from less successful entrepreneurial processes…and that formal education as provided by business classes, only succeeded in increasing the pace of gestation activities, not in affecting critical outcomes” (Davidsson and Honig, 2003, p. 313).

C.2 Self-Efficacy

Proponents of the entrepreneurial self-efficacy perspective believe in one's "ability to successfully perform the various roles and tasks of entrepreneurship" (Chen *et al.*, 1998; De Noble *et al.*, 1999; McGee *et al.*, 2009, Robinson and Sexton, 1994; Zellweger *et al.*, 2011; Piperopoulos and Dimov, 2015). "Individuals tend to avoid tasks about which they have low self-efficacy, whereas on the contrary they are drawn and perform better on tasks where they believe they have higher self-efficacy" (Piperopoulos and Dimov, 2015, p. 972). Entrepreneurial self-efficacy is known as one of "triggers of entrepreneurial intentions" (Bae *et al.*, 2014, p. 220). Studies have provided evidence that entrepreneurship education teaching techniques have an influence on student self-efficacy (von Graevenitz *et al.*, 2010, p. 93).

Research has shown that positive self-efficacy, when combined with entrepreneurship education, is a reliable predictor of increased EI in students (Chen *et al.*, 1998, Pittaway *et al.*, 2010). Others have shown that entrepreneurship education may affect the EA in students (Piperopoulos and Dimov, 2015). There is still the question about how EI and EA are interrelated and whether these measures affect actual entrepreneurial behavior. This paper will explore this interrelationship using a correlation analysis.

III. Method

A. Hypothesis

We want to determine if there is a relationship between a student's entrepreneurial attitude scores and their reported entrepreneurial intent both before and after taking an introductory course in entrepreneurship. If there is a correlation between the two, this would suggest that entrepreneurial intent is a component of entrepreneurial attitude based on the TPB proposed by Ajzen. That being the case, instructors may modify/adjust androgogy in entrepreneurship education, using a combination of theoretical and practical teaching methods, to help the student develop a stronger EA and thus increase their intent to actually launch ventures. The potential to actualize entrepreneurial behavior is the intended outcome. We thus propose:

Proposition 1: Entrepreneurial attitudes are positively related to one's entrepreneurial intention.

According to the TPB, attitude is one of three precursors to intentions, along with subjective norms and perceived behavioral control. It is also one of the more difficult elements of the model to measure. With three precursors, it would be expected that the amount of variance in the EI accounted for by EA would be about 33.33%. We would expect somewhat less of the variance to be accounted for in the pre-test because of the limited exposure to entrepreneurship. Accordingly, we hypothesize:

H1: *The amount of variance in EI scores accounted for by the EAO scores, as measured by the coefficient of determination, r^2, will be less than 33.33% in a pre-test analysis.*

H2: *The amount of variance in EI scores accounted for by the EAO scores, as measured by the coefficient of determination, r^2, will exceed 33.33% in the post-test analysis.*

B. *Measurement*

Entrepreneurial intention was measured using the Kolvereid scale and method using the average of three different measures of entrepreneurial intentions, see Kolvereid and Bullvag (1996). This provides an index of entrepreneurial intent. Kolvereid and Bullvag's (1996) questions were "What is the probability that you ever will start a new business?" (0-100 per cent). This question was adopted from Brenner *et al*. (1991).

- "Imagine you could choose between being self-employed and employed by someone. What would you prefer?" (1 = Would prefer to be employed by someone; 7 = Would prefer to be self-employed).
- "What is the probability that you during your working life will pursue a career as self-employed rather than being employed by someone?" (0-100 per cent).

In the questionnaire, all responses were obtained on a 7-point Likert-type scale from strongly agree to strongly disagree.

The EAO tool used in the study measures entrepreneurial attitudes using the following attitude subscales (Robinson *et al*., 1991):

- Perceived self-esteem in business (SE), pertaining to the self-confidence and perceived competency of an individual in conjunction with his or her business affairs.
- Perceived personal control of a business (PC), concerning the individual's perception of control and influence over his or her business.
- Need for Achievement in business (ACH), referring to concrete results associated a business venture.
- Innovation in business (INN), relating to perceiving and acting upon business activities in new and unique ways.

Each EAO item on the attitude sub-scales was scored using a ten-point strongly-disagree to strongly-agree scale.

Data was collected over four semesters (Fall 2015 – Spring 2017). 575 students participated. Pre- and post-tests were conducted with both undergraduate and MBA students who were taking introductory level courses in entrepreneurship at a large teaching university in the western US. The undergraduate courses were designed to teach using a more practical orientation, while the MBA classes were designed with a more theoretical orientation. The data was collected anonymously by the instructors, and the information was then exported after each semester into electronic spreadsheet format. The statistical processing was carried out first with Minitab, and then using Regression Analysis of Time Series (RATS) software to do cross-sectional analysis. Since our data does not involve time series, we did not check for cointegration. Descriptive statistics were used to determine the relationships between EI and EA. The Pearson correlation coefficient was used to measure correlation between these two variables.

C. Sample and Participant Selection

Using a convenience sample, 575 students were asked to complete pre- and post-tests as part of their coursework in entrepreneurship courses. 166 of these were graduate students. These courses were introductory survey courses in entrepreneurship.

Out of the 575 students, 196 of them completed both the pre- and post-tests. 74 of these were graduate students. Some of the students chose not to complete both the EAO and EI assessments. We chose to include the 160 students in the sample who completed both assessments with no missing responses. Those meeting these criteria included 61 graduate students and 99 undergraduate students. Of the 160 total students, 26.25% were female and 73.75% were male.

D. Analysis

Surveys were carried out as a class exercise in each of the participating courses. Students filled in questionnaires on-line at both the beginning and end of the semester. Participation was voluntary and anonymous to the researchers. All data were anonymous. The questionnaire was developed based on current surveys from the literature (Robinson *et al*., 1991, Kolvereid and Moen, 1996) and consisted of questions based on the measurement of the EAO, using its four subscales and the measurement of EI using the Kolvereid scale. Students used a unique identifier and password known only to them in filling out the survey in order to match data sets between the pre- and post-test. Additional demographic questions included course section, semester, instructor, age, and gender.

Correlational analysis, using the Pearson *r*, was used to see if there was a correlation between EA and EI to verify if there is two-way relationship between EA and EI.

IV. Results

Summary statistics of the sample are included in tables 1 and 2. Table 1 describes the summary statistics for the measurement of EA. Table 2 describes the summary statistics for the measurement of EI.

Table 1: Data Description and Summary Statistics of All Students for Pre- and Post-Tests of the Four EA Sub-Scales. Sample Period: Fall 2015-Spring 2017 Semesters

Variables	Mean	Standard Error	Minimum	Maximum
Pre-test EA Self Esteem (SE) in Business Score	71.963750	9.755827077	43.1	93.6
Pre-test EA Self Esteem (SE) in Business Score	75.160000	9.292204077	48.6	96.7
Pre-test EA Perceived Personal Control (PC) of a Business Score	66.321250	10.148051134	39.4	93.4
Pre-test EA Perceived Personal Control (PC) of a Business Score	70.757500	10.251513464	37.8	95.0
Pre-test EA Achievement (ACH) in Business Score	77.456875	9.841048813	36.8	97.5
Pre-test EA Achievement (ACH) in Business Score	80.575625	8.614998964	57.2	100.0
Pre-test EA Innovation (INN) in Business Score	67.793750	9.956696729	30.0	96.5
Pre-test EA Innovation (INN) in Business Score	70.630000	9.623763827	32.6	93.2

Table 2: Data Description and Summary Statistics for Pre- and Post-Test Entrepreneurial Intent Scores (Kolvereid Method)

Variables	Mean	Standard Error	Minimum	Maximum
Pre-test	45.825000	19.299216265	8.0	80.0
Post-test	52.887500	19.651039789	8.0	80.0

A. Correlation

A correlational analysis was run separately for undergraduate and MBA students on both the pre-test and post-test data. The data analysis indicated a significant positive correlation between all but one of the four subscales of the EAO and the Kolvereid EI scale for the undergraduate students. However, the data indicated a lesser, but still positive correlation between the change in the four subscales of the EAO and the Kolvereid EI scale for the MBA sample. The proportion of variability was explained by using the square of the regression coefficient, r^2, which is known as the coefficient of determination.

Table 3: Pearson Correlation of Pre-Test of EI and EA Scores - for Undergraduate Students (N=99) who Completed Both Pre- and Post-Tests

Pre-test EA	Pre-test EI	r^2
Self Esteem Score (SE)	$P < 0.0065$	0.0739
Personal Control Score (PC)	$P < 0.0001$	0.2280
Achievement Score (ACH)	$P < 0.0001$	0.2897
Innovation Score (INN)	$P < 0.0001$	0.2987

Table 4: Pearson Correlation of Post-Test of EI and EA Scores - for Undergraduate Students (N=99) who Completed Both Pre- and Post-Tests

Post-test EA	Post-test EI	r^2
Self Esteem Score (SE)	$P < 0.0008$	0.1102
Personal Control Score (PC)	$P < 0.0001$	0.3561
Achievement Score (ACH)	$P < 0.0001$	0.3383
Innovation Score (INN)	$P < 0.0001$	0.3933

The coefficient of determination, was as low as $r^2 = 7\%$ in the pre-test, and as high as $r^2 = 39\%$ in the post-test for undergraduate student sample, with most in the 20% to 40% range. All of the r^2 increased for each of the EA subscales in the undergraduate sample.

For the MBA sample (see Tables 5 and 6) the coefficient of determination ranged from a low of $r^2 = 7.25\%$ to a high of $r^2 = 34.32\%$ in the pre-test, while the post-test ranged from a low of $r^2 = 7.04\%$ to a high of $r^2 = 29.9\%$. Particularly, this shows a decrease in the MBA sample of Self Esteem EA r^2 scores from *7.25%* in the pre-test to *7.04%* in the post-test. While all of the other EA subscale r^2 post-test scores showed an increase, the r^2 scores were all below the *33.33%* threshold expected in Hypothesis 1b.

Table 5: Pearson Correlation of Pre-Test of EI and EA Scores - for MBA Students (N=61) who Completed Both Pre- and Post-Tests

Pre-test EA	Pretest EI	r^2
Self Esteem Score (SE)	$P < 0.035$	0.0725
Personal Control Score (PC)	$P < 0.0001$	0.1680
Achievement Score (ACH)	$P < 0.0001$	0.1793
Innovation Score (INN)	$P < 0.0001$	0.3432

Table 6: Pearson Correlation of Post-Test of EI and EA Scores - for MBA Students (N=61) who Completed Both Pre- and Post-Tests

Post-test EA	Post-test EI	r^2
Self Esteem Score (SE)	$P < 0.0388$	0.0704
Personal Control Score (PC)	$P < 0.0001$	0.2400
Achievement Score (ACH)	$P < 0.0001$	0.2626
Innovation Score (INN)	$P < 0.0001$	0.2995

We then checked to see if our dependent variables have the same finite variance. We wanted to understand whether the relationship between the variables stayed the same at all points. We checked to see if the variance of the errors were constant. While there was significant standard deviation in the data, the sample sizes for each of the samples were large enough to ensure that the correlations were significant.

B. Support for the Hypotheses

As the results indicate, *Hypothesis 1* was supported in both the undergraduate and MBA samples with the exception of one EAO subscale (Self-Esteem) in the pre-test. *Hypothesis 2* was supported in the undergraduate sample, post-test analysis with the EAO Innovation ($r^2 = 39.33\%$), Achievement ($r^2 = 33.83\%$), and Personal Control ($r^2 = 35.61\%$) subscales but not on the Self-Esteem subscale ($r^2 = 11.02\%$).

Results for *Hypothesis 2* in the MBA sample were well below expectations as all of the post-test r^2 scores were below the *33.33%* threshold. We even found that the post-test EAO Self-Esteem r^2 score decreased by *0.21%* and the Innovation r^2 score decreased by *4.37*% as compared to the pre-test.

V. Discussion

A. Theory of Planned Behavior

Krueger *et al*. (2000, p. 414) have stated that "a strong intention to start a business should result in an eventual attempt, even if immediate circumstances such as marriage, child bearing, finishing school, a lucrative or rewarding job, or earthquakes may dictate a long delay." The TPB suggests that EA, in addition to one's subjective norms and perceived behavioral control, influence one's intent, which then influences one's entrepreneurial behavior. The results of this analysis question whether a "long delay" described by Krueger *et al*. (2000) impacts the eventual entrepreneurial attempt (or behavior). There was a significant difference between changes in pre-test and post-test results for undergraduate and MBA students.

Results for *Hypothesis 1* support the TPB model in that EA and EI are linked from a correlation viewpoint for both undergraduate and MBA students who took their first entrepreneurship course. Conversely, results for *Hypothesis 2* were different for MBA students as compared to undergraduate students. While the undergraduate students showed post-test r^2 scores above the *33.33%* threshold for the EA subscales of Personal Control, Achievement and Innovation, all of the MBA r^2 EA subscale scores were under *30%*. We are still unsure what means govern this effect. There is a difference between

MBA and undergraduate students and how they reported their entrepreneurial attitudes before and after taking an introductory entrepreneurship course. Why are there differences between the results of the undergraduate and MBA students? This discrepancy may be due to the teaching methods used. The MBA students were taught from a more theoretical framework, whereas the undergraduate students were taught from a more experiential framework. This may indicate that differences in teaching methodology between human capital and entrepreneurial self-efficacy have different outcomes on EA. If the same teaching methods were used to teach entrepreneurship to both of these groups, there may have been a different result for *Hypothesis 2* for the MBA students. Yet, as Piperopoulos and Dimov (2015) stated, “It would be naïve to expect that all entrepreneurship courses should be taught in a practically oriented mode, as this may well not be feasible (due for example to resource limitations) and/or appropriate due to the content/context the course wishes to cover” (p. 983). That being said, there was less impact on MBA students in terms of positive EA change.

Apart from teaching orientation, are there other differences between these two types of student. One difference is the amount of prior work/industry experience. We may infer, if one accepts the TPB, that there may be a difference in subjective norms or the perception of behavioral control for students after they have graduated with an undergraduate degree and then return for graduate studies. This questions whether work experience after receiving an undergraduate degree has an influence on one’s subjective norms, as these relate to attitudes toward entrepreneurial behavior. If there is a correlating relationship between EA and EI, as inferred by *H1*, the TPB suggests that the other two factors (Subjective Norms and Perceived Behavioral Control) may be affected by the differences between undergraduate and MBA students.

B. Differences Between EA Subscale Results

There was a strong *Pearson correlation* between EI scores and the EA subscale measures of the need for Personal Control in business, the need for Achievement in business, and the attitude towards Innovation. However, the coefficient of determination results indicated that the measure of EA towards self-esteem in business was less influenced by the entrepreneurship courses taught.

What is different about self-esteem as compared to the other subscale measures? Is there something about the teaching practices used in entrepreneurship education that diminishes the entrepreneurial self-esteem of post-secondary students? In an introductory entrepreneurship course, there may be a realization among some students that becoming an entrepreneur is not something that they want to pursue (von Graevenitz *et al*., 2010, pp. 98-9). This realization would imply that one’s self-esteem in becoming an entrepreneur would diminish.

Conversely, an introductory entrepreneurship course for some students may help them to realize that entrepreneurship is something that they really enjoy (von Graevenitz *et al*., 2010, p. 91). In this particular sample of students, the undergraduate students taking these courses were a combination of students from different schools/colleges/faculties from across the university. Compared to MBA students, undergraduate students have a greater ability and option to change their majors and/or complete minors in other/new disciplines.

The implication for education is that by influencing either EA or EI, there may be a resulting influence on the other measure. We infer that, as the attitude change literature points to increasing uses of experiential education teaching methods as key components to positively influencing entrepreneurial attitudes in post-secondary students, these same teaching methods may suggest influencing a higher EI. The practical teaching orientation, typically using experiential education teaching methods based on engaging entrepreneurship student’s entrepreneurial attitudes (cognitively, emotionally, and behaviorally), may not only influence one's entrepreneurial attitude, but this correlation suggests that these methods may also influence their entrepreneurial intent.

Our results support the original proposition, in that there is a strong relationship between EA and EI. The results further indicate that while EA may be a significant precursor to EI, as proposed in the TPB model, EI may also be a precursor to EA. Although attitude may be a critical element in developing EI, the correlation suggests that methods to increase student EA may also need to be considered as important parts of future entrepreneurial educational programming and andragogy development.

VI. Future Research

Many questions are raised by the results of this research to be answered with further analysis of the data and additional data gathering. First, further analysis of the pre-test, post-test differences in both the EI and EA need to be explored to establish the impact and directionality of changes based on the educational experiences. Addressing the differences in teaching methods and the use of a separate control group may also explain some of the discrepancies found between the MBA and undergraduate students. Additional research should also explore more how EI may be a precursor to EA. An exploration into particular methodologies and teaching methods for entrepreneurship education that have greater impacts on both EA and EI, may help guide the androgogy. Finally, the development of positive "Subjective Norms" and "Perceived Behavioral Controls" in entrepreneurship educational programming should be studied to assess their unique impact on EI and ultimately entrepreneurial behavior.

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Performance Efficiency Evaluation of U.S. Credit Unions Around the 2009 Global Recession: A Data Envelopment Analysis Approach

By LIJUAN SUN, XU SUN, AND MONIKA K. RABARISON *

This paper examines the impact of the latest economic recession on performance efficiency of U.S. credit unions using Data Envelopment Analysis (DEA), a non-parametric method. We find that larger credit unions and credit unions with lower loss loan provisions tend to have higher efficiency. Our results reveal that, compared to the pre-recession period, the recession and the post-recession periods affected the efficiency of Federal Credit Unions (FCUs) and Federally Insured State-Chartered Credit Unions (FISCUs) differently. FISCUs have significantly higher efficiency than FCUs before the recession but FCUs exhibit higher efficiency during the recession and post-recession periods.

Keywords: Credit Union; Data Envelopment Analysis; Recession; Performance Efficiency

JEL Classification: G21; G01; C14: L25

I. Introduction

Credit unions (hereafter CUs) are important financial institutions for the U.S. economy despite their small size ($198.5 billion on average) and market shares (7.1%) relative to banks. They not only serve individual customers, but also provide financing to businesses, specifically to small business firms. This industry rose the total membership to over 103 million by year 2015 and it is also reported that over 73% of CUs experienced increasing in total assets[1].

Previous literature on financial institutions mostly focuses on evaluating the performance and efficiency in large institutions, such as commercial banks (hereafter CBs). Little research has been done on the performance efficiency of CUs, primarily due to the cooperative feature of CUs (Bauer, 2008). CUs are member-owned cooperatives that build capital by retaining earnings. They do not issue equity. This kind of cooperative nature in CUs makes the traditional methods of examining performance efficiency difficult. Some recent studies (e.g., Smith, 2012; Anderson and Liu, 2013) focus on the difference of performance by examining the efficiency between small CUs and large depository CBs. Different from prior studies, in this paper we use a non-parametric Data Envelopment Analysis (DEA) to estimate the performance efficiency of U.S. credit unions around the 2009 Great Recession. The DEA technique evaluates the performance of decision-making units (DMUs) to successfully transform inputs into outputs relative to their peers (Charnes *et al.,* 1978; Hsiao *et al*., 2010; Harris *et al*., 2013).

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[1] From *Credit Union Reports*, Credit Union National Association.

Credit unions in U.S. can be chartered by the federal government and regulated by the National Credit Union Administration (NCUA), or chartered by state governments. Therefore, we also use Panel Fixed Effects, Tobit, Generalized Linear Model (GLM), and System Generalized Method of Moments (GMM) regressions to investigate whether Federal Credit Unions (FCUs) and Federally Insured State-Chartered Credit Unions (FISCUs) react differently to market wide economic shocks. In addition, we examine the impact of assets size, loan loss provision, assets/liability management level, and productivity ratio on CUs' performance efficiency. This study contributes to the literature on CUs performance efficiency around the latest recession and on comparisons of efficiency between FCUs and FISCUs. To the best of our knowledge, this study is also the first attempt to examine recession impacts on performance efficiency of CUs using a DEA approach.

Our findings are consistent with the unique characteristics of the CU industry. The results from univariate analyses show that the efficiency of CUs increases from the pre-recession period to the post-recession period, implying that CUs did weather the recession. However, the results from multivariate analyses reveal that the recession has a significant negative impact on CU efficiency. When looking at the comparison of changes in efficiency between FCUs and FISCUs, we document that, on average, being FCUs implies higher efficiency during the recession and post-recession periods while FISCUs have a significantly higher operational efficiency than FCUs before the recession.

The remainder of this paper is organized as follows. In the next section, we survey related literature and present our research questions. Section III describes the data and sample selection. We explain our methodological approach in Section IV and present our empirical results in Section V. Section VI reports the results from robustness tests and Section VII concludes.

II. Literature and Proposed Hypotheses

Ownership structure and capitalization methods distinguish CUs from other financial intermediaries, such as CBs, in that CUs are mutually owned and not-for-profit institutions. Members of CUs are both the owners of the financial institution and the consumers of its output or suppliers of its input (Smith *et al.*, 1981; Smith, 1984). Bruce (2009) reports that, while the financial crisis has not left CUs unscathed, CUs appear to be healthier than their bank counterparts since not-for-profit credit union members benefit from both their own investment and depositors' funds. CU lending has been steadier than bank lending through business cycles, including the recent financial crisis, than bank lending (Anderson and Liu, 2013; Burger and Dacin, 1992; Smith, 2012; Smith and Woodbury, 2010). The regulatory and technological environment of CUs has changed dramatically since the 1980s' deregulation stream. The Dodd-Frank Wall Street Reform and the Consumer Protection Act subject CUs to similar consumer protection provisions and reporting rules as CBs (Wheelock and Wilson, 2013).Thus, CUs tend to take less risk during a bubble and are less likely to experience the effects of financial crises as seriously as CBs when the bubble bursts. Moreover, CUs gain from the failure of CBs as some commercial bank customers move to CUs for safety considerations.

CUs in the U.S. can be chartered by the federal government or by state governments. The National Credit Union Share Insurance Fund (NCUSIF) provides insurance coverage to all FCUs and to some FISCUs. While state-chartered CUs are primarily regulated by state supervisory agencies (SSAs), the NCUA also cooperates with SSAs to assess the financial and operational conditions of FISCUs. In general, FISCUs are considered to have advantages compared with

FCUs. According to the National Association of State Credit Union Supervisors[2], in contrast to FCUs, FISCUs are subject to state laws and regulations that meet the needs of the citizens of the state. Legislators and governors allow FISCUs a greater opportunity to affect credit union policy and generally provide more input into their governance than their federal counterparts. Moreover, the "Field of Membership" (FOM) that governs CUs' membership allows "for the mixing and matching of communities and Select Employee Groups for state-chartered credit unions".[3] The question is whether such advantages translate into higher performance efficiency and persist around economic downturns.

Two major performance theoretical models exist for CUs. One model, proposed by Smith *et al.*, (1981) and Smith (1984), argues that the performance should be examined by the benefits from receiving higher deposit rates and paying lower loan rates than the market since the goal of CUs is not to minimize costs but to maximize utility. Bauer (2008) extends Smith *et al.* (1981) model to examine the abnormal CU performance by constructing return vectors. Bauer *et al.* (2009) use this methodology and argue that this method and return vectors are well-specified and powerful with small changes in observed ex-post event performance.

The other theoretical model of CU performance efficiency is based on minimizing operating costs, thus maximizing the owner/customer's benefits, which corresponds to the maximization of service provisions that include quantity, price, and other components. Under this framework, most empirical studies focus on technical efficiency. Fried *et al.* (1993) conduct a performance evaluation of CUs in terms of price, quantity, and variety of services offered to members subject to resource availability and operating environment. They use parametric and non-parametric estimators (Free Disposal Hull, hereafter FDH) methods to detect a small but statistically significant portion of the performance variation. The study also finds that large CUs are more efficient than small CUs. Fried and Lovell (1994) enhance the FDH methodology to measure the efficiency and evaluate the performance of CUs. Frame and Coelli (2001) examine efficiency by using a parametric transcendental logarithmic (translog) cost function using data from CUs with more than $50 million of total assets. They find that CUs with residential common bonds have higher costs than those with occupational or association bonds.

Several studies have examined the impacts of mergers, acquisitions, and diversifications on performance efficiency of CUs. Most of these studies are under the frame of minimizing cost to maximize profit function. For example, Fried *et al.* (1999) investigate the impacts of mergers by using DEA to estimate efficiency and find that acquiring firms experience no deterioration in service provision and on average, acquired firms receive an immediate improvement that last three years following a merger. However, the aggregate findings indicate roughly that 50% of acquiring firms and 20% of acquired firms experience a decline following the merger. The performance change is also small.

Goddard *et al.* (2008) find that larger CUs are better in diversifying non-interest income than small ones by considering ROA and ROE ratios using data from 1993 to 2004. Wheelock and Wilson (2013) examine the scale efficiency and change in technology efficiency by constructing a cost analog of the Malmquist Productivity Index. They find that large CUs become less efficient over time and cost-productivity falls on average, especially in small ones. Wheelock and

[2] NASCUS (2008) Quick guide. Accessed from http://www.nascus.org/pdf/quick_guide/QG-State-Charter.pdf.

[3] A Select Employee Groups is a CU business partner that provides membership eligibility to the CU for its employees at no cost and without having to start up its own CU.

Wilson (2011) find increasing return to scale among CUs of all sizes, suggesting that further consolidation and growth are better for CUs.

In recent years, DEA has become one of the popular measurement methodologies for performance efficiency in financial institutions. Simply speaking, based on multiple inputs and outputs (decision making units, DMUs), DEA produces the relative efficiency for each DMU relative to the generated productivity frontier by all DMUs. The relative efficiency of an institution is determined as the ratio of a weighted sum of outputs to a weighted sum of inputs under assumptions on returns to scale as well as model orientation. DEA identifies the most proficient input-output combinations and develops a best practice efficiency frontier against the peers. However, studies on performance efficiency on CUs using DEA are very limited. Berger and Humphrey (1997) review 130 studies and find that cost efficiency is more important than market concentration in explaining financial institution profitability. Nonetheless, both measures only weakly explain performance variation. Regressions of efficiency on sets of explanatory variables have been unable to explain more than just a small portion of its total variation. From the survey, Berger and Humphrey (1997) conclude that DEA is an appropriate method to evaluate CU performance efficiency used within a profit frontier framework, as it is popular in the commercial bank literature.

The impact of recession on CBs is well documented (Fahlenbrach *et al.*, 2012, Fang *et al.*, 2013). However, there are few studies examining the impact of recession on CUs performance efficiency (Wheelock and Wilson, 2011; Bauer, 2008). One argument is that CUs may benefit from the financial shocks because CUs do not rely on stock or bond financing since they are financed with member deposits (Birchall and Ketilson, 2009). Smith and Woodbury (2010) analyze 15 years of quarterly call report data from banks and CUs during the period 1986 to mid-2009. Their report shows that commercial loan performance for both CBs and CUs are impacted by the business cycle. CUs delinquency and charge-off rates tend to be more sensitive to the business cycle than those of banks, though when aggregated, loan performance is more similar. They find that CUs' loan portfolios appear to be about 25% less sensitive to macroeconomic shocks than bank loan portfolios.

Given the existing studies, in this paper, we aim to fill the gap in the literature by addressing the following empirical questions:

1. *What is the impact of the 2007-2009 recession on CU performance efficiency?*
2. *Do the performance efficiencies of FCUs and FISCUs differ around the recession?*

On one hand, we expect the efficiency of CUs to be affected positively by the recession because of the increase in CU's assets due to investors moving to CUs for flight to safety and the CUs' advantages from not being reliant to the financial markets although five of the largest corporate credit unions invested in problematic mortgage-backed securities. On the other hand, we expect the efficiency of CUs to be affected negatively by the economic downturn marked with the high number of business failures, home foreclosures, and unemployment. In addition, the increase in CUs' assets due to the sudden shift in investors' behavior could lead to suboptimal management and affect CUs' efficiency negatively. Moreover, since FCUs and FISCUs are governed under different policies and regulations, we expect them to react differently to economic shocks.

III. Data

A. Data Source and Sample Selection

We use quarterly call report data from the NCUA during year 2000-2013. Following Wheelock and Wilson (2013), we omit observations with reported non-positive loans or investments, or with the calculated values for price of capital (X_1), price of labor (X_2), savings pricing (Y_5) or loan price (Y_6) outside the interval (0, 1), as well as those with non-positive capital or labor. We drop any quarter that does not have complete data items. Based on FDIC classification, we divide the sample into two groups to capture the performance efficiency difference between FCUs and FISCUs. This sample selection yields a revised sample of 836 FCUs and 896 FISCUs. Following Brunnermeier (2009), we divide the study period into three sub-periods: pre-recession refers to 2000q1 through 2007q4, recession period refers to 2008q1 through 2009q2, and post-recession refers to 2009q3 through 2013q2.

B. Descriptions of Variables

We construct two input variables and six output variables. The description of each input and output variables is provided in Table 1. Following Frame and Coelli (2001) and Wheelock and Wilson (2011), we identify two input variables, the price of financial capital (X_1) and the price of labor (X_2). The price of capital (X1) is identified as capital expenses divided by the total shares and deposits, where capital expenses include gross occupancy expense, office operations expense, advertising expense, travel and conference expense, loan expenses, operating expenses fees, professional and outside services, other operating expenses, and miscellaneous operating expenses (Wheelock and Wilson, 2011). The price of labor is defined as employees and officers' compensation and benefits divided by number of full time and half- or part-time employees. The first four output quantities are real estate loans (Y_1), commercial loans (Y_2), consumer loans (Y_3), and investments (Y_4). Investments include total investments, cash on deposit, and cash equivalent. These measures are based on NCUA performance report. These four variables capture the vast majority of CU assets. We consider two additional outputs, savings pricing (Y_5) and loan prices (Y_6) to ensure an institution is not unfairly considered as less efficient due to more costly output composition.

Pursuant to previous studies, we consider measures of capital adequacy, liquidity, asset quality and management, and productivity. That is, we include the following controlling variables in our models: assets, capital ratio, loan loss provision, assets to total shares and deposit ratio, productivity ratio and past performance efficiency. We also present the description of each of these variables in Table 1.

Table 1: Description of Variables

Proxy		Description
<u>*Inputs*</u>		
X_1	Price of capital	Capital expenses / Total shares and deposits
X_2	Price of labor	{Labor expenses / (Number of full time employees + Number of half- and part-time employees)} / Total operating expenses Cost = Capital × X_1 + Labor × X_2
<u>*Outputs*</u>		
Y_1	Real estate loan	(Amount of first mortgage real estate loans + Amount of other real estate loans) / Total loans and leases
Y_2	Commercial loans	(Amount of commercial loans + Amount of agricultural loans to members; for years 2004–2006, Member business loans, total amount outstanding) / Total loans and leases
Y_3	Consumer loans	{Total loans and leases - (Amount of real estate loans +Amount of commercial loans)} / Total loans and leases
Y_4	Investment	(Total investments, Cash on deposit and Cash equivalent) / Total loans and leases
Y_5	Saving price	(Dividends on shares + Interest on deposits) / Total shares and deposits
Y_6	Loan price	Interest and fee income on loans, total / Total loans and leases
<u>*Variables in Regressions*</u>		
ESCORE		Efficiency score estimated using Data Envelopment Analysis (DEA)
Size		CU size = Natural logarithm of Total Assets
Capital ratio		Net worth / Total assets
Loan loss provision		Loan loss provision ratio = Provision for loan and lease / Total loan
Asset/liability		Asset/liability management = Total loans / Total shares and deposits
Productivity ratio		Members / Potential members
Funding cost		Cost of funds / Average assets
Corporate CU		Corporate credit union = 1 (0 otherwise)
Lag ESCORE		Lag value of efficiency score = Lag (ESCORE) We also define *Lag2 ESCORE* as the value of ESCORE lagged twice.
FCU		*FCU* = 1 if the credit union is a Federal Credit Union (0 if Federally Insured State-Chartered Credit Union)
Recession		*Recession* = 1 during the recession period (0 otherwise)
Post		*Post-recession* =1 after the recession period (0 otherwise)

Note: This table presents the two inputs and six outputs used to estimate credit union efficiency scores using Data Envelopment Analysis (DEA), and the variables used in the regression analyses.

IV. Methodology

A. Data Envelopment Analysis (DEA)

In the first stage, we construct an overall performance efficiency measurement using DEA as proposed by Charnes *et al.* (1978) to measure the aggregate change in technical process, pure efficiency, and scale efficiency. In the second stage, we use regression models to investigate the effect of the recession on CUs' efficiency generated from previous step.

To measure the performance efficiency of CUs, we construct a model of cost function. Following Wheelock and Wilson (2011) and Frame and Coelli (2001), we model CUs as service providers which seek to minimize non-interest costs subject to labor, capital, and the level and type of output they produce as in Bauer (2008), Fried *et al.* (1993), Fried *et al.* (1999) and Wheelock and Wilson (2013). The DEA method evaluates the performance of decision-making units (DMUs) compared to their peers (Charnes *et al.*, 1978; Harris *et al.,* 2013; Hsiao *et al.*, 2010). Prior empirical studies provide evidence that banks with higher efficiency scores present higher performance efficiency. Similarly, empirical studies using DEA to evaluate the efficiency of CUs suggest that credit unions have a lot of room to improve with efficiency scores (e.g., Fried *et al.*, 1993). We estimate CU efficiency using Charnes *et al.* (1978) model of DEA to capture efficiency as the minimum consumption of inputs for a given level of outputs.

Following Hsiao *et al.* (2010), we define the input-oriented efficiency measure, *ESCORE*, as the reciprocal of the inefficiency measure, θ_j, for credit union j, CU_j, as follows:

$$\begin{aligned} &\theta_j = Max\ \theta \\ s.t.\ &\frac{X_{ij}}{\theta} \geq \sum_{j=1}^{N} \lambda_j X_{ij},\ i = 1, \dots, I \\ &Y_{rj} \leq \sum_{j=1}^{N} \lambda_j Y_{rj}, r = 1, \dots, R \\ &\lambda_j \geq 0, \end{aligned} \tag{1}$$

where θ_j is the estimated inefficiency for CU_j, X_{ij} is the input *i* for CU_j, and Y_{rj} is the output *r* for CU_j.

Table 2: Comparison of FCU and FISCU Inputs and Outputs

Panel A: Mean values and t*-statistics of mean differences (FCU)*

	Pre (1)	Recession (2)	Post (3)	(2) - (1)	(3) - (2)	(3) - (1)
W_1	0.014	0.013	0.012	-7.8***	-5.0***	-17.4***
W_2	0.011	0.009	0.009	-7.4***	-1.3	-11.4***
Y_1	0.144	0.210	0.222	24.6***	3.8***	39.1***
Y_2	0.014	0.031	0.039	14.7***	6.4***	28.5***
Y_3	0.842	0.759	0.740	-25.4***	-5.3***	-42.3***
Y_4	0.176	0.639	0.835	28.7***	9.8***	49.4***
Y_5	0.021	0.014	0.007	-44.8***	-48.4***	-125.3***
Y_6	0.079	0.062	0.058	-23.9***	-5.9***	-41.0***

Panel B: Mean values and t*-statistics of mean differences (FISCU)*

	Pre (1)	Recession (2)	Post (3)	(2) - (1)	(3) - (2)	(3) - (1)
W_1	0.013	0.012	0.013	-7.5***	4.5***	-3.2***
W_2	0.057	0.051	0.049	-2.4**	-1.1	-4.7***
Y_1	0.163	0.221	0.227	21.6***	2.0**	31.6***
Y_2	0.020	0.038	0.047	12.2***	5.0***	22.7***
Y_3	0.816	0.741	0.726	-20.9***	-3.5***	-32.6***
Y_4	0.130	0.601	0.846	21.2***	6.5***	23.1***
Y_5	0.016	0.013	0.007	-23.5***	-42.8***	-96.2***
Y_6	0.065	0.055	0.058	-13.3***	3.2***	-9.1***

Panel C: t*-statistics of mean differences in DEA inputs and outputs (FCU - FISCU)*

	Pre (1)	Recession (2)	Post (3)
W_1	9.6***	4.0***	-6.1***
W_2	-51.2***	-20.7***	-27.6***
Y_1	-14.0***	-3.0***	-2.2**
Y_2	-9.7***	-4.5***	-6.4***
Y_3	15.0***	4.1***	4.2***
Y_4	7.9***	1.4	-0.3
Y_5	48.9***	9.3***	3.0***
Y_6	30.1***	7.1***	-1.1

, * These symbols indicate statistical significance at the 5% and 1% levels, respectively.

Table 2 presents the means and mean-differences in inputs and outputs used to estimate CU performance efficiency to compare the inputs and outputs across the three sub-periods for FCUs in Panel A, FISCUs in Panel B, and between FCUs and FISCUs in Panel C. On average, both FCUs and FISCUs exhibit statistically significant decreases in both capital and labor prices (W_1 and W_2) from the pre-recession period to the recession period ((2) – (1)), and from the pre-recession period to the post-recession period ((3) – (1)) at the 1% level. In term of the outputs, real estate loans, commercial loans, and investments (Y_1, Y_2, and Y_4) appear to decrease across the sub-periods while consumer loans, savings pricing, and loan prices (Y_3, Y_5, and Y_6) increase. The increase in consumer loans might be attributed to the significant decreases in real loans and commercial loans since we calculate consumer loans as total loans minus total real loans and commercial loans. Both decreases and increases are statistically significant at the 1% level.

The *t*-statistics of mean-differences between FCUs and FISCUs, reported in Panel C, imply that the price of capital (W_1) is higher for FCUs compared to FISCUs in the pre-recession and recession periods, but lower after the recession. In contrast, the price of labor (W_2) appears to be lower for FCUs over all three sub-periods. Real estate loans (Y_1) and commercial loans (Y_2) are lower for FCUs while consumer loans (Y_1) and savings pricing (Y_3 and Y_5) are higher. The mean difference in investments (Y_4) between FCUs and FISCUs is statistically significant and positive only during the pre-recession period. On average, loan prices (Y_6) are higher for FCUs before and during the recession.

Following Hsiao *et al.* (2010), we consider two DEA test statistics to examine the equality of efficiency scores among the three sub-periods and between FCUs and FISCUs. Under the assumption that the inefficiency score, θ_j, is exponentially distributed, we consider the following test statistic:

$$T_{exp} = \left[\sum_{j\in N_1} \frac{\theta_j - 1}{N_1}\right] \div \left[\sum_{j\in N_2} \frac{\theta_j - 1}{N_2}\right] \tag{2}$$

which is evaluated by the *F*- distribution with ($2N_1$, $2N_2$) degrees of freedom. N_1 and N_2 are the number of observations (CU-quarters) pertaining to each of any two compared groups, respectively.

If θ_j is assumed to be half-normally distributed, the test statistic is given as:

$$T_{hn} = \frac{\sum_{j\in N_1} (\theta_j - 1)^2 / N_1}{\sum_{j\in N_2} (\theta_j - 1)^2 / N_2} \tag{3}$$

which is evaluated by the *F*-distribution with (N_1, N_2) degrees of freedom.

In addition to these two-DEA based tests, we report the conventional *t*-statistics tests as well.

B. Research models

To estimate the effect of the recession and the post-recession periods on CU performance efficiency, we first test the following basic model on our unbalanced panel of CUs:

$$\begin{aligned} ESCORE_{i,t} = \beta_1 ESCORE_{i,t-1} + \beta_2 Recession_{i,t} + \beta_3 Post_{i,t} + \beta_4 Controls_{i,t} \\ + u_i + \varepsilon_{i,t} \end{aligned} \tag{4}$$

where $ESCORE_{i,t}$ denotes the performance efficiency score of CU *i* at time *t*; $ESCORE_{i,t-1}$ is the lag of the variable *ESCORE; Recession* $_{i,t}$ is a dummy variable with the value of 1 in the recession period, 0 otherwise; *Post* $_{i,t}$ is a dummy variable with the value of 1 in the post-recession period, 0 otherwise; $Controls_{i,t}$ represents selected CU characteristics as control variables; u_i represents time-invariant fixed effects,[4] and finally $\varepsilon_{i,t}$ is the error term.

Next, to investigate whether the impact of the recession and the post-recession periods on CU performance efficiency differs for FCUs and FISCUs, we consider the variable *FCU* that takes the value of 1 if the CU is federally charted (0 if state-charted), and its interactions with the variables *Recession* and *Post*, respectively. Therefore, we consider the following model:

$$\begin{aligned} ESCORE_{i,t} = \alpha + \beta_1 ESCORE_{i,t-1} + \beta_2 FCU_{i,t} + \beta_3 Recession_{i,t} + \beta_4 Post_{i,t} \\ + \beta_5 Recession \times \; FCU_{i,t} + \beta_6 Post \times \; FCU_{i,t} + \beta_7 Controls_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{5}$$

In Table 3, we present the mean values of the selected control variables and the comparisons of their mean differences for FCUs and FISCUs over each of the three sub-periods and between FCUs and FISCUs.

[4] The null hypotheses of the Breusch-Pagan test and Hausman test are rejected at the 1% level of statistical significance. Therefore, we control for CU fixed effects in the panel regressions.

Table 3: Comparison of Financial Characteristics

Panel A: Mean values and t*-statistics of mean differences around recession (FCU)*

Variable	Pre (1)	Recession (2)	Post (3)	(2)- (1)	(3) - (2)	(3) - (1)
Size	18.947	19.355	19.495	23.1***	7.4***	41.4***
Capital ratio	0.089	0.112	0.104	30.8***	-12.4***	25.1***
Loan loss provision	0.003	0.006	0.006	17.9***	1.7*	29.5***
Productivity ratio	0.471	0.279	1.023	-6.1***	1.0	0.7
Asset/Liability	0.732	0.747	0.670	4.3***	21.1***	24.9***
Funding cost	0.020	0.013	0.007	-52.2***	52.5***	140.5***

Panel B: Mean values and t*-statistics of mean differences around recession (FISCU)*

Variable	Pre (1)	Recession (2)	Post (3)	(2) - (1)	(3) - (2)	(3) - (1)
Size	18.234	18.638	18.815	14.0***	5.4***	26.0***
Capital ratio	0.107	0.123	0.114	17.2***	-8.6***	12.4***
Loan loss provision	0.003	0.005	0.006	11.3***	6.9***	26.7***
Productivity ratio	0.344	0.248	0.230	-23.7***	-3.5***	28.5***
Asset/Liability	0.769	0.785	0.699	5.0***	-24.6***	-30.3***
Funding cost	0.014	0.012	0.007	-23.6***	-47.6***	-101.8***

Panel C: t*-statistics of mean differences (FCU – FISCU)*

Variable	Pre (1)	Recession (2)	Post (3)
Size	51.5***	23.2***	31.1***
Capital ratio	-29.8***	-10.6***	-17.6***
Loan loss provision	0.4	4.1***	-0.8
Productivity ratio	4.1***	5.6***	1.0
Asset/Liability	-19.3***	-9.0***	-10.5***
Funding cost	57.2***	9.1***	5.5***

Note: This table presents the means of credit union selected financial characteristics and provides comparisons of these characteristics for the sample Federal Credit Unions (FCUs) and Federally Insured State-Chartered Credit unions (FISCUs). We divide the study period into three sub-periods: pre-recession (1) from 2000q1 through 2007q4, recession period (2) from 2008q1 through 2009q2, and post-recession (3) from 2009q3 through 2013q2. Means for each measure are shown in panels A and B, along with *t*-statistics of group mean differences among the three sub-periods. Panel C presents the *t*-statistics of group mean differences between FCUs and FISCUs across the three sub-periods.

*, *** These symbols indicate statistical significance.

As shown in panels A and B of Table 3, FCUs and FISCUs present similar trends in most of the selected financial characteristics used as control variables. Size and loan loss provision increase during and after the recession, and are larger after the recession compared to those before the recession. From Panel C of Table 3, FCUs are larger on average than FISCUs. They have lower capital ratio, lower asset/liability management, but higher funding cost and higher productivity ratio than FISCUs. During the recession, FCUs' loan loss provision is higher than that of FISCUs.

V. Results

A. Univariate Results

Table 4 presents summary statistics on credit union efficiency and univariate results from comparing the efficiency of FCUs to that of FISCUs and across the study three sub-periods. The results in Panel A show that, from the pre-recession period, the efficiency of credit unions increased on average during and after the recession. Overall, the mean (median) efficiency score of FCUs is lower at 0.22 (0.16) than for FISCUs at 0.34 (0.30).

However, it is noticeable that the efficiency of FCUs presents better improvement compared to that of FISCUs across the sub-periods. On average, the efficiency score of FCUs increased by 40% (0.15 to 0.21) from the pre-recession period to the recession, and by more than 52% (0.21 to 0.32) from the recession period to the post-recession period. For FISCUs, the efficiency score increased only by 12.5% (0.32 to 0.36) from the pre-recession period to the recession, and by only about 3% (0.36 to 0.37) from the recession period to the post-recession period.

The latter results are consistent with the statistics test results of equality of efficiency reported in Panel B. Although, the DEA-based test results are not statistically significant, except for comparing the efficiency scores during and after the recession, the *t*-statistics reflect statistically significant differences in efficiency scores at the 1% level across the three sub-periods. We find non-conclusive evidence in comparing the efficiency of FCUs to that of FISCUs: the DEA-based tests are not statistically significant while the *t*-statistics are negative and reveal statistically significant differences between FCUs and FISCUs efficiency scores (i.e. FCUs are less efficient than FISCUs). In the next section, we report our findings from regression analyses to shed some light on this issue.

Table 4: Descriptive Statistics and Comparisons of Efficiency Scores

Panel A: Efficiency scores of FCU and FISCU

	FCU				*FISCU*			
	Obs.	Mean	Median	St. dev.	Obs.	Mean	Median	St. dev.
Whole Period	24,217	0.22	0.16	0.19	37,659	0.34	0.30	0.19
Pre (1)	12,062	0.15	0.10	0.16	24,501	0.32	0.29	0.19
Recession (2)	3,659	0.21	0.15	0.19	4,519	0.36	0.33	0.20
Post (3)	8,496	0.32	0.27	0.20	8,639	0.37	0.34	0.20

Panel B: Statistics test results of equality of efficiency scores

	t-statistics		
	(2) - (1)	(3) - (2)	(3) - (1)
FCU	17.5***	27.7***	64.5***
FISCU	11.4***	2.8***	18.6***
	Pre (1)	Recession (2)	Post (3)
FCU - FISCU	-92.4***	-34.4***	-17.2***
	Exponentially distributed test statistics (T_{exp})		
	(2) - (1)	(3) - (2)	(3) - (1)
FCU	0.4	2.3***	0.8
FISCU	0.2	1.9***	0.5
	Pre (1)	Recession (2)	Post (3)
FCU - FISCU	0.4	0.5	0.7
	Half-normally distributed test statistics (T_{hn})		
	(2) - (1)	(3) - (2)	(3) - (1)
FCU	1.3***	2.8***	1.5***
FISCU	0.3	1.8***	0.5
	Pre (1)	Recession (2)	Post (3)
FCU - FISCU	0.2	0.2	0.3

Note: This table reports summary statistics on efficiency scores of the sample Federal Credit Unions (FCUs) and Federally Insured State-Chartered Credit Unions (FISCUs) from 2000q1 through 2013q2 in Panel A. Credit union efficiency is estimated by Data Envelopment Analysis (DEA). We divide the study period into three sub-periods: pre-recession (1) from 2000q1 through 2007q4, recession period (2) from 2008q1 through 2009q2, and post-recession (3) from 2009q3 through 2013q2. Panel B shows the statistics test results of mean difference of efficiency scores across the three sub-periods and between FCUs and FISCUs. In addition to *t*-statistics, we report two DEA-based test statistics: T_{exp} and T_{hn}, based on exponentially distribution and on half-normally distribution of inefficiency scores, respectively.

*** This symbol indicates statistical significance at the 1% level.

B. Panel Fixed-Effects and Tobit Regression Results

In Table 5, we present the results from panel fixed-effects regressions of credit union efficiency score on selected financial variables as described by Equation (4). As expected, the previous quarter efficiency score is statistically and positively related to the current efficiency score. We find that, however, the recession impacts FCUs and FISCUs differently. While the coefficient on *Recession* for FCUs is not statistically significant, the recession has a negative and statistically significant impact on FISCUs and on the whole sample after controlling for CU financial variables. On one hand, compared to the pre-recession period, the recession decreases the efficiency score of FISCUs and the whole sample significantly at the 1% level by 0.02 and 0.01, respectively. On the other hand, during the post-recession period, the efficiency score of FCUs increases by 0.02 but that of FISCUs decreases by 0.01, both at the 1% level of statistical significance. Goddard *et al.* (2015) report that the probability of credit unions survival increases with size. We find that, larger credit unions appear to be more efficient, which is contrary to the findings reported in Harris *et al.* (2013) for CBs. The signs and significances of the coefficients on other control variables are consistent with those on CB efficiency in Harris *et al.* (2013).

Table 5: Results from Panel Fixed-Effects Regressions

	FCU	FISCU	Whole Sample[a]
Lag ESCORE	0.74***	0.70***	0.76***
	(45.98)	(35.69)	(63.77)
Recession	0.000	-0.02***	-0.01***
	(0.14)	(-13.14)	(-11.99)
Post	0.02***	-0.01***	0.00***
	(13.21)	(-6.44)	(3.65)
Size	0.03***	0.05***	0.04***
	(7.25)	(13.13)	(14.95)
Capital ratio	-0.11***	0.00	-0.04**
	(-3.72)	(0.29)	(-2.51)
Loan loss provision	-0.41***	-0.04	-0.10*
	(-4.92)	(-0.85)	(-1.70)
Funding cost	-1.24***	0.41***	-0.41***
	(-11.31)	(5.13)	(-6.11)
Productivity ratio	-0.00***	-0.00	-0.00***
	(-8.89)	(-0.04)	(-5.16)
	(-4.74)	(-7.38)	(-7.44)

Table 5 - Results From Panel Fixed-Effects Regressions: Continues

	FCU	FISCU	Whole Sample[a]
Corporate CU	0.00	0.01***	0.01**
	0.37)	(3.95)	(2.34)
Intercept	-0.54***	-0.83***	-0.69***
	(-6.22)	(-12.40)	(-13.63)
CU fixed effects	Yes	Yes	Yes
Quarter fixed effects[b]	No	No	No
Observations	15,045	25,380	40,425
(Within) R-squared	0.78	0.61	0.71
Number of CUs	850	916	1,766

Note: This table presents the results from panel fixed-effects regressions of efficiency score (*ESCORE*) of the sample Federal Credit Unions (FCUs) and Federally Insured State-Chartered Credit Unions (FISCUs) on the selected variables defined in Table 1 for the period 2000q1-2013q2. All regressions include CU fixed effects. We report *t*-statistics calculated from robust standard errors in parentheses.
[a] Controlling for CU fixed effects do not allow us to include the time-invariant variable *FCU* in this model.
[b] When controlling for quarters, the *Recession* variable and most quarters are dropped due to collinearity.
*, **, *** These symbols indicate statistical significance at the 10%, 5% and 1% levels, respectively.

We follow Hsiao *et al.* (2010) and Harris *et al.* (2013) to use Tobit regressions to test Equation (4) on the sub-samples of FCUs and FISCUs, and to test Equation (5) on the whole sample. In the whole sample model, we include the variable *FCU* and its interactions with *Recession* and with *Post*, respectively. We report the results from these Tobit regressions in Table 6.

Table 6: Results from Tobit Regressions

	FCU	FISCU	Whole Sample
Lag ESCORE	0.92***	0.93***	0.93***
	(169.90)	(285.04)	(322.46)
FCU			-0.025***
			(-22.13)
Recession	0.01***	-0.01***	-0.01***
	(5.80)	(-14.97)	(-14.28)
Recession × FCU			0.02***
			(13.76)
Post	0.03***	0.00***	0.00
	(18.13)	(3.28)	(0.91)
Post × FCU			0.03***
			(27.15)
Size	0.01***	0.01***	0.01***
	(11.55)	(25.33)	(29.43)

Table 6: Results from Tobit Regressions: Continues

	FCU	FISCU	Whole Sample
Capital ratio	-0.07***	0.02***	0.00
	(-3.83)	(3.01)	(0.37)
Loan loss provision	-0.41***	-0.03	-0.11**
	(-6.60)	(-0.50)	(-1.97)
Funding cost	-0.16*	0.25***	0.19***
	(-1.87)	(6.53)	(3.38)
Productivity ratio	-0.00***	0.01***	-0.00***
	(-4.51)	(4.05)	(-3.06)
Asset/Liability	-0.04***	-0.01***	-0.02***
	(-12.76)	(-3.03)	(-11.84)
Corporate CU	0.00	0.00	0.01***
	(0.97)	(0.88)	(3.28)
Intercept	-0.11***	-0.12***	-0.11***
	(-8.69)	(-22.16)	(-23.23)
Observations	15,045	25,380	40,425
F-statistic	6,843***	35,528***	36,143***
FCU + *Recession* × *FCU* = 0			*p*-value = 0.008
FCU + *Post* × *FCU* = 0			*p*-value < 0.001
Recession + *Recession* × *FCU* = 0			*p*-value < 0.001
Post + *Post* × *FCU* = 0			*p*-value < 0.001

Note: This table presents the results from Tobit regressions of efficiency score of the sample Federal Credit Unions (FCUs) and Federally Insured State-Chartered Credit Unions (FISCUs) on the selected variables defined in Table 1 for the period 2000q1-2013q2. The dependent variable, *ESCORE,* is bounded between 0 and 1. In the Whole Sample model, we include the variable *FCU* and its interactions with *Recession* and with *Post*, respectively. We report *t*-statistics calculated from robust standard errors in parentheses. We perform Wald tests to check for statistical significance of the full effects of *FCU*, *Recession*, and *Post* when considering the interaction variables. We report the respective *p*-values at the bottom of the table.
*, **, *** These symbols indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

The results reported in Table 6 for the sub-samples of FCUs and FISCUs are similar to those reported in Table 5, except that the positive coefficient on *Recession* becomes statistically significant at the 1% level. This result, compared to the pre-recession period, implies that the recession affects positively the efficiency of FCUs. The coefficient on *Recession* is still negative and statistically significant for FISCUs, suggesting that the recession impacts FCUs and FISCUs differently.

From the whole sample model in Table 6, the negative and statistically significant coefficient (-0.025) on *FCU* implies that, on average and holding all else constant, FCUs are less efficient than FISCUs before the recession. The negative and statistically significant coefficient (-0.01) on *Recession* indicates that the recession decreases the efficiency of FISCUs by one percentage point, a result that is not depicted with the univariate analyses. The coefficient on the interaction term denoted *Recession* × *FCU* is positive (0.02) and statistically significant at the 1% level. This result emphasizes that FCUs fare better during the recession than before the recession, and that the impact of the recession on FCUs is more positive than on FISCUs. Similarly, the coefficient on the interaction term *Post* × *FCU* is positive (0.03) and statistically significant at the 1% level. Thus, FCUs fare also better after the recession than before the recession, and that the post-recession impacts FCUs more positively than FISCUs.

Specifically, we also perform four Wald tests to determine whether (1) the sum of the coefficients on *FCU* and *Recession* × *FCU* (-0.025 + 0.02 = -0.005)*, (2)* the sum of the coefficients on *Recession* and *Recession* × *FCU* (-0.01 + 0.02 = 0.01)*, (3)* the sum of the coefficients on *FCU* and *Post* × *FCU* (-0.025 + 0.03 = 0.005), and (4) the sum of the coefficients on *Post* and *Post* × *FCU* (0.00 + 0.03 =0.03) are statistically and significantly different from 0 at the 1% level. We report the results from these tests at the bottom of Table 6. We find that the full effects of *FCU, Recession*, and *Post* when considering the interaction terms are all statistically significant. For instance, the sum of the coefficients on *Recession* and *Recession* × *FCU* (-0.01 + 0.02 = 0.01) is statistically significant at the 1% level (p-value < 0.001), suggesting that the recession impacts positively the efficiency of FCUs.

Overall, the results in Table 6 show that the recession and the post-recession periods impact the efficiency of CUs, but their effects are more positive for FCUs than FISCUs.

VI. Robustness Tests

A. Generalized Linear Model (GLM) regression results

Some researchers (e.g., Papke and Wooldridge, 2008; Ramalho *et al.,* 2010) criticize the use of log-odd estimations such as Tobit when the fractional dependent variable is naturally bounded in the interval [0, 1] rather than censored at the bounds. Efficiency scores outside of this interval are not feasible (i.e. there is no negative efficiency or efficiency greater than one), thus the zeros and the ones are true values rather than censored ones. Therefore, we retest Equation (4) and Equation (5) using GLM regressions as proposed by Papke and Wooldridge (2008). The results are reported in Table 7.

Table 7: Results From Generalized Linear Models (GLM)

	FCU	FISCU	Whole Sample
Lag ESCORE	4.89***	4.35***	4.61***
	(109.41)	(105.17)	(152.29)
FCU			-0.35***
			(-31.62)
Recession	0.18***	-0.08***	-0.08***
	(13.78)	(-13.37)	(-12.59)
Recession × FCU			0.233***
			(17.71)
Post	0.36***	-0.01	-0.01*
	(24.33)	(-1.12)	(-1.91)
FCU × Post			0.39***
			(36.05)
Size	0.04***	0.08***	0.06***
	(6.51)	(17.18)	(16.83)
Capital ratio	-0.82***	-0.16**	-0.30***
	(-5.23)	(-2.55)	(-3.27)
Loan loss provision	-4.67***	-0.09	-1.15**
	(-8.90)	(-0.21)	(-2.14)
Funding cost	0.84	1.92***	1.32***
	(1.17)	(4.72)	(3.65)
Productivity ratio	0.00***	0.03***	0.00*
	(4.85)	(3.80)	(1.74)
Asset/Liability	-0.21***	-0.11***	-0.19***
	(-6.54)	(-8.89)	(-10.39)
Corporate CU	0.03	-0.01	0.02
	(0.88)	(-0.77)	(0.86)
Intercept	-3.27***	-3.53***	-3.20***
	(-25.90)	(-49.27)	(-55.91)
Observations	15,045	25,380	40,425

Table 7: Results From Generalized Linear Models (GLM): Continues

	FCU	FISCU	Whole Sample
$FCU + Recession \times FCU = 0$			p-value < 0.001
$FCU + Post \times FCU = 0$			p-value < 0.001
$Recession + Recession \times FCU = 0$			p-value < 0.001
$Post + Post \times FCU = 0$			p-value < 0.001

Note: This table presents the results from GLM regressions of efficiency score (*ESCORE*) of the sample Federal Credit Unions (FCUs) and Federally Insured State-Chartered Credit Unions (FISCUs) on the selected variables defined in Table 1 for the period 2000q1-2013q2. In the Whole Sample model, we include the variable *FCU* and its interactions with *Recession* and with *Post*, respectively. We report z-statistics calculated from robust standard errors in parentheses. We perform Wald tests to check for statistical significance of the full effects of *FCU*, *Recession*, and *Post* when considering the interaction variables. We report the respective p-values at the bottom of the table.

*, **, *** These symbols indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

In Table 7, for the sub-sample of FCUs, the positive coefficients on *Recession* (0.18) and *Post* (0.36) are statistically significant. For the sub-sample of FISCUs, the negative coefficient on Recession (-0.01) is also statistically significant, while the coefficient on *Post*, though still positive, is not significant. When we analyze the whole sample, both the interaction terms of *FCU* with *Recession* and with *Post* remain positive and significant at the 1% level. These results are consistent with those from the panel fixed-effects and Tobit regressions.

B. Dynamic panel regression results

Since we include the previous quarter efficiency score, *Lag ESCORE*, in our models, we also replicate the previous analyses using Arrellano-Bover/Blundell-Bond dynamic panel Generalized Method of Moments (System GMM) regressions on our unbalanced panel of CUs to control for potential endogeneity. Table 8 shows that we have the results from system GMM regressions with one lag of the dependent variable only when we limit the study period to prior 2012 (Panel A). We suspect that this issue is due to the omitted first two quarters of 2012. For the entire study period (Panel B), the system GMM regressions include two lagged values of the dependent variable.

Table 8: Results From System GMM Regressions

	Panel A (Year < 2012)[a]			*Panel B (Entire study period)*		
	FCU	FISCU	Whole Sample	FCU	FISCU	Whole Sample
Lag ESCORE	0.11***	0.11***	0.09***	0.34***	0.22***	0.18***
	(3.77)	(3.11)	(3.79)	(5.84)	(3.79)	(4.33)
Lag2 ESCORE				0.24***	0.10***	0.12***
				(5.46)	(5.14)	(4.91)
FCU			-0.29***			-0.27***
			(-12.83)			(-11.56)
Recession	0.05	0.01	0.06***	0.03	-0.00	0.01
	(1.35)	(1.44)	(3.63)	(0.63)	(-0.01)	(0.89)
Recession × FCU			0.05*			0.05**
			(1.81)			(2.33)
Post	0.08**	0.02*	0.08***	0.12***	0.02	0.08**
	(2.43)	(1.79)	(4.21)	(2.59)	(1.39)	(2.19)
FCU × Post			0.06**			0.09*
			(2.28)			(1.74)
Size	0.01	0.07***	0.09***	-0.08***	0.06***	0.07***
	(0.22)	(8.83)	(11.42)	(-2.59)	(6.31)	(8.89)
Capital ratio	0.02	-0.14***	0.01	-0.03	-0.16***	-0.05
	(0.32)	(-5.46)	(0.29)	(-0.33)	(-5.77)	(-1.41)
Loan loss provision	-0.24	-0.61***	-0.28**	-1.16*	-0.74***	0.55***
	(-0.67)	(-4.30)	(-2.24)	(-1.93)	(-4.05)	(-2.91)
Funding cost	-2.73***	0.28**	-1.21***	-0.07	0.83***	-0.06
	(-7.78)	(2.25)	(-8.82)	(-0.08)	(3.24)	(-0.17)
Productivity ratio	0.00	-0.01	0.00	0.00	-0.03	0.00
	(0.24)	(-0.80)	(0.64)	(0.24)	(-1.61)	(0.60)
Asset/Liability	-0.46***	-0.04	-0.22***	-0.44***	-0.03	-0.20***
	(-4.68)	(-1.46)	(-9.29)	(-3.28)	(-0.59)	(-4.73)
Corporate CU	-0.02***	0.01***	-0.00	-0.02***	0.02***	-0.00
	(-3.12)	(3.34)	(-0.43)	(-4.09)	(5.45)	(-1.26)

Table 8: Results from System GMM Regressions: Continues

	Panel A (Year < 2012)[a]			*Panel B (Entire study period)*		
	FCU	FISCU	Whole Sample	FCU	FISCU	Whole Sample
Intercept	0.41	-0.99***	-1.10***	1.81***	-0.80***	-0.89***
	(0.74)	(-6.97)	(-8.21)	(3.47)	(-5.33)	(-7.48)
Observations	14,361	24,695	39,056	9,044	14,949	23,993
Number of CUs	850	916	1,766	850	916	1,766

Note: This table presents the results from Arrellano–Bover/Blundell–Bond dynamic panel (System GMM) regressions of efficiency score (*ESCORE*) of the sample Federal Credit Unions (FCUs) and Federally Insured State-Chartered Credit Unions (FISCUs) on the selected variables defined previously in Table 1. Panels A and B report the results for the period before 2012 and the entire study period, respectively. In the Whole Sample models, we include the variable *FCU* and its interactions with *Recession* and with *Post*, respectively. We report *z*-statistics calculated from robust standard errors in parentheses. We perform Wald tests to check for statistical significance of the full effects of *FCU*, *Recession*, and *Post* when considering the interaction variables. As in tables 6 and 7, all the *p*-values are less than 0.001 (unreported to save space).
[a] Estimation with only one lag of efficiency score was not feasible on the entire study period, probably because the entire study period does not include the 2012 quarters 1 and 2.
*, **, *** These symbols indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

VII. Conclusion

This study contributes to the literature on performance efficiency and the comparison of performance efficiency between the two different types of credit unions using a non-parametric Data Envelopment Analysis (DEA). We construct a measurement of efficiency using a DEA approach, test the impact of the 2007-2009 recession on a sample of U.S. credit unions, and compare the efficiency scores of FCUs and FISCUs over the pre-recession, recession, and post-recession periods.

We find that larger credit unions and credit unions with lower loan loss provision are more efficient. Overall, our results from Panel Fixed-Effects and Tobit regressions imply that, despite the CUs' non-direct reliance to the financial markets, the sluggish economy during and after the recession decreased their performance efficiency. Despite investors' flight to safety, that could have improved their performance, CUs were certainly affected by the increased number of business failures and home foreclosures, and the higher unemployment rate.

We also provide evidence that FISCUs were more efficient than FCUs before the recession. This latter finding is consistent with the FISCUs' advantages from the involvement of state government and the flexibility of state regulations, noted by NASCUS (2008). However, we further document that the recession impacted FCUs and FISCUs differently. During and after the recession, FCUs appeared to be more efficient than their state-charted counterparts. Both FISCUs and FCUs are insured by NCUSIF and NCUA has adopted a 12-month examination cycle to detect problems in order to protect FCUs and FISCUs from failures. However, it could be the case that FCUs were more closely monitored by NCUA than FISCUs, which are primarily overseen by the state supervisory authorities.

Our findings still hold when replicating the analyses using Generalized Linear Model (GLM) and System Generalized Method of Moments (GMM) regressions. These outcomes indicate that not-for-profit and cooperative CUs play important role for the participants, federal and state governance, and policy makers. We acknowledge that the changes in CUs' performance efficiency around the 2009 global recession reported in this study could also be due to policy changes triggered by the recession rather than the recession itself. Areas for further research would include the impact of regulatory changes on CU performance, further analysis of differences between credit unions, and comparisons of CU performance with microfinance institutions and other financial institutions.

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Top Management Team Pay and Company Performance Before and After Say-on-Pay

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Top management team pay rose enough to cause an outcry that resulted in companies having to offer shareholders nonbinding say-on-pay votes to approve or disapprove pay beginning in 2011. The votes were supposed to reduce excessive pay, but tests of their efficacy have not yet appeared. This paper tests the efficacy of the votes by examining top management team pay before and after the say-on-pay mandate. Our model explains top management team pay with company characteristics using fixed effects regression and robustness checks. Results from a sample of large U.S. companies suggest that both nominal and real pay fell in the five years before say-on-pay, but do not suggest that pay either fell or rose in the five years after say-on-pay.

Keywords: Compensation, Company Performance, Say-on-Pay Votes, Corporate Governance, Managerial Power, Optimal Contracting

JEL Classification: G340, J310, J330

I. Introduction

Top management team pay become controversial due to a perceived unfairness to stakeholders, supported by evidence of a mismatch between company performance and top management team pay (Murphy, 1999; Boyer, 2005). According to an Economic Policy Institute report, from 1978 to 2016, chief executive officer pay rose over 900 percent, while typical worker pay increased just over 10 percent (Mishel and Schieder, 2017). In addition, the rise in chief executive officer pay was 70 percent higher than the rise in the stock market. This occurred while there seemed to be no scarcity of human capital for executive positions – the annual supply of executive talent reported by the Digest of Education Statistics shows increases in the number of Master's degrees awarded in business from over 57,000 in the 1980-81 academic year to over 191,000 in the 2011-2012 academic year. Adding to the controversy were studies that said top management power increased (Bayless, 2009; Benson and Davidson, 2010; Nyberg *et al.*, 2010;

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Boyer, 2005; Bebchuk and Fried, 2006), and that the power may override board governance of pay (Bebchuk and Fried, 2006). However, evidence suggests that shareholders value pay for performance (Krause *et al.*, 2014), which prompted a demand for stockholder participation in corporate governance that culminated in a say-on-pay voting requirement.

Many studies have examined executive and top management team pay compared to company performance, although none have yet examined the impact of say-on-pay voting on the pay from a sample of companies. The studies fueled a controversy, because some suggest performance does not explain pay, while others suggest that performance does explain pay. Studies that suggest performance does not explain pay say: performance is not linked to pay (Gong *et al.*, 2011); board oversight is lax (Bebchuk and Fried, 2006; Mangen and Magnan, 2012); pay from stock options creates incentives for top management to manipulate short-term stock prices (Bebchuk and Fried, 2006); shareholder intervention is needed to monitor pay (Root, 2004); pay from stock removes the link between pay and performance due to irrational stock price movements (Bogle, 2008); and pay disclosures are manipulated to get shareholder approval (Mangen and Magnan, 2012). Studies suggesting that performance explains pay say: pay attracts, retains, and motivates top management (Ellig, 2002; Valenti, 2013; Conyon, 2006; Agarwal, 2010); pay from stock and options motivates top management to increase stock values (Jayaraman and Milbourn, 2012); models capturing real-life settings explain pay (Edmans and Gabaix, 2009; Filatotchev and Allcock, 2010); pay aligns with company performance and size, compensation committees, and consultants are independent, and say-on-pay votes usually approve pay (Gong, 2011; Hemphill, 2012; Conyon, 2014); efficient labor markets control pay (Murphy and Zabojnik, 2004; Gabaix and Landier, 2008; Weiss, 2011; Cao and Wang, 2013); a moral limit prevents top management from accepting excessive pay (Moriarty, 2009); compensation programs generating shareholder value explain pay (Schneider, 2013); and institutional investors are monitoring pay (Ellig, 2014).

Even though research never settled the controversy, the outcry over excessive pay became acute during the 2009 financial crisis (Mangen and Magnan, 2012). The crisis drew attention to corporate governance and led to passage of the Dodd-Frank Wall Street Reform and Consumer Protection Act in 2010 (Dodd-Frank). Dodd-Frank made all U.S. public companies offer shareholders nonbinding say-on-pay votes that approve or disapprove top management team pay (Dodd-Frank, Subtitle E, Section 951). Enforcement of the requirement went to the Securities and Exchange Commission (SEC), which made say-on-pay votes mandatory at all shareholder meetings after January 21, 2011. In anticipation of say-on-pay votes, shareholders receive pay justifications from companies that could be biased (Mangen and Magnan, 2012). Therefore a need exists to test the extent to which say-on-pay may have produced its intended result. However, no studies were found that examined the impact of the new say-on-pay mandate on top management team pay. Our study examines the impact of say-on-pay on top management team pay after considering company performance and control variables by looking at pay from a sample of large companies both five years before and five years after the introduction of say-on-pay with fixed effects regression and robustness checks. The contribution of our study is that it could be the first look at the impact of say-on-pay on top management team pay.

II. Theory and Hypotheses

The theory behind our model uses elements of both Optimal Contracting Theory and Managerial Power Theory (Conyon, 2014). Optimal Contracting Theory says boards act for shareholders in arms-length negotiations to set top management team pay (Bebchuk and Fried, 2006), but testing has mixed results (Weiss, 2011). Stock price reactions to say-on-pay voting requirements suggest some pay was excessive (Cai and Walkling, 2011), and pay should have had a stronger relationship to economic profit (Farris *et al.*, 2014). Yet pay appears related to market capitalization, earnings, and sales (Gabaix and Landier, 2008). Special recognitions explain pay but did not reveal a direct benefit to shareholders (Wade *et al.*, 2006). Some actions, such as securitizing assets, might be good for companies without showing up in performance measures (Riachi and Schwienbacher, 2013). Although company size and industry classification partially explained pay (Farris *et al.*, 2014), some pay was high enough to compel organized efforts that led to pay reductions (Ertimur *et al.*, 2011). The mixed results from testing Optimal Contracting Theory led to the development of Managerial Power Theory. Managerial Power Theory says existing corporate governance mechanisms do not allow optimal contracting due to managerial power (Bebchuk and Fried, 2006), partial ownership (Jensen and Meckling, 1976), and imperfect labor and capital markets (Mortensen, 1986). Say-on-pay voting enhances existing mechanisms because say-on-pay expands pay governance to include shareholders. After say-on-pay, shareholders were able to cast a nonbinding vote on top management team pay, strengthening optimal contracting and controlling managerial power. Of special interest is whether say-on-pay was successful in enhancing corporate governance and reducing excessive pay, which is the focus of our study. Our study uses variables that should justify top management team pay. Justification exists if there is a positive association between pay and market capitalization because management makes decisions that impact stock prices and should be paid according to the stock price impact of those decisions. Top management teams that make decisions leading to higher stock prices should get higher pay, and those that make decisions that lead to lower stock prices should get less pay. However, stock prices may not reflect all efforts by top management teams to increase company value (Dutta and Reichelstein, 2005; Bogle, 2008; Victoravich, 2010; Chen *et al.*, 2015). For example, market capitalization may not fully reflect larger operating margins through product differentiation or strong branding that increase earnings, or smaller operating margins that increase sales. Thus, shareholders should be willing to pay top management teams more for higher market capitalizations but should also be willing to pay more for decisions leading to higher intrinsic company values regardless of market capitalization. Therefore market capitalization, earnings, and sales provide opportunities to test for the alignment of top management team pay with company performance:

Hypothesis 1. Top management team pay has a positive relationship to market capitalization.
Hypothesis 2. Top management team pay has a positive relationship to earnings.
Hypothesis 3. Top management team pay has a positive relationship to sales.

In addition to examining the impact of company performance on top management team pay in the period before and the period after say-on-pay, it is especially useful to see if say-on-pay had any effect on limiting top management team pay. Evidence of a limiting effect exists if top management team pay, after considering company performance and control variables, fell or did not increase beyond the rate of inflation after say-on-pay voting was required. In addition, if the pay rose before say-on-pay but fell afterwards, strong support for the intended efficacy of say-on-pay exists. However, even a decrease in pay before say-on-pay could say something about the concern building for a governmental response to the outcry surrounding top management team pay. Therefore, the change in the base level of top management team pay before and after say-on-pay is considered to look for evidence of the impact of say-on-pay:

Hypothesis 4. The change in top management team pay after say-on-pay is less than the change in inflation.

After considering company performance and control factors, top management team pay changes below the rate of inflation after say-on-pay suggest to policymakers and investors that corporate governance is more effective because of say-on-pay. Alternatively, pay changes above the rate of inflation after say-on-pay suggest that say-on-pay was not as effective as some hoped in the effort to limit excessive pay, and more action may be necessary to strengthen corporate governance.

III. Methodology

The methodology section includes descriptions of our data samples, variable measures, and variable analyses.

A. Data Samples

The samples for this study include companies in the Dow Jones Industrial Average (DJIA) index as of year-end 2016. The DJIA is a price-weighted index of 30 U.S. blue-chip companies, created by Charles Dow in May of 1896, and produced by S&P Dow Jones Indices LLC (S&P). S&P produces the index with three people from S&P and two from The Wall Street Journal who respond at any time to company actions and market developments with decisions to replace companies in the index. Most companies in the index are on the New York Stock Exchange; however, four companies in the index are on the NASDAQ. Companies in the index are from all sectors except transportation and utilities. Companies chosen for the DJIA do not meet specific quantitative rules; however, they must pass standards for reputation, growth, investor interest, sector representation, and a headquarters, incorporation, and revenue base in the United States (S&P Dow Jones Indices, 2017). The DJIA stands for a much larger group of U.S. stocks because correlations between movements in the DJIA and larger stock indexes are high (CME Group, 2017). Therefore, companies in the DJIA give insight for many other companies. Also, the DJIA group of companies has a sample size adequate for making inferences.

The DJIA company data in our study are in two samples, one spanning five years before, and the other spanning five years after say-on-pay was first required in 2011. Using those samples allows for an analysis before, and another analysis after say-on-pay, looking at relationships between company performance and pay, and changes in the base level of top management team pay. Top management team pay data are from Execucomp. Data used to explain top management team pay are from Compustat, with a few missing observations extracted from Edgar. All data are from the same companies in the DJIA at the end of 2016 with data going back to 2006. Only one company of the 30 was excluded from our sample, Visa Inc., because it did not publicly trade until 2008 and therefore did not have complete data going back to 2006. Our sample includes seven companies that replaced others in the DJIA index over the time span of this study: Apple Inc. (entered the DJIA in 2015); The Goldman Sachs Group, Inc., Nike, Inc., UnitedHealth Group Incorporated (entered the DJIA in 2012); Cisco Systems, Inc. and The Travelers Companies, Inc. (entered the DJIA in 2009); and Chevron Corporation (entered the DJIA in 2008). All companies that entered the DJIA during the period of study have complete data sets for both samples. Companies removed from the DJIA are not in either sample. Company data are from the year in which a fiscal year ends. For example, Wal-Mart Stores, Inc.'s fiscal year ends in January, so the fiscal year ending January 2016 provided data identified as 2016.

B. Variable Measures

B.1. Dependent Variable

The dependent variable in the model for this study is *TMT Pay*. *TMT Pay* is pay to the top management team reported to the SEC in company DEF 14-A filings. Those filings usually show fiscal year compensation paid to five members of the top management team. Compensation includes salary, bonus, stock, options, retirement plan contributions, and perquisites, which captures the most extensive set of pay components publicly available. The top management team includes the chief executive officer, the chief financial officer, and the three other highest-paid executives. Analyzing pay from the top management team is better than analyzing pay to only the chief executive officer, because pay for the team is less likely to have outliers than pay to a single executive. The dependent variable is not adjusted for inflation over the period of study because the test and control variables should be impacted by inflation in roughly the same way as the dependent variable.

B.2. Test Variables

The test variables in our model are *Market Cap*, *Earnings*, and *Sales* obtained from Compustat. *Market Cap* is market capitalization, the market price of company common stock multiplied by the number of shares outstanding at fiscal year-end (Bayless, 2009; Gabaix and Landier, 2008; Cao and Wang, 2013). Market capitalizations are as of each company's fiscal year-end. *Earnings* is the net income for a company's fiscal year (Gabaix and Landier, 2008). *Sales* is gross revenue for the company's fiscal year (Benson and Davidson, 2010; Balsam *et al.*, 2011; Gong, 2011; Cao and Wang, 2013; Conyon 2014). All three test variables indicate better performance for shareholders when they increase, so positive associations are expected between *TMT Pay* and each test variable. Test variables are also unadjusted for inflation because all three variables should be impacted approximately the same by changes in inflation.

B.3. Control Variables

The control variables in our model are *Financing Costs, Company Size,* and *Market Risk*. These variables control rather than produce pay. *Financing Costs* are cash dividends on stock plus interest on debt, extracted from Compustat. Cash dividends may directly increase market capitalizations by the discounted value of expected dividends, but dividends could also limit executive pay by forcing executives to conserve cash for dividends (Easterbrook, 1984; Bhattacharyya *et al.*, 2008). In a similar way, interest on debt may also limit executive pay to conserve cash for interest payments (Jensen, 1986). Therefore dividends and interest are financing costs that might control pay and have a negative association to pay. *Company Size* is total company assets at fiscal year-end, also extracted from Compustat. Total company assets controls pay because top management should expect pay in direct proportion to the dollar value of assets managed, but greater total assets do not always signal greater performance (Cao and Wang, 2013; Waldron *et al.*, 2013; Fong *et al.*, 2015). Thus, total assets should have a positive association to pay. *Market Risk* is the annual Scholes-Williams beta for each company, taken from CRSP (Lippert and Porter, 1997), which should have a positive association to pay since it may take additional pay for executives to work for a riskier company. Some studies have also used an industry variable as a control variable (Lippert and Porter, 1997; Firth *et al.*, 2007). However, the fixed effects specification employed in our study makes an industry control variable unnecessary, since industry does not change for companies in our study, which was verified for our samples. In addition, *Financing Costs* and *Company Size* are not adjusted for inflation because both are denominated in dollars and should change approximately the same as the dependent and test variables. *Market Risk* was not adjusted for inflation because the market risk premium in the betas should account for inflation.

C. Variable Analyses

All four hypotheses are best suited for testing using a fixed-effects regression because so many company-specific variables, such as industry, are difficult to explicitly include in the analysis, and are implicitly considered in the fixed-effects specification (Benson and Davidson, 2010; Conyon, 2014). However, cross-correlation of the errors might not allow the use of a fixed-effects specification. Therefore a Pesaran test was applied to all nominal values of the variables in a combined sample spanning 2006 through 2016 to test for cross-sectional correlation (dependence) of the errors and produced a CD statistic of -0.008 with an insignificant *p*-value (0.994), suggesting that cross-sectional correlation of the errors is not a problem. In addition, a Hausman (1978) specification test applied to the same sample to compare the need for a random-effects specification to the need for a fixed-effects specification resulted in a Chi-square statistic of 6.95 with a significant *p*-value (0.0084), suggesting the rejection of a random-effects specification in favor of a fixed-effects specification. The fixed effects specification is used with two samples: one spans five years before say-on-pay and requires changes in variables from 2006 to 2010, and the other spans five years after say-on-pay and requires changes in variables from 2012 to 2016. Variable changes were transformed to percentage changes in decimal form because nominal changes had more outliers. The coefficients on the three test variables are tests of the first three hypotheses by giving estimates of how changes in company performance predict changes in top management team pay. The intercepts in the fixed effects regressions test the fourth hypothesis by giving an estimate of the change in base pay with no change in a performance or control variable. All regressions test for outliers with Cook's D statistic using a common critical value of 0.80. All regressions check for multicollinearity by reporting variance inflation factors that show the potential for a problem, and address multicollinearity with a final regression for each sample using the stepwise procedure to reduce the influence of multicollinearity on the estimated coefficients.

IV. Results

Results are from two different samples examining top management pay and looking for changes in the base levels of pay during two different time periods. The first time period covers five years before say-on-pay, and the second time period covers five years after say-on-pay. Neither sample includes 2011, the year say-on-pay was first required to be offered to shareholders. For both samples, descriptive statistics are in Table 1, correlations are in Table 2, fixed effects regressions are in Table 3, robustness checks using nominal value regressions are in Table 4, and nonparametric robustness checks are in Table 5.

Descriptive statistics in Table 1 show means, trimmed means, standard deviations, minimums, medians, and maximums for each variable, in both the sample before say-on-pay (Period = Before) and the sample after say-on-pay (Period = After). The means for the *TMT Pay* variable suggest that top management team pay increased more after say-on-pay (22.0 percent increase) than it did before say-on-pay (16.5 percent increase). However, the trimmed means (without the top and bottom five percent of values) and medians suggest something different. The *TMT Pay* trimmed means and medians are smaller after say-on-pay. In addition, all variables have trimmed means and medians that are smaller than their means, and standard deviations are greater than their respective means for all variables, which suggests the presence of outliers and the need to identify them for removal, which is done in each regression using Cook's D test.

Table 1: Descriptive Statistics Before and After Say-on-Pay

Variable	Period	Mean	Trimmed Mean	Standard Deviation	Minimum	Median	Maximum
TMT Pay	Before	16.5%	15.4%	52.9%	-86.2%	11.2%	149%
	After	22.0%	12.2%	78.7%	-66.2%	9.2%	374%
Market Cap	Before	9.5%	1.1%	60.8%	-49.2%	-0.8%	295%
	After	39.9%	37.4%	41.2%	-26.6%	34.2%	176%
Earnings	Before	33.7%	16.8%	120%	-80.6%	17.2%	605%
	After	45.2%	0.5%	264%	-102%	-1.1%	1,400%
Sales	Before	24.2%	18.5%	47.8%	-33.7%	15.7%	238%
	After	-0.9%	-1.5%	26.7%	-53.6%	0.0%	67.1%
Financing Costs	Before	39.2%	33.0%	70.8%	-75.5%	32.8%	321%
	After	49.9%	38.2%	87.4%	-29.8%	24.0%	447%
Company Size	Before	44.7%	36.4%	67.2%	-23.2%	27.2%	337%
	After	8.0%	7.3%	26.0%	-46.7%	1.2%	82.7%
Market Risk	Before	10.5%	6.2%	56.7%	-59.5%	-3.5%	196%
	After	0.0%	-0.5%	24.7%	-40.6%	-5.1%	55.2%

Note: N = 29 for all variables in each period.
Period Before is before say-on-pay (2006 to 2010); After is after say-on-pay (2012 to 2016).
Trimmed Mean is the mean after removing the smallest and largest five percent of observations.

Pearson correlations of variable pairs are in Table 2a for the sample before say-on-pay and in Table 2b for the sample after say-on-pay. The tables have correlations that show relationships between all pairs of variables, starting with the dependent variable, *TMT Pay,* which is in the first column. The first column of correlations for the sample from before say-on-pay shows that all explanatory variables are significantly correlated to *TMT Pay.* However, the first column in the sample from after say-on-pay shows that no explanatory variables are significantly correlated to *TMT Pay*. This suggests that more variation in *TMT Pay* is likely to be explained by regressions in the sample from before say-on-pay than in the sample from after say-on-pay. In addition, correlations from both samples show many highly significant correlations between the test and control variables, which calls for measuring and addressing multicollinearity. Multicollinearity is measured by monitoring variance inflation factors in the regression output and addressed with the Stepwise technique to reduce the factors and the influence of multicollinearity on coefficient estimates.

Table 2a: Correlations of Variables Before Say-on-Pay

	TMT Pay	**Market Cap**	**Earnings**	**Sales**	**Financing Costs**	**Company Size**
Market Cap	0.443 (0.016)					
Earnings	0.514 (0.004)	0.880 (0.000)				
Sales	0.583 (0.001)	0.827 (0.000)	0.796 (0.000)			
Financing Costs	0.500 (0.006)	0.224 (0.242)	0.253 (0.186)	0.320 (0.091)		
Company Size	0.556 (0.002)	0.834 (0.000)	0.793 (0.000)	0.934 (0.000)	0.276 (0.148)	
Market Risk	0.156 (0.418)	-0.107 (0.581)	-0.019 (0.920)	-0.046 (0.814)	0.062 (0.747)	-0.052 (0.787)

N = 29. Pearson correlations with *p*-values below them in parentheses.

Table 2b: Correlations of Variables After Say-on-Pay

	TMT Pay	Market Cap	Earnings	Sales	Financing Costs	Company Size
Market Cap	-0.030 (0.877)					
Earnings	0.018 (0.927)	0.261 (0.172)				
Sales	0.048 (0.803)	0.634 (0.000)	0.204 (0.288)			
Financing Costs	-0.209 (0.276)	0.117 (0.545)	0.102 (0.597)	0.533 (0.003)		
Company Size	-0.107 (0.582)	0.337 (0.074)	0.066 (0.733)	0.645 (0.000)	0.786 (0.000)	
Market Risk	-0.080 (0.680)	0.399 (0.032)	0.021 (0.914)	0.509 (0.005)	-0.023 (0.906)	0.165 (0.392)

N = 29. Pearson correlations with *p*-values below them in parentheses.

Fixed effects regression results are in Table 3a for the five-year sample from before say-on-pay was required, and results are in Table 3b for the five-year sample from after say-on-pay was required. The results for each sample include output from three fixed effects regressions using maximum likelihood estimation (MLE). MLE is used because it is asymptotically more efficient than the minimum distance estimator as discussed in Hsiao *et al.* (2002). The results from using all sample observations are in the first column of both tables 3a and 3b; results that used observations after removing outliers that had Cook's D values that exceeded 0.80 are in the second column; and results that applied the Stepwise technique to observations after removing outliers are in the third column.

Results from using the sample of companies before say-on-pay reveal potential distortions from outliers and multicollinearity. Results from using all observations cast doubt on the first three hypotheses: significant positive relationships between top management team pay (*TMT* Pay) and market capitalization (*Market Cap*), earnings (*Earnings*), and sales (*Sales*) are not evident, even though the F-statistic of the regression is significant at a 0.05 percent confidence level. However, by removing outliers and limiting the impact of multicollinearity using the Stepwise technique, the second hypothesis is supported: top management team pay and company earnings are significantly and positively related. Another example of distortion appears in testing Hypothesis 4. Testing Hypothesis 4 looks at the intercept terms from the fixed effects regressions that estimate the change in top management team pay without the impact of explanatory variables. In the results from the sample before say-on-pay, the intercept using all observations is insignificant. However, after removing outliers and using the Stepwise procedure, the intercept is significant at the 0.05 percent confidence level, and negative, showing an estimated drop in the base level of top management pay of 21.7 percent, without considering the impact of performance or control variables. A look at the reductions in the variance inflation factors from removing outliers, and additional reductions from using the Stepwise technique, show the reduction of potential multicollinearity distortions and increase the usefulness of the results.

Results from using the sample of companies after say-on-pay show distortions from outliers and multicollinearity severe enough to render insignificant both the regression from all observations and the regression from the observations without outliers. However, after mitigating the impact of multicollinearity by applying the Stepwise technique, the regression is significant at the 0.05 confidence level. Without outliers and using the Stepwise technique, support exists for Hypothesis 1, from a significant and positive relationship between top management team pay (*TMT Pay*) and company market capitalization (*Market Cap*). Support for Hypothesis 2 and Hypothesis 3 is not evident. However, Hypothesis 4 is supported because the intercept fails to show that the base level of top management team pay rose above the inflation rate in the sample after say-on-pay.

Table 3a: MLE Fixed Effects Regressions Explaining TMT Pay Before Say-on-Pay

Predictors	All Observations	Outliers Removed	Outliers Removed Stepwise
Intercept	-0.115	-0.229	-0.217
	(0.338)	(0.056)	(0.045)
Market Cap	-0.247	-0.094	
	(0.453)	(0.763)	
	[6.00]	[1.20]	
Earnings	-0.123	0.508	0.593
	(0.413)	(0.015)	(0.001)
	[4.88]	[1.32]	[1.04]
Sales	0.350	0.304	
	(0.487)	(0.556)	
	[8.74]	[2.90]	
Financing Costs	0.247	0.123	
	(0.052)	(0.304)	
	[1.13]	[1.30]	
Company Size	0.150	0.656	0.938
	(0.672)	(0.127)	(0.000)
	[8.69]	[3.09]	[1.04]
Market Risk	0.126	0.101	
	(0.391)	(0.443)	
	[1.04]	[1.05]	
F	3.60	4.35	12.49
	(0.012)	(0.006)	(0.000)
Adj. r-square	35.80%	43.61%	46.91%
N	29	27	27

Variables are changes from 2006 to 2010 in decimals.
Outliers removed were AAPL and KO which had Cook's D statistics exceeding 0.80.
p-values are in parentheses below coefficient estimates.
Variance Inflation Factors are in brackets below *p*-values.

Table 3b: MLE Fixed Effects Regressions Explaining TMT Pay After Say-on-Pay

Predictors	All Observations	Outliers Removed	Outliers Removed Stepwise
Intercept	0.698	-0.039	0.002
	(0.037)	(0.835)	(0.986)
Market Cap	-0.534	0.447	0.389
	(0.319)	(0.139)	(0.044)
	[2.02]	[2.24]	[1.01]
Earnings	0.0062	0.256	
	(0.919)	(0.446)	
	[1.11]	[3.70]	
Sales	1.92	-0.582	
	(0.091)	(0.520)	
	[3.67]	[9.63]	
Financing Costs	-0.554	-0.164	-0.1436
	(0.096)	(0.348)	(0.097)
	[3.37]	[3.77]	[1.01]
Company Size	0.32	0.323	
	(0.771)	(0.565)	
	[3.37]	[3.47]	
Market Risk	-1.060	-0.123	
	(0.191)	(0.778)	
	[1.64]	[1.91]	
F	0.83	1.23	3.44
	(0.560)	(0.334)	(0.049)
Adj. r-square	0.00%	4.98%	15.78%
N	29	27	27

Variables are changes from 2012 to 2016 in decimals.
Outliers removed were VZ and WMT which had Cook's D statistics exceeding 0.80.
p-values are in parentheses below coefficient estimates.
Variance Inflation Factors are in brackets below *p*-values.

As a check for robustness of the fixed effects regression results, nominal values from both samples were used in an MLE regression that contained a binary variable to test for a change in top management team pay from the five years before to the five years after say-on-pay votes were required to be offered. This approach involved using 290 observations, since there are 29 companies in each year of the two five-year samples. The results are in Table 4 and show three regressions: one with all observations, another after removing several outliers, and still another that applied the Stepwise technique to the subsample after removing the outliers. The significance of the regression (F-statistic), explanatory ability of the regression (adjusted r-square), and variance inflation factors (VIF) all improve by removing outliers and applying the Stepwise technique. The Stepwise technique results support Hypothesis 2 with a significantly positive relationship between top management pay (*TMT Pay*) and company earnings (*Earnings*) and support the result found for the fixed effects regression done in the sample of companies from before say-on-pay. The Stepwise technique results also support Hypothesis 4, due to the absence of the binary variable *Period*. *Period* was coded zero for company data in the five years before say-on-pay (2006 through 2010), and one for company data in the five years after say-on-pay (2012 through 2016). The insignificance of the *Period* variable is consistent with the insignificance of the intercept term in the fixed effects regression using the sample from after say-on-pay. Both MLE regression and fixed effects MLE regression results suggest that base level top management team pay did not increase at a rate greater than inflation in the five years after say-on-pay was required to be offered to company shareholders.

A final check for robustness of the fixed effects regression results used several rudimentary nonparametric tests on the top management pay variable, *TMT Pay*. The results from the nonparametric robustness checks are in Table 5. The first test was a Mood's Median test, chosen for its minimal sensitivity to outliers, that looked for a significant difference in the median of the *TMT Pay* variable before say-on-pay compared to the median of the *TMT Pay* variable after say-on-pay. Although the *TMT Pay* median after say-on-pay is lower than the median before say-on-pay, the difference in the medians is not significant. This supports the fixed effects regression results which did not have evidence that top management pay was higher after say-on-pay was required.

Another robustness check involved two Runs tests, chosen because the test looks merely at the number of changes showing up in the sample data above or below a predetermined cutoff. The first Runs test was on *TMT Pay* from the sample using observations before say-on-pay, and the second Runs test was on *TMT Pay* from the sample using observations after say-on-pay. A Runs test attempts to reject randomness in the data, which in this case compared the number of variable values above a prescribed cutoff to the number below a cutoff. The prescribed cutoffs for the two tests are the increase in the CPI in the time period covered by each sample. In the sample before say-on-pay, the period is January 2006 to December 2010, and the cutoff is 0.1053, obtained using the CPI Inflation Calculator found at the U.S. Bureau of Labor Statistics website. For the sample after say-on-pay, the period is January 2012 to December 2016, and using the same CPT Inflation Calculator, the cutoff is 0.0651. Thus the Runs tests looked for evidence of nonrandom occurrences of *TMT Pay* values above and below the inflation change cutoffs for each sample. Nonrandom occurrences could not be rejected in either sample by the Runs tests. This does not support the fixed effect regression results from before say-on-pay that suggested a decrease in top management pay, but it does support the findings of the fixed effect regression using the sample after say-on-pay where no change in pay was evident.

Table 4: MLE Regression Robustness Check

Predictors	All Observations	Outliers Removed	Outliers Removed Stepwise
Intercept	17,167,342	23,295,697	24,106,969
	(0.012)	(0.000)	(0.000)
Market Cap	0.000045	-0.000000	
	(0.252)	(0.997)	
	[4.82]	[4.68]	
Earnings	0.000125	0.000360	0.000464
	(0.798)	(0.363)	(0.022)
	[4.86]	[4.64]	[1.21]
Sales	0.000046	0.000010	
	(0.084)	(0.666)	
	[1.70]	[1.76]	
Financing Costs	0.001124	0.001501	0.001642
	(0.004)	(0.000)	(0.000)
	[2.18]	[2.22]	[1.26]
Company Size	0.000005	0.000004	
	(0.415)	(0.448)	
	[2.12]	[2.12]	
Market Risk	16,385,124	14,457,401	15,331,276
	(0.009)	(0.005)	(0.001)
	[1.21]	[1.22]	[1.07]
Period	4,414,661	3,405,724	
	(0.270)	(0.293)	
	[1.12]	[1.12]	
F	11.78	14.92	34.37
	(0.000)	(0.000)	(0.000)
Adj. r-square	20.70%	25.35%	25.86%
N	290	288	288

Variables are nominal values for 2006 thru 2010 and 2012 thru 2016.
Outliers removed were AAPL in 2012 and WMT in 2016 which had Cook's D statistics exceeding 0.80.
p-values are in parentheses below coefficient estimates.
Variance Inflation Factors are in brackets below *p*-values.

Table 5: Nonparametric Robustness Checks

Mood's Median Test: *TMT Pay* Before and After Say-on-Pay

Period	Median	N <= Overall Median	N > Overall Median	95% Median CI
Before	0.112	14	15	(-0.022, 0.345)
After	0.092	15	14	(-0.103, 0.258)
Overall	0.107			

Null hypothesis H_0: The population medians are all equal

Alternative hypothesis H_1: The population medians are not all equal

DF	Chi-Square	*p*-Value
1	0.07	0.793

Note: Period is Before for *TMT Pay* before Say-on-Pay, and After for *TMT Pay* after Say-on-Pay

Runs Test: TMT Pay Before Say-on-Pay

N	K	Number of Observations ≤ K	Number of Observations > K
29	0.1053	14	15

Null hypothesis H_0: The order of the data is random

Alternative hypothesis H_1: The order of the data is not random

Number of Runs Observed	Number of Runs Expected	*p*-Value
12	15.48	0.187

Note: K is the increase in the CPI from January 2006 to December 2010 calculated using the CPI Inflation Calculator found at the U.S. Bureau of Labor Statistics website.

Runs Test: TMT Pay After Say-on-Pay

N	K	Number of Observations ≤ K	Number of Observations > K
29	0.0651	14	15

Null hypothesis H_0: The order of the data is random

Alternative hypothesis H_1: The order of the data is not random

Number of Runs Observed	Number of Runs Expected	*p*-Value
14	15.48	0.574

Note: K is the increase in the CPI from January 2012 to December 2016 calculated using the CPI Inflation Calculator found at the U.S. Bureau of Labor Statistics website.

V. Discussions

Discussions are necessary to examine our results based on theory, interpret our results as having some policy implications for corporate governance, and qualify our results by suggesting some limitations of the study that call for more research.

The Optimal Contracting Theory suggests that mechanisms already existed to control top management pay. This theory has support from our findings that company performance measured by market capitalization and earnings are positively associated with top management team pay. The theory also has support from our findings that the control variables of company size measured by total assets and company risk measured by beta are positively associated with pay. Still further support for the theory comes from our findings that show company cash flow commitments measured by interest and dividend expense are negatively associated with pay. However, all these measures together only explain a small fraction of the variation in top management team pay during either period in our study. Therefore say-on-pay seems justified as another corporate governance mechanism helping to control excessive top management pay. The issue then is if say-on-pay was an effective corporate governance mechanism.

A conclusion about the effectiveness of say-on-pay should consider Managerial Power Theory and our results. Our results support the Managerial Power Theory because after say-on-pay voting was required to be offered to shareholders, top management pay becomes more of a mystery. The ability of the fixed effects regression model to explain top management team pay is much greater before the say-on-pay voting requirement than after the requirement. The only performance measure significant after the requirement is market capitalization, and the only control measure significant after the requirement is financing costs. Performance factors thought to justify pay, such as earnings and sales, do not explain pay after say-on-pay. Factors thought to control pay, such as company size and market risk, do not explain pay after say-on-pay. In addition, while correlations of top management pay with all three company performance measures and two of the three control measures are significant before say-on-pay, after say-on-pay no company performance variable nor any control variable is significantly correlated with top management pay. More support for the Managerial Power Theory comes from the fact that our results suggest that base level top management team pay did not increase after the say-on-pay requirement was instituted. This is surprising given that the Consumer Price Index rose by over six and a half percent in the study period after the say-on-pay requirement, which is the increase necessary for top management teams to maintain the value of their pay. Thus it is possible that say-on-pay prevented an increase in top management team pay, even one that would have maintained the value of pay, by curbing managerial power.

The policy implications of finding no evidence that top management pay increased after the say-on-pay requirement are straightforward. The nonbinding say-on-pay vote could have been successful in controlling top management team pay. Of course, we cannot conclude that the vote had any effect on pay, since no evidence of a pay increase in the five years after say-on-pay could have occurred without say-on-pay. Our results simply suggest that an undetected increase is a step in the right direction for those who believe pay is excessive. Of course, those who believe pay is still excessive might want to see say-on-pay become a binding vote in the hopes that pay reductions will ensue through greater shareholder participation.

An important limitation of our study is that our regressions do not explain most of the variation in top management team pay in our samples. This suggests that some explanatory variables may be missing from our model, which calls for more research to look for other variables that explain top management team pay. Another possible limitation is that economies of scale could justify *nonlinear* relationships between executive pay and some explanatory variables that would increase the explanation of variation in pay. For example, as some explanatory variables increase, top management team pay might increase, but at a decreasing rate. Finally, samples from other time periods should be used to check for robustness across different economic conditions and regulatory climates. Therefore our results are only suggestive since this is the first known study to explore the impact of say-on-pay on top management team pay, requiring more research to verify our results.

In conclusion, while our study hardly settles the executive pay controversy, it offers some evidence to suggest that say-on-pay did have the intended impact on top management team pay. Our results suggest keeping say-on-pay at least as a non-binding vote, and giving consideration to making the vote binding. In addition, our results suggest the need to find other factors that explain top management team pay in the period after say-on-pay.

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Flat Versus Graduated Tax Regimes: Economics-Based vs. Psychology-Based Explanations for Individual Preferences

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This study examines preference for a method of taxation under two competing theories; standard economic theory and optimism bias. Specifically, we focus on the contradiction between the tax rate structure taxpayers claim to favor when their decision does not involve self-interest, and the tax rate structure they actually choose when the decision does involve self-interest. We find that participants favor a flat tax rate over graduated tax rates in significantly higher proportions when the choice involves self-interest as opposed to a setting without self-interest.

Keywords: Flat Tax, Graduated Tax, Economic Theory, Optimism Bias

JEL Classification: M4

I. Introduction

Taxpayer preference for a method of taxation likely involves at least two related factors - the effect of the method of taxation on society and the economy (public interest) and the effect of the method of taxation on the individual (self-interest). Recent polling data captures the complexity of preferences related to a method of taxation. A 2013 Gallup poll finds “The majority of Americans believe that money and wealth in the U.S. should be more evenly distributed, and a slight majority support the idea of the government helping to achieve that goal by ‘heavy’ taxes on the rich.” However, many other polls indicate strong public support for a flat tax (Reason-Rupe Poll, 2014; Rasmussen Reports, 2012), which prior studies have shown would result in *lower* marginal tax rates on high-income individuals (Slemrod, 2006; Piotrowski and Guyette, 2011). If the public generally believes that the U.S. should have a more even income redistribution, support for a flat tax rate is puzzling.

In this study, we conduct an experiment in which participants choose whether to have income taxed using a flat tax rate structure or a graduated tax rate structure. In the control group, the participants *recommend* a revenue-neutral method of taxation (either a flat tax rate or graduated tax rates) for a specific type of high variance taxable income that individuals within their geographical area may receive (there is little or no self-interest involved in the decision). In the control group, the after-tax monetary payment for the participants is constant regardless of the participants’ recommendation for tax structure.

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The test condition introduces self-interest, as the participant is informed that they have received a specific type of high variance taxable income and must *choose* which tax rate structure to apply to their income. The participants' after-tax monetary payment depends both on chance and on their choice of tax rate structure (either a flat tax rate or graduated tax rates). The after-tax expected value for participants under either tax structure - flat or graduated – is equal (see footnote 8). However, the variance of the after-tax income depends on the choice of tax structure and, as we demonstrate, the variance is higher under the flat tax regime.

We develop predictions to explain taxpayer preferences for a method of taxation. According to standard economic theory, all else being equal, people should prefer less risk and lower variance in outcomes (Markowitz, 1952).[1] A flat tax will produce after-tax outcomes with a higher variance than a graduated tax with the same expected value. This is because graduated tax rates reduce variance by increasing after-tax returns when outcomes are below average, and decreasing after-tax returns when outcomes are above average. Therefore, under economic theory, it is logical to predict taxpayers will select the method of taxation with lower risk.

However, standard economic theory fails if people do not understand variance. March and Shapira (1987) find that managers exhibit risk preferences that do not align with conventional decision theory. Further, certain psychological biases support taxpayer preferences for a flat tax regime when their self-interest is at stake. For example, Helweg-Larsen and Shepperd (2001) define optimism bias as the belief that you are less likely to experience a bad event and more likely to experience a good event than other people. Under this bias, people may *over*emphasize the probability of receiving a *high* level of income and *under*emphasize the probability of receiving a *low* level of income. Graduated tax rates will decrease after-tax income when income levels are above average, shifting preferences toward a flat tax. In other words, people may prefer a flat tax - where high levels of income are *not* taxed at a higher rate - because people believe they will likely receive high levels of income and want to maximize their after-tax returns.

We find the percentage of participants choosing a flat tax rate structure within the test group – when participants are choosing a method of taxation for themselves - is significantly higher than the percentage of participants choosing a flat tax structure within the control group – when participants are choosing a method of taxation for individuals within their state. Our results support the idea that people display optimism bias and choose the method of taxation that will result in the lowest tax liability when choosing a method of taxation for themselves.

The rest of the paper is organized as follows. Section II reviews the methods of taxation, and our predictions. Section III describes our experiment and results. Sections IV and V provide our discussion, conclusion, limitations and suggestions for future research.

II. Literature Review and Hypothesis

A. Flat Tax Rates and the Calculation of Taxable Income

Economists and politicians have been promoting flat rate income tax proposals for decades, and recently, prominent political figures have advocated variations of a flat tax as desirable public policy.[2] A flat tax is a single tax rate applied to a taxpayer's taxable income. A "pure" flat tax is

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[1] In this paper, we use the terms risk, variance in outcomes, and variance in returns interchangeably.

[2] Steve Forbes, Arlen Specter, Rand Paul, Rick Perry, Rick Santorum, Ben Carson, Ted Cruz, Herman Cain, Newt Gingrich, and David Camp have all supported flat tax proposals.

straightforward. There are no deductions, no exemptions, and no credits; the taxpayer multiplies his or her gross income by the tax rate to calculate the tax liability.

However, the large majority of flat tax proposals from economists and politicians do not describe a "pure" flat tax, but rather a "modified" flat tax, which includes changes to the tax rate structure, the definition of taxable income, and the allowable tax deductions. For example, a flat tax proposal may specify an income level beneath which no taxes are paid, and a small number of allowable deductions (e.g., charitable contributions and home mortgage deductions are common), and different rules (or different rates) for calculating business income. These proposals are actually two-rate systems (0% and the flat rate) rather than a pure single rate flat tax.

Flat tax proposals typically lack detail, making it difficult to determine whether taxpayer support for a flat tax is related to the simplified tax rate structure (one tax rate applied to taxable income instead of several tax rates), or to the elimination of many deductions and credits that can be used in sophisticated tax planning, or to a combination of these factors. In this experiment, we focus on tax rates, highlighting the simplified tax rate structure in a flat tax and excluding other variations in flat tax proposals such as the elimination of deductions and credits.

B. Graduated Tax Rates and the Calculation of Taxable Income

The U.S. currently uses graduated tax rates for individuals, which are applied to taxable income using tax brackets. Taxable income is divided into ranges, and each range is taxed at a higher rate than the range below. For example, the 2017 U.S. individual income tax brackets were 10%, 15%, 25%, 28%, 33%, 35%, and 39.6%.[3] As a taxpayer's taxable income enters a higher tax bracket, only the portion of income that falls into that bracket is taxed at the higher rate, with the remaining amount taxed according to the lower tax bracket(s). Taxable income is defined in the Internal Revenue Code and tax regulations issued by the Department of Treasury and the Internal Revenue Service. The U.S. tax code provides numerous exemptions, deductions, and credits, many of which have limits.

Slemrod (2006) argues that graduated tax rates are often misunderstood, and that misconceptions surrounding graduated tax rates are likely to play a large role in public support for a flat tax structure. In this experiment, we isolate the concept of tax rate structure – a flat tax rate vs. graduated tax rates – from the definition of taxable income. In the control group, the participants recommend that either a flat tax or graduated tax rates be applied to a specific amount of taxable income (either $1 or $3) individuals in their state may receive. In the test group, the participants are told they will receive a specific amount of taxable income (either $1 or $3), and then must choose whether to have that income taxed using a flat tax rate or graduated tax rates before the amount of taxable income is known. In both the test group and the control group, we define taxable income for the participants and ask for their tax rate structure preference.

Although we isolate the effect of tax rates from other factors, we acknowledge that some of our participants may have difficulty separating the general concept of calculating taxable income – which they may believe is fair or unfair, or in their self-interest or not – from the single concept of tax rate structure. We also acknowledge that some of our participants may perceive that a flat tax rate system would make it less costly to calculate taxes due, potentially saving time (and therefore money). We attempt to minimize this effect by including only three tax rates in our graduated tax rate regime.

[3] The Tax Cuts and Jobs Act of 2017 maintained a similar graduated-rate structure for individual taxpayers into 2018 and beyond. The 2018 rates are 10%, 12%, 22%, 24%, 32%, 35%, and 37%.

C. Polling Data and the Importance of Framing

In the U.S., public support for a flat tax has significant variation across studies. Several studies find that a majority of the public favor a flat tax. For example, Slemrod (2006) finds that 53% of survey respondents favor a flat tax, and Piotrowski and Guyette (2011) find that 53% of undergraduate and masters level business students in their sample favor a flat tax.[4] However, Brady and Frisby (2011) from the Hoover Institution at Stanford find a lower level of public support, as only 28% of their respondents express a preference for a flat tax. Keene (1983) reviews three tax polls conducted by major survey organizations that reveal widely divergent support for the flat tax, ranging from 27% - 62%. Keene concludes that the differences are attributable to variations in the phrasing of each question.

Roberts *et al.* (1994) examine how framing of the question – either as an abstract question or a concrete question – influences the participant's perception of fairness. Roberts *et al*. (1994) ask undergraduate students to indicate their opinion on the fairness between two different methods of taxation (progressive tax rates compared with a flat tax rate, progressive tax rates compared with regressive tax rates, and flat tax rates compared with regressive tax rates), and students choose either "much less fair", "a little less fair", "both the same", "a little more fair", or "much more fair". In this abstract context, Roberts *et al*. (1994) find the majority of students believe progressive tax rates are more fair than both flat and regressive tax rates. Roberts *et al.* (1994) also ask undergraduate students to indicate, in terms of fairness, how much more income tax a taxpayer should pay compared to another taxpayer in different scenarios. Students select either "the same", "twice as much", "three times", "four times", or "five times". They find that a majority of students assign a tax burden consistent with (i) a flat tax (e.g., a taxpayer with taxable income of $40,000 should pay "twice as much" as a taxpayer with taxable income of $20,000), or (ii) a regressive tax (e.g., when the students' hypothetical taxable income tripled, the students indicated they should pay less than three times as much as another taxpayer) in this context.

D. Standard Economic Theory and Risk

Almost all theories on choice make two assumptions; first, that people prefer larger expected returns to smaller expected returns, and second, that people prefer smaller risks to larger risks, provided all other factors are constant (Lindley, 1971; Arrow, 1965). Applying these assumptions to taxpayer preference for a method of taxation, suggests that taxpayers will prefer a method that results in the largest expected return and the lowest after-tax variance – and that this preference is magnified when it affects them personally. Below, we explain the difference in the variance of a graduated tax and a flat tax.

Actual returns on any investment or investment portfolio are variable and can be expected to follow a distribution around an expected value. A revenue neutral flat tax will have the same expected value as the graduated tax rates:

$$EVx = EVx_{\text{Graduated Tax}} = EVx_{\text{Flat Tax}}. \tag{1}$$

[4] It may be rational for business students to prefer a flat tax regime if they are focusing on their self-interest. Students may believe the flat rate they will face in the future will be less than the graduated rate at their expected level of income.

With equal expected values in after-tax profits, most taxpayers should prefer a graduated tax structure because there is less variance in outcomes and thus less overall risk. All other things being equal, after-tax returns within a flat tax rate structure have a wider distribution pattern than under a graduated tax rate structure. This is evident by reviewing the variance calculation:

$$\text{Variance} = \frac{1}{n} \sum (x_i - EVx)^2, \tag{2}$$

where x_i represents the actual after-tax profit for an investment (under either the graduated tax rate system or the flat tax rate system).

Under the graduated tax rate system, tax will be higher at the high end of the distribution, causing after-tax profits (x_i) at the high end of the distribution curve to be lower than they would be under a revenue neutral flat tax. This will shrink the value of $(x_i - EVx)^2$ for observations at the high end of the distribution within a graduated tax rate structure, thus lowering the overall variance in after-tax returns.

Also, under the graduated tax rate system, tax will be lower at the low end of the distribution, causing after-tax profits (x_i) at the low end of the distribution curve to be higher than they would be under a revenue neutral flat tax. This will also shrink the value of $(x_i - EVx)^2$ for observations at the low end of the graduated tax rate structure, also lowering the overall variance. Since lower variance is associated with lower risk (Markowitz, 1952), taxpayers should generally prefer the lower variance graduated tax rate structure.

E. Understanding Variance and Optimism Bias

Prior research suggests, however, that people may not understand variance and may not act according to standard economic theory, particularly when it pertains to them personally (Rabin and Thaler, 2001; Thaler and Johnson, 1990). March and Shapira (1987) find that the majority of managers do not consider risk to be a measure of the distribution of possible outcomes; rather, a "risky choice" is one that may result in a bad outcome. March and Shapira (1987) also find that managers tend to focus on the amount at risk ($1,000 vs. $1) and not the probability of a loss. Further, they find that managers have little desire to quantify the risk of various alternatives into a single construct for comparative purposes.

When taxpayers ignore risk, or do not fully understanding risk, they are unlikely to act according to standard economic theory, and instead may be prone to certain psychological biases such as the optimism bias. Helweg-Larsen and Shepperd (2001) define optimism bias as the belief that you are less likely to experience a bad event and are more likely to experience a good event than other people in the same circumstances. For example, texting while driving is okay for you because you are less likely than others to get into an accident. Similarly, you should buy a lottery ticket because you are lucky but everyone else that buys a lottery ticket is wasting money.

Under this bias, people *over*emphasize the probability that *they* will receive a *high* level of income (a good event) and *under*emphasize the probability that *they* will receive a *low* level of income (a bad event). Thus, people that display optimism bias are likely to prefer flat tax rates over graduated tax rates because graduated tax rates will result in lower after-tax income when income levels are above average. In other words, people prefer a flat tax for themselves - where high levels of income are *not* taxed at a higher rate - because they believe they will receive high levels of income and they prefer larger after-tax returns.

In summary, we predict that taxpayers will choose a tax rate structure consistent with the optimism bias (a flat tax) when the tax rates affect them personally, as opposed to when it does not. And when it does not, rational economic theory - which predicts a preference for less risk - will be more predictive (graduated tax rates). This effect may explain the differences in polling data regarding taxpayer preferences toward flat tax proposals. If polling questions are framed to impart a feeling of self-interest, taxpayer response to polling questions may be influenced in a different direction than if no self-interest is implied by the question.

III. Data and Methodology

A. Experiment

We test our hypothesis using a 1 x 2 behavioral experiment.[5] We recruit anonymous participants (n=272) from two sources, 121 participants from Amazon mTurk and 151 participants from Qualtrics. We require that each mTurk participant is a U.S. citizen, 18 years or older. We use US census data to gather a sample of Qualtrics participants representative of the US population in terms of income, age, education, and gender.

Table 1 contains demographics and political preferences for our participants and presents the sample demographics within the test group and the control group.

Table 1: Participant Political Preference, Gender, Age, Education, and Income

		Group		Totals
		Test Group	**Control Group**	
Political Preference	Strongly favor Democrats	29	28	57
	Somewhat favor Democrats	36	30	66
	Neutral toward both parties	30	34	64
	Somewhat favor Republicans	25	21	46
	Strongly favor Republicans	16	23	39
Gender	Male	60	73	133
	Female	75	63	138
	Prefer not to answer	1	0	1

[5] Institutional Research Board approval was granted by the universities for the use of human subjects.

Table 1: Participant Political Preference, Gender, Age, Education, and Income: Continues

		Group		Totals
		Test Group	Control Group	
Age[6]	18 to 29	40	35	75
	30 to 44	49	50	99
	45 to 64	27	36	63
	65 and above	19	14	33
	Prefer not to answer	1	0	1
Income*	$0 - $50,000	34	32	66
	$50,001 – $100,000	19	25	44
	$100,001 - $150,000	13	9	22
	$150,001 – $200,000	5	6	11
	$200,000 and above	3	5	8
Education*	No high school degree	5	11	16
	High school graduate	28	17	45
	Some college or AA degree	19	21	40
	Bachelor's degree	16	17	33
	Master's degree or higher	6	11	17

* Information on participant Income and Education was gathered from the Qualtrics participants only.

Participants are paid $2 each for approximately five minutes of participation. Participants in the test group (but not the control group) earn an additional payment that ranges from $0.65 to $1.95. Participants are randomly assigned to the control group or the test group. In the control group, participants read a hypothetical scenario where the state government provides lottery tickets to people in exchange for recyclable bottles. The lottery tickets have a 50% probability of returning $1.00 and a 50% probability of returning $3.00. The participant is asked to recommend a tax rate structure, either a flat tax or a graduated tax, to policy makers that will apply to the taxable income from the lottery tickets. The participant is told that the two tax rate structures are revenue neutral. Participants' compensation for completing the experiment ($2.00) is not affected by their recommendation (see Appendix A for the full case).[7]

[6] One participant did not enter a categorical answer, leaving the sample with only 271 responses for age.
[7] In the control group, participants are informed that the government will generate approximately $500 million of revenue from the lottery ticket program. Members of the control group may, to a limited extent, consider the impact of the method of taxation they recommend on their personal gains as well, since they too are members of the population.

In the test group, participants read a scenario in which the participant has received a lottery ticket and must choose the tax structure to apply to his or her winnings (similar to variable returns on an investment). The lottery tickets have the same payout structure - a 50% probability of returning $1.00 and a 50% probability of returning $3.00, and the participants do not know their taxable income at the time of the tax rate structure choice. The participant is asked to choose between a flat tax of 35% or a graduated tax schedule (a 20% tax on $0.01 - $1.00, a 40% tax on $1.01 – $2.00, and a 60% tax on $2.01 - $3.00). The participant will keep the after-tax income in addition to the $2.00 show-up fee. In the test group, total participant compensation is affected by the tax rate structure choice (See Appendix B for the full case).[8]

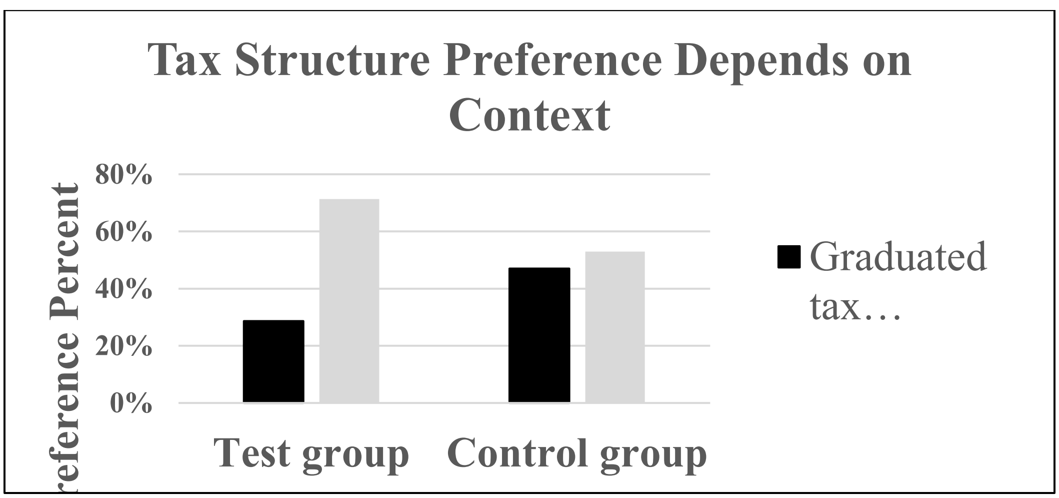
Our independent variable is the condition (personal risk or no personal risk) in which participants indicate their discrete preference for tax structure. Our dependent variable is the choice of tax structure - either graduated tax rates or a revenue neutral flat tax. We also include a variable that measures whether participants understand how to calculate a tax liability using graduated tax rates.

IV. Results and Discussion

A. Results

We use a non-parametric test (Chi Squared test of two proportions) to compare participants' preference between a flat tax and a graduated tax structure within the test group and the control group. Two hundred seventy-two participants were randomly assigned to either the control group (136) or the test group (136). Each participant indicated a preference for either a flat tax or graduated tax rates. Figure 1 graphically represents the results of our experiment.

Figure 1: Tax Structure Preference



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[8] In the test group, the choice between graduated rates and a flat tax is revenue neutral in that the expected value of after-tax profits for both tax structures is $1.30, (the E(X) of before-tax revenue is $2.00, while E(X) of tax expense is $0.70). Variance of after-tax profit calculated as σ^2 = ∑ [x-E(X)]2p(x), is $0.25 for the graduated tax choice and $0.4225 for the flat tax choice (creating a riskier environment for the flat tax choice).

Seventy-two participants (52.9%) chose the flat tax in the control group and ninety-seven participants (71.3%) chose the flat tax in the test group, a statistically significant difference in proportions of 0.184, $p = .001$. Figure 1 graphically represents the results. Table 2 presents the test of two proportions.[9]

Table 2: Test of Two Proportions

			Group		
			Test Group	**Control Group**	**Totals Within Groups**
Choice Group	Flat tax choice	Count	97	72	169
		Expected count	84.5	84.5	169
		Percentage of the flat tax choosers that are within the test or control group	57.4%	42.6%	100.0%
		Percentage of the test or control group choosing a flat tax	71.3%	52.9%	
	Graduated tax rate choice	Count	39	64	103
		Expected count	51.5	51.5	103
		Percentage of graduated tax rate choosers that are within the text or control group	37.9%	62.1%	100.0%
		Percentage of the test or control group choosing graduated tax rates	28.7%	47.1%	
Totals Within Groups		Count	136	136	272
		Expected count	136.0	136.0	272.0
		Percentage within groups	100.0%	100.0%	100.0%
There is a statistically significant difference in proportions of 0.184, $p = .001$, Fisher's Exact Test					

Table 2: Chi Squared test comparing participants' preference between a flat tax and a graduated tax structure within the test group and the control group. Two hundred seventy-two participants were randomly assigned to either the control group (136) or the test group (136). Seventy-two (52.9%) chose the flat tax in the control group and ninety-seven participants (71.3%) chose the flat tax in the test group, a statistically significant difference in proportions of 0.184, p = .001.

[9] We tested the data from each of the sources independently. We found **a** statistically significant difference in proportions of 0.235, $p = .008$ in the mTurk sample and a statistically significant difference in proportions of 0.145, $p = .046$ in the Qualtrics sample. As these results are qualitatively similar, we have combined the observations and reported results for the combined sample.

B. Discussion

These results support our hypothesis that taxpayers will tend to choose a flat tax regime when they perceive that tax rates affect them personally and tend to choose graduated tax rates when they do not. This effect may be due to an optimism bias when they choose a method of taxation for themselves as opposed to choosing a method that primarily affects others. Participants in the test condition may believe they are more likely than others to receive high levels of income and therefore a majority of these participants select a flat tax – the method of taxation that will yield a lower tax liability with high levels of income. The proportion of participants choosing a flat tax is significantly greater in the test group, where the participants' compensation is affected by their choice of method of taxation and chance, than in the control group, where the participants compensation is not affected by their choice.[10]

After completion of the experiment we collected demographic information from the participant and asked participants to calculate the tax liability when given an amount of taxable income and graduated tax brackets. We included this calculation to check for active involvement from the participants and to determine whether our participants understood and could apply the concept of graduated tax rates. We find that 63% of our participants correctly calculated a tax liability using graduated tax rates.[11]

V. Summary

A. Conclusions

In a behavioral experiment, we examine preference for tax rate structure; either a flat tax or graduated tax rates. Our results support prior research, indicating that the context of the decision significantly affects taxpayer preference for a particular tax structure. We find that given a specific amount of high variance taxable income, participants indicate a significantly higher preference for flat tax rates when choosing a method of taxation for themselves than when participants choose a method of taxation for others.

Our results may help explain why public support for a flat tax increases in some situations and decreases in others. We find that participants in our setting do not follow the predictions of standard economic theory as we do not find evidence that taxpayers chose a method of taxation that will minimize risk. Our research also supports prior studies suggesting that taxpayers do not (fully) understand variance.

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[10] There are some differences in demographics between the test group and the control group as seen in Table 1. To examine whether our demographic variables have a significant influence on tax regime choice, we performed a logit analysis using "Choice" as the dependent variable and the Group, plus the demographic variables as independent variables. As in the test of two proportions, Group is a significant influence on Choice. However, none of the demographic variables were significant in the choice of tax regime. Because the test of two proportions results appear to be robust, and because demographics do not appear to affect the results, we believe the test of two proportions is the more appropriate method in this context for testing our hypothesis.

[11] We repeated the Chi Squared test using only the 172 participants (63%) who answered the test question correctly. Our inferences do not change when dropping the 100 participants who did not answer the question correctly. Forty-one participants (52.6%) chose the flat tax in the control group and 66 participants (70.2%) chose the flat tax in the test group, a statistically significant difference in proportions of 0.176, $p = .018$.

Tax structure is an important feature of our economic and political landscape. The Tax Cuts and Jobs Act recently became law.[12] The results of this study should be of interest to polling organizations, policy makers, and the public as they discuss support for the tax law changes imposed by the Act. We believe it is important to be aware of the extent to which individual preferences can be altered by the context of a question. Compliance with the tax system of the United States is largely voluntary; therefore, public support is crucial for effective revenue collection. Public opinion polls should reflect "real" public opinion, and increase the ability of policy makers to legislate tax systems that will foster public support.

B. Limitations

The study is limited in that the results may not generalize to the U.S. population. For example, our sample contained more Democrats than polls indicate are contained in the general population. However, the large sample size and significant results for both self-identified Republicans and Democrats mitigates this limitation. Although there is no apparent correlation between out demographic variables and choice of tax regime in this experiment, we cannot rule out the possibility that the correlations exist in the general population.

The results are limited in that they only examine the effect of tax rates on the preference between our current tax structure and recent flat tax proposals. They do not examine the effect of other flat tax proposal features such as larger standard deductions and changes to personal exemptions. Further, our results may be affected because a limited amount of money was at risk, and our results may not generalize to circumstances when the economic consequences are greater.

C. Future Research

Additional research is needed to examine the effect of other flat tax proposal attributes on tax structure preference, including the effect of modifications to the standard deductions and personal exemptions. These features, as well as a simplified tax rate structure, could factor into a comprehensive explanation of why individuals prefer one tax rate structure over another.

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Appendices

Appendix A

No-Risk Condition Provided to Participants (Control Group)

Assume that your state legislature is creating an incentive program to encourage more people to recycle plastic bottles, and at the same time help fund public education.

To accomplish this goal, the state will give a lottery ticket to each person that brings in a predetermined number of used plastic bottles. The number of plastic bottles required for each lottery ticket will be set so that the program is economically competitive with the cash redemption value received from existing commercial recycling companies. In effect, the state will enter the recycling industry, but will use the lottery ticket as a novel way of providing compensation in exchange for recyclable bottles. The legislature hopes that using the lottery ticket format for payment will attract people who would not otherwise bother to recycle plastic bottles.

Each lottery ticket has a 50% chance of paying $1.00 and a 50% chance of paying $3.00. The state will finance the payouts by selling the recycled plastic to commercial enterprises. The payments are exempt from existing federal and state income tax, **and are instead subject to a special income tax**.

The special income tax on lottery ticket profits will fund essential educational programs throughout the state. Two alternative tax structures are under consideration, **each generating approximately $500 million each year**:

1. A **flat tax** (all lottery ticket payouts would be taxed at the same tax rate), or
2. A **graduated tax** rate structure (lower lottery ticket payouts would be taxed at a lower tax rate, higher lottery ticket payouts would be taxed at a higher tax rate).

Please make a recommendation to the state legislature regarding the type of income tax that should be applied to the lottery ticket winnings:

1. **Flat tax, or**
2. **Graduated tax**

Appendix B

Outcome Risk Condition Provided to Participants (Test Group)

Assume that your state legislature has created an incentive program to encourage more people to recycle plastic bottles. By turning in the required number of recyclable plastic bottles, you have received a lottery ticket as compensation. Each lottery ticket has a 50% chance of paying $1.00 and a 50% chance of paying $3.00. The payments are exempt from existing federal and state income tax, and are instead subject to a special income tax. However, you can choose the type of tax as described below.

Please make the choice described below.

You have:

(1) A 50% chance of making $1.00, and
(2) A 50% chance of making $3.00

A tax will be subtracted from whichever amount you win.
However, you can choose the form of the tax.

It can be either:

(1) A flat rate tax, 35% of your winnings,

or

(2) A graduated tax determined by the following schedule:
(a) 20% of the first dollar ($0.00 to $1.00)
(b) 40% of the next dollar ($1.01 through $2.00)
(c) 60% of the next dollar ($2.01 through $3.00)

Please choose one of these two tax structures:

1. **Flat tax, or**
2. **Graduated tax**