THE SOUTHERN BUSINESS AND ECONOMIC JOURNAL

Volume 45, Number 2 **2022**

Published by
AUBURN UNIVERSITY at MONTGOMERY
COLLEGE OF BUSINESS

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THE SOUTHERN BUSINESS AND ECONOMIC JOURNAL

Editors
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Editors
The Southern Business and Economic Journal
Department of Business Administration
Auburn University at Montgomery
PO Box 244023
Montgomery, AL 36124-4023

THE SOUTHERN BUSINESS AND ECONOMIC JOURNAL

Indexed in PAIS Bulletin and EBSCO Publishers Online ISSN: 0743779X

Volume 45, Number 2 2022

Articles

Published by the Auburn University at Montgomery College of Business

Relationship of Organization Culture Mediation of Employee Turnover Intention Within the Fortune 500

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Abstract

The study explored how organizational culture mediates the relationship between leadership and employee turnover intention among Fortune 500 organizations within the United States. Qualtrics, a third-party platform, provided a sample of the population, 80 respondents. Data analysis followed multiple regression to identify the relationships between the variables and explore mediation. The findings resulted in significant relationships between laissez-faire leadership style and turnover intention, organizational culture, and turnover intention, and both transformational and transactional leadership styles with organizational culture. The study found that the relationship between leadership and turnover intention was not mediated by organizational culture.

Keywords: organizational culture, employee turnover, mediation, leadership style

The United States Bureau of Labor Statistics (BLS) reported that 3.5 million employees voluntarily quit their jobs in January 2020 (STATISTICS, 2020). Employees who decide to quit creates additional costs to an organization's bottom line by impacting organizational performance through decreased productivity, increased training, and lost experience (Cho et al., 2009; Hee et al., 2018). Thus, organizations seek strategies to identify turnover intention to retain employees (Gope et al., 2018). Employees that leave an organization result from the combination of their desire to leave with expectations of available jobs that creates the intention to leave (Hee et al., 2018; Lee et al., 2017). A variety of factors influence turnover intention, such as organizational culture (Cronley & Kim, 2017) and leadership (Azanza et al., 2015). How leadership and organizational culture influence turnover intention remains unclear.

The study explored if organizational culture mediated the relationship between leadership (transformational, transactional, and laissez-faire) and employee turnover intention within Fortune 500 organizations located in the United States. Qualtrics, a third-party platform, provided a sample of the population, 80 respondents. For purposes of this study, we define transformational, transactional, and Laissez-faire leadership style in the following manner (Antonakis, 2001); Transformational Leaders develop trust-centric management practices with followers developing consensus support regarding vision, goals, and objectives (Joyce Covin et al., 1997; Piccolo & Colquitt, 2006). At the core, the transformational leader motivates followers with supportive mentoring and positive engagement built upon continuous improvement with encouragement and reward for exceeding expectations and innovative approaches (Bass, 1999; Stewart, 2006; Waldman et al., 2015). Transactional Leadership is commonly associate with reward and punishment motivational relationships (Bass, 1990). The focus of such leaders is on accelerated progress toward the established vision of the form through expectations that performance meets or exceeds expectations within predetermined timeframes and goals. Laissez-faire Leadership is characterized by leaders who delegate responsibilities and avoid interfering in the tactics or strategies of managers in their pursuit of goals. It is frequently characterized as a hands-off style, yielding decision-making authority to subordinates with little interference

(Schermerhorn Jr et al., 2008). Organizational culture is a vastly encompassing concept which has many and varied definitions. A single, universal definition of organizational culture does not exist; however, a conceptual understanding of what is referred to as organizational culture is important to recognize how cultures develop and how they can be managed within a firm. To reference organizational culture for our research, we relied on commonly accepted in research literatures as stared by Schein (2010):

> A pattern of shared basic assumptions that the group learned as it solved its problems of external adaptation and internal integration that has worked well enough to be considered valid and, therefore, to be taught to new members as the correct way you perceive, think, and feel in relation to those problems.

Data analysis followed multiple regression to identify the relationships between the variables and explore mediation. The findings resulted in significant relationships between laissez-faire leadership style and turnover intention, organizational culture, and turnover intention, and both transformational and transactional leadership styles with organizational culture. Lastly, the study found that the relationship between leadership and turnover intention was not mediated by organizational culture.

March and Simon categorized organizational variables influencing turnover intention as (a) push-to-leave, (b) pull-to-leave, and (c) pull-to-stay (Hom et al., 2017). Push-to-leave variables relate to factors that influence an employee's desire to leave, such as leadership (Waldman et al., 2015). An employee's expectations about job availability are considered pull-to-leave factors (Hom et al., 2017). The combination of pull-to-leave and push-to-leave factors results in employee turnover intention (Waldman et al., 2015). To retain employees, organizations focus on pull-to-stay as factors the organization can impact through retention strategies (Eberly et al., 2017). Pull-to-stay challenges often occur due to misunderstood organizational vision, lack of performance feedback, decreased opportunities for professional progression, and leadership's inability to build positive relationships (Carasco-Saul et al., 2015). Thus, the complexity of pull-to-leave and push-to-leave factors creates challenges for an organization to develop pull-to-stay strategies to decrease employee turnover intention.

Turnover intention research identified leadership as a critical factor impacting an employee's thoughts about leaving an organization (Carasco-Saul et al., 2015). Supangco found that employees perceived leadership as a representation of an organization's behavior (Supangco, 2015). In comparison, Cronley and Kim identified that organizational culture influenced employee turnover intention (Cronley & Kim, 2017). Las Heras further determined that as individuals affect the organizational culture, the organizational culture influences employees (Las Heras et al., 2015). Although previous research identified specific factors that influenced turnover intention, research also showed variables that influenced turnover intention through mediators.

Azanza et al. determined that authentic leadership influenced employee turnover intention through work engagement (Azanza et al., 2015). Cronley and Kim (identified that organizational culture influenced job satisfaction, which affected an employee's turnover intention (Cronley & Kim, 2017). The possibility exists that this occurs based on transactions between parties related to social exchanges theory. Previous research had not shown if organizational culture mediated the relationship between leadership and employee turnover intention. Therefore, this study's primary focus was the extent to which organizational culture mediated the relationship between leadership and employee turnover intention.

Data and Methods

The purpose of the explanatory quantitative study was to apply social exchange theory to assess the mediating effect of organizational culture as measured by the Organizational Culture Survey (Glaser et al., 1987) on the relationship between transformational, transactional, and laissez-faire leadership as measured by the Multifactor Leadership Questionnaire (Avolio, 2004), and employee turnover intention as measured by the Turnover Intention Scale (Jackofsky & Slocum Jr, 1987). Social exchange theory described relationships as social interactions between parties based on behaviors displayed by one party and responded to from the other party (Homans, 1958). The interactions contribute to forming the organizational culture. Thus, employees influence organizational culture, but organizational culture also affects how employees work and interact (Kim & Vandenberghe, 2021). Therefore, this study investigated how organizational culture influenced the relationship between leadership and turnover intention to address the gap in the turnover intention body of knowledge.

Research Questions and Hypotheses

RQ1. To what extent does organizational culture mediate the relationship between transformational leadership and employee turnover intention?

H1$_0$. Organizational culture does not statistically significantly mediate the relationship between transformational leadership and employee turnover intention.

H1$_a$. Organizational culture does statistically significantly mediate a relationship between transformational leadership and employee turnover intention.

RQ1a. To what extent does transformational leadership explain employee turnover intention?

H1a$_o$. Transformational leadership does not statistically significantly explain employee turnover intention.

H1a$_a$. Transformational leadership does statistically significantly explain employee turnover intention.

RQ1b. To what extent does transformational leadership explain organizational culture?

H1b$_0$. Transformational leadership does not statistically significantly explain organizational culture.

H1b$_a$. Transformational leadership does statistically significantly explain organizational culture.

RQ1c. To what extent does organizational culture explain employee turnover intention?

H1c$_0$. Organizational culture does not statistically significantly explain employee turnover intention.

H1c$_a$. Organizational culture does statistically significantly explain employee turnover intention.

RQ1d. To what extent do transformational leadership and organizational culture explain employee turnover intention?

H1d$_0$. Transformational leadership and organizational culture do not statistically significantly explain employee turnover intention.
H1d$_a$. Transformational leadership and organizational culture do statistically significantly explain employee turnover intention.

RQ2b. To what extent does transactional leadership explain organizational culture?
H2b$_0$. Transactional leadership does not statistically significantly explain organizational culture.
H2b$_a$. Transactional leadership does statistically significantly explain organizational culture.
RQ2c. To what extent does organizational culture explain employee turnover intention?
H2c$_0$. Organizational culture does not statistically significantly explain employee turnover intention.
H2c$_a$. Organizational culture does statistically significantly explain employee turnover intention.
RQ2d. To what extent do transactional leadership and organizational culture explain employee turnover intention?
H2d$_0$. Transactional leadership and organizational culture do not statistically significantly explain employee turnover intention.
H2d$_a$. Transactional leadership and organizational culture do statistically significantly explain employee turnover intention.

Population

The target population consisted of employees working within Fortune 500 organizations in the United States. The study focused on employees currently working for at least one year within the same organization without considering other demographics. The BLS reported that in January 2020, the total workforce in the United States was 158.7 million full-time employees (STATISTICS, 2020). Fortune 500 organizations employ 17.5% of the entire U.S. workforce (Donnelly, 2017). Thus, Fortune 500 organizations employ approximately 27.7 million of the U.S. workforces.

Sample

Qualtrics, a third-party research platform, provided a sample frame using Qualtrics Audience Panel (Qualtrics XM - Experience Management Software, 2020). Qualtrics' web-based recruiting tools identified approximately 100,000 potential participants who meet the study's inclusion criteria. The inclusion criteria required participants to be full-time employees to identify those with consistent leadership and organizational culture interactions. Those currently employed were the focus of the inclusion criterion, as the study's topical area centered on turnover intention. The study required respondents with a minimum of 12 months of employment to ensure experience with leadership and the organization's organizational culture.

The exclusion criteria consisted of employees not working within the United States as country cultures differ worldwide, influencing organizational culture. The study excluded participants under 18 years of age. After inclusion and exclusion criteria filtered the Qualtrics Audience Panel, a random sampling strategy provided all Audience Panel members an equal opportunity to participate in the study.

To assuage concerns about common method variance (CVM), the authors implemented strict anonymity and confidentiality. This assures participants that their responses will remain anonymous and confidential. This can encourage more honest and unbiased responses, reducing the likelihood of common method variance caused by social desirability or self-presentation biases. Further, counterbalancing techniques including randomized question orders were implemented in order to prevent CVM (Podsakoff et al., 1997; Podsakoff et al., 2003).

Following G*Power 3 with an a priori analysis of one-tail, effect size, $f^2 = 0.15$, significance level, $\alpha = 0.05$, statistical power $(1 - \beta) = 0.8$ resulted in a minimum sample size of 80. The 100 respondents increased the statistical power $(1 - \beta) = 0.986$. Demographic information describing the sample consisted of gender, age group, and length of employment. As shown in Table 1, 55% of participants identified as male and 45% female. Table 1 identifies the sample by age group. Much of the sample consisted of 34% between 41 to 50 years old. Lastly, the demographic description included the length of current employment. The selection in Table 1 showed that 82% have worked for over eight years within their organization.

Table 1: *Sample Sociodemographic Characteristics of Participants*

Characteristics	*n*	%
Gender		
Female	45	45
Male	55	55
Age group		
18-30	8	8
31-40	31	31
41-50	34	34
51-60	17	17
>60	10	10
Years of employment		
1-3	5	5
4-7	13	13
>8	**82**	**82**

Note. N= 100

Multiple Regression Analysis

After meeting the assumptions and reliability, the multiple regression analysis was conducted. The model summary, Table 2, depicts R^2 = .145. Thus, the independent variables predict 14.5% of turnover intention. Analysis of variance (ANOVA) checks the validity of the model, represented in Table 3. The *F*-value was statistically significant, *F* (3, 92) = 6.450, $p < .001$. Therefore, the model was a significant fit for the data.

Table 2: Regression Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.417[a]	.174	.147	2.610	.174	6.450	3	92	.001	1.896

Predictors: Transformational, transactional, laissez-faire leadership. Dependent variable: turnover intention.

Table 3: ANOVA Dependent and Independent Variables

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	131.803	3	43.934	6.450	.001
	Residual	626.687	92	6.812		
	Total	758.490	95			

Note. Dependent Variable: Turnover intention.
Independent Variables: Transformational, transactional, and laissez-faire leadership style.

Analysis of the coefficients in Table 4 depicted statistical values for unstandardized and standardized coefficients, t-tests, and significance. The beta values (B) for both transactional and laissez-faire leadership show that these independent variables are negatively associated with turnover intention. The results showed that transformational leadership has a statistically significant positive connection with turnover intention. The coefficients indicated that the independent variables are not significant predictors of turnover intention. Furthermore, the variance inflation factor (VIF) values showed that the independent variables exhibit acceptable collinearity levels below 5.

Table 4: Coefficients for Analysis of Collinearity Statistics

	Unstandardized Coefficients					95.0% Confidence Interval for B			
Variable	B	Std. Error	Beta	*t*	Sig.	Lower Bound	Upper Bound	Tolerance	VIF
1 (Constant)	14.687	2.024		7.256	.000	10.667	18.708		
Transformational	.458	.517	.137	.886	.378	-.569	1.485	.379	2.642
Transactional	-.496	.609	-.108	-.815	.417	-1.705	.712	.511	1.959

Laissez faire	-1.103	.357	-.360	-3.094	.003	-1.811	-.395	.664	1.507

Testing

Following Table 4, the coefficients indicated to what extent the beta values, t-tests, and significance values predict the relationship between the variables and the outcome. Transformational leadership style (*b* = 0.458, *B* = 0.137, *t* = 0.886, *p* = .378) did not significantly predict turnover intention resulting in not rejecting the null hypothesis, $H1a_o$. Transactional leadership style (*b* = - 0.496, *B* = - 0.108, *t* = - 0.815, *p* = .417) did not significantly predict turnover intention resulting in not rejecting the null hypothesis, $H2a_0$. Laissez-faire leadership style, (*b* = - 1.103, *B* = - 0.360, *t* = - 3.094, $p < .05$) significantly predicted turnover intention resulting in rejecting the null hypothesis, $H3a_0$. Therefore, the study identified both transformational and transactional leadership style as non-significant predictors of turnover intention.

The model summary in Table 5 depicted the independent variables (transformational, transactional, and laissez-faire leadership style) that predict 52.6% of organizational culture. The ANOVA model's validity shown in Table 6 found the *F*-value was statistically significant, *F* (3, 92) = 34.085, $p < .001$. Therefore, the model was a significant fit for the data.

Table 5: Regression Model Independent and Mediator Variables

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.726[a]	.526	.511	16.628	.526	34.085	3	92	.000

Note. Predictors: Transformational, transactional, and laissez-faire leadership. Mediator variable: Organizational culture.

Table 6: ANOVA Independent and Mediator Variables

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	28272.506	3	9424.169	34.085	.000
	Residual	25437.452	92	276.494		
	Total	53709.958	95			

Note. Predictors: Transformational, transactional, and laissez-faire leadership. Mediator variable: Organizational culture.

The coefficients in Table 7 showed that transformational leadership style (*b* = -14.428, *B* = -0.511, *t* = -4.379, $p < .001$) significantly predicted organizational culture, resulting in rejecting the null hypothesis, $H1b_0$. Transactional leadership style (*b* = - 9.698, *B* = -0.251, *t* = -2.502, $p < .05$) significantly predicted organizational culture, resulting in rejecting the null hypothesis, $H2b_0$. Laissez-faire leadership style, (*b* = .934, *B* = .036, *t* = 0.411, *p* = .682) did not significantly predict organizational culture, resulting in not rejecting the null hypothesis, $H3b_0$. Therefore, the study found that both transformational and transactional leadership style significantly predict organizational culture.

Table 7: Coefficients of Independent and Mediator Variables

Model	Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Collinearity Statistics	
	B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Tolerance	VIF
1(Constant)	150.548	12.896		11.674	.000	124.935	176.161		
Transformational	-14.428	3.295	-.511	-4.379	.000	-20.971	-7.884	.379	2.642
Transactional	-9.698	3.877	-.251	-2.502	.014	-17.398	-1.998	.511	1.959
Laissez-faire	.934	2.272	.036	.411	.682	-3.578	5.445	.664	1.507

Note. Predictors: Transformational, transactional, and laissez-faire leadership. Mediator variable: Organizational culture.

The model summary in Table 8 depicted R^2 = .066. Thus, organizational culture predicts 6.6% of turnover intention. ANOVA, Table 9, identified the *F*-value as significant, F (3, 94) = 6.639, $p < .05$. Thus, the model was a significant fit for the data. The data in Table 10 analyzed the connection between organizational culture and turnover intention. Organizational culture (*b* = -.031, *B* = -.257, *t* = -2.577, $p < .05$) significantly predicted turnover intention, resulting in rejecting the null hypothesis, $H1c_0$, $H2c_0$, and $H3c_0$. Therefore, the study found that organizational culture significantly predicted employee turnover intention.

Table 8: Regression Model Summary Mediator and Dependent Variables

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.257	.066	.056	2.745

Note. Mediator Variable: Organizational culture. Dependent variable: Turnover intention

Table 9: ANOVA Mediator and Dependent Variables

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	50.037	1	50.037	6.639	.012
	Residual	708.453	94	7.537		
	Total	758.490	95			

Note. Mediator variable: Organizational culture. Dependent Variable: Turnover intention

Table 10: Coefficients of Mediator Variable, Organizational Culture

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	14.255	.892		15.983	.000
	Organizational Culture	-.031	.012	-.257	-2.577	.012

Hypotheses testing resulted in answering the three key research questions and each of the four sets of sub-questions. The results identify if an explanatory relationship existed between the variables. Below, Table 11 presents the results of the hypotheses.

Table 11: Hypotheses Results

Hypothesis		*t*-value	*p*-value	Null hypothesis rejected
$H1_0$	OC mediates Transformational Leadership and Turnover Intention			Not Rejected
$H1a_o$	Transformational to turnover intention	0.886	= .378	Not Rejected
$H1b_0$	Transformational to organizational culture	-4.379	< .001	Rejected

$H1c_0$	Organizational culture to turnover intention	-2.577	< .05	Rejected
$H1d_0$	Transformational Leadership and Organizational Culture to Turnover Intention			Not Rejected
$H2_0$	Organizational culture mediates Transactional Leadership and Turnover Intention			Not Rejected
$H2a_0$	Transactional to turnover intention	-0.815	= .417	Not rejected
$H2b_0$	Transactional to organizational culture	-2.502	< .05	Rejected
$H2c_0$	Organizational culture to turnover intention	-2.577	< .05	Rejected
$H2d_0$	Transactional Leadership and Organizational Culture to Turnover Intention			Not Rejected
$H3_0$	Organizational culture mediates Laissez-Faire Leadership and Turnover Intention			Not Rejected
$H3a_0$	Laissez-Faire to turnover intention	-3.094	< .05	Rejected
$H3b_0$	Laissez-Faire to organizational culture	0.411	= .682	Not rejected
$H3c_0$	Organizational culture to turnover intention	-2.577	< .05	Rejected
$H3d_0$	Laissez-Faire Leadership and Organizational Culture to Turnover Intention			Not rejected

Discussion of the Results

The study explored the relationship between the variables and if the mediator influenced the relationship between the independent and dependent variables. Following Baron and Kenny's (1986) mediation analysis, three regression analyses must prove valid to identify mediation. The first ordinary least squares suggested that leadership predicted employee turnover intention. Findings resulted in a statistically significant negative relationship between laissez-faire leadership style and turnover intention. Thus, the study rejected the null hypothesis, $H3a_0$. The transformational leadership and turnover intention relationship resulted in not significant. Simultaneously, the transactional leadership and turnover intention relationship resulted in not significant. Therefore, the research failed to reject both null hypotheses, $H1a_0$ and $H2a_0$.

The second regression proposed that leadership predicted organizational culture. The findings showed that both transformational and transactional leadership resulted in a significant negative relationship with organizational culture ($H1b_0$ and $H2b_0$), but laissez-faire leadership showed not significant ($H3b_0$). The third regression stated that leadership and organizational culture together predicted employee turnover intention. The findings showed that transformational and transactional leadership had no significant relationship with turnover intention. Thus, the study failed to reject the first two null hypotheses, $H1_0$ and $H2_0$. However, the study showed a negative relationship between laissez-faire leadership and turnover intention, but no significant relationship with organizational culture. Therefore, the findings failed to reject the third null hypothesis, $H3_0$.

Practically, the findings suggested a possible link through organizational culture that leadership influences turnover intention. Leadership lacked statistical significance to influence turnover intention, except for the laissez-faire leadership style.
The study found that transformational and transactional leadership styles statistically significantly influenced organizational culture, except the laissez-faire leadership style. Organizational culture showed a statistically significant impact on turnover intention. Thus, the possibility exists that leadership may indirectly influence turnover intention through organizational culture.

Theoretically, the leadership process involves various leadership styles to influence and motivate employees. Social exchange theory suggested that leadership's ability to influence and motivate occurs through interactions with employees to build relationships (Chernyak-Hai & Rabenu, 2018). Previous research found that transformational leadership consisted of a statistically significant negative relationship with turnover intention (Alatawi, 2017; Eberly et al., 2017; Gope et al., 2018; Gyensare et al., 2016; Maaitah, 2018). In comparison, this study identified no significant relationship regarding transformational leadership. However, laissez-faire leadership resulted in a significant relationship with turnover intention. Therefore, the theoretical perspective indicated that an employee's turnover intention increases with leaders demonstrating a laissez-faire leadership style.

Conclusions

With 82% of the respondents identifying their employment length of greater than eight (8) years, the likelihood of high turnover intention was unlikely. This study identified broad aspects of leadership and organizational culture without further identifying specific characteristics that may influence turnover intention. While the study examined organizational culture as a mediator, the results found that leadership predicted 52% of organizational culture with mixed results between leadership and employee turnover intention. Although the relationships between either transformational or transactional leadership and turnover intention resulted in not significant, laissez-faire leadership showed a significant relationship. The findings suggested that leaders with a hands-off approach to employees increasingly impact an employee's intention to leave.

A social exchange theory lens suggested that relationships built through relation-oriented behaviors, such as transformational leadership, build positive relationships. Task-oriented behaviors, such as transactional leadership, form a give-and-take relationship. In contrast, the hands-off approach of laissez-faire leadership lacks building relationships through interactions. Previous research on laissez-faire leadership and turnover intention was not identified. This study found the relationship to be negatively significant, which coinciding with the concept of social exchange theory. Although this study did not corroborate the relationship between transformational leadership and turnover intention with previous research, the study corroborated research between leadership and organizational culture and organizational culture and turnover intention.

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Student Responsiveness to Extra Credit Opportunities

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Abstract

Students may allocate their time to take advantage of extra credit opportunities, when offered. This research quantifies student tendencies to participate in extra credit activities using data that was obtained from principles students at three different universities. Students were given extra credit opportunities to earn relatively large and well-defined rewards in return for small out of class participation. Few students participated, but better students participated more. Female and male students' participation did not significantly differ. Finally, microeconomics students participated significantly more than macroeconomics students.

1. Introduction

Students may put more effort into extra credit assignments than into ordinary coursework, though the contribution of extra credit work to the student's grade may be marginal. There are two credible hypotheses relating student quality to utilization of extra credit opportunities. The first hypothesis is that students with low grades most need the extra credit and, hence, will most likely utilize it. The second hypothesis is that students who put high effort into making good grades apply the same high effort to extra credit, while low effort students apply the same low effort to extra credit that they apply to other work. We explore student motivations to complete extra credit, including student quality and gender. In this work, three professors at two universities conducted an experiment by giving students identical extra credit opportunities in their principles of economics courses.

2. Literature Review

There is a substantial literature on students taking advantage of extra credit opportunities in psychology. Undergraduate students are an important source of human subjects for psychological studies. Laboratory or survey results generated from undergraduates vary from the general population in age, intelligence, and other attributes, creating problems when researchers generalize to overall population. However, if the students that are willing to participate in research in return for extra credit are themselves different from the overall student population, the generalizability problem compounds. Henley, et.al, (1994) reported no difference demographically or in test scores between students who volunteered for research studies to receive extra credit and students who did not volunteer. This result from the Henley study differed from other studies, however. Harrison, et.al. (2011), Padilla-Walker, et.al. (2005), Padilla-Walker (2006) and Hardy (2002) concluded that students who participated in extra credit opportunities tended to be higher performers. Not all these investigations into who takes advantage of extra credit come from psychology. Moore (2007), using developmental education (remedial) biology students, also found that better performing students within that group were more likely to take advantage of extra credit assignments than weaker students.

All of these studies' extra credit opportunities were virtually non-contingent—if a student showed up for a research study, or turned in the requested assignment, they received the extra credit. If the extra credit assignment was contingent, a weaker student might reasonably conclude that if he/she made a 50 on an exam they would probably only get half the extra credit points. Hence the payoff would be smaller than for a student who was making 90's on exams. But since the aforementioned opportunities awarded showing up, differences in expected return was not an issue.

The reward for extra credit is an improved final grade. That reward is received in the future. The effort, perhaps minor, to get the extra credit is incurred in the present. There is an abundant literature that humans have hyperbolic time discount functions—future rewards are discounted but at a decreasing rate as the time period increases. Of particular interest here are the "marshmallow" studies by Mischel et.al. (1972). Mischel gave 4-year-olds a marshmallow on a plate and told them that he was going to leave the room for a few minutes. If the child did not eat the marshmallow before he got back, he would give them two marshmallows. Not surprisingly, most preschoolers could not hold out until Mishel came back. Some ate the marshmallow immediately. The average time before eating was less than 3 minutes. Only about 30 percent waited the full time—15 minutes.

Mischel kept up with these subjects over time. In adolescence, quick eaters had more behavioral problems and lower S.A.T. scores. A child that ate his/her marshmallow in 30 seconds or less had a S.A.T. score 210 points lower than one who could wait 15 minutes (Mischel, et.al., 1988). The differences between low and high delayers persisted as the subjects aged (Lehrer, 2009). High delayers tend to be more successful in their careers.

3. Experiment

We conducted an extra credit experiment with university principles of economics students. The extra credit opportunities were standardized across the professors by awarding bonus points to the overall average. Because each extra credit opportunity added 1% to the semester-long overall average, students could easily understand the potential gains from the opportunities without worrying over complex grading formulae. During the semester there were three opportunities for extra credit, so that each student could earn a total of three extra percentage points to their overall average. Since the opportunities only asked for participation—visiting during office hours and asking a question—each student could foresee that they could complete the assignment merely be attempting it. That is, the assignment did not depend on the student's detailed course knowledge, writing ability or mathematical skills. Each professor read the following announcement as the time allotted to complete each extra credit opportunity began.

> This is an announcement of an extra credit opportunity. You will earn a 1% bonus on your semester grade for asking a question during my office hours at any time within the next two weeks. There will be three such opportunities during the semester. The first opportunity will be during the second and third weeks of the semester; the second opportunity will be

during the seventh and eighth weeks of the semester; and the last opportunity will be during the final two weeks of the semester. Each student can earn a maximum of 1% on his/her semester grade during each two-week period.

4. Descriptive Statistics

The experiment involved a total of 281 students. Since each student could potentially take advantage of three opportunities, the total number of potential extra credit assignments completed was 843. Of this possible 843 completions, 152 extra credit assignments were actually completed—18.0%. 71 students completed one visit, 27 students completed two visits, and 9 students completed three visits.

Descriptive statistics are given in Table 1. We summarize them here. Note that each variable is labeled as “Dep” for “dependent variable” or Indep for “independent variable.” Dependent variables involved extra credit visits to a professor’s office, including the total number of visits for a student (Visits) and a dummy variable measuring whether the student visited at least once (At Least One Visit).

Table 1: Descriptive Statistics

Variable	Definition	Mean
Total Visits (Dep)	Total visits by a single student	0.54
At Least One Visit (Dep)	1 if the student visited during any opportunity, 0 otherwise	0.38
Adjusted GPA (Indep)	Student GPA, 4.0 scale, excluding the economics grade	3.02
Prof1 (Indep)	Prof1=1 if student is in Professor 1's class, 0 otherwise	0.15
Prof2 (Indep)	Prof2=1 if student is in Professor 2's class, 0 otherwise	0.35
Prof3 (Omitted)	Prof3=1 if student is in Professor 3's class, 0 otherwise	0.50
Hours (Indep)	Credit hours the student has attempted	54.4
Micro (Indep)	1 if the course is principles of microeconomics, 0 otherwise	0.29
Grade (Indep)	Grade in course, 4=A, 3=B, 2=C, 1=D, 0=F	2.13
GPA Error (Indep)	Residual from regression predicting GPA using Grade	0.0
Female (Indep)	1 if student is Female, 0 otherwise	0.41

Data came from students in three professors' courses at two universities, giving rise to two dummy variables included in our regressions (Prof1, Prof2), the third dummy variable omitted to avoid perfect collinearity.

Of all students in the experiments, 81 were taking principles of microeconomics and 200 were taking principles of macroeconomics, and our Micro dummy variable is based on this (Micro=1 if the student is in principles of microeconomics).

Student maturity might be measured by the cumulative number of credit hours completed when the course was begun (Hours). The average student in the course had completed 54.4 credit hours—nearly completing the sophomore year.

We measured each student's grade in the course (Grade), net of the extra credit opportunity, so as not to include the same information in our dependent and independent variables. Of a possible 4 quality points, an "A" grade, the average student scored 2.13 quality points in the course—omitting the extra credit points—slightly above a flat C average. Students in the experiments had an average grade point average of 3.02 on a 4.0 scale—omitting the grade in the course in question (Adjusted GPA). Each instructor's students, on average, had higher GPAs than their grades in principles of economics. Given that the average grade in the course was significantly lower, it is likely that many students were disappointed with their performance. We refer to students with high grades in the course and/or high GPA's as "good students."

We included the students' gender (Female), which was equal to one if the student was female. Of the 281 students in the courses, 114 were female (40.6%) and 167 were male (59.4%).

5. Results

We used multiple regression to analyze the data from the experiments and report the results in Table 2. We used a negative binomial model for specification 1 and a probit model for specification 2. Both dependent variables in the regressions had to do with students participating in the extra credit opportunities.

Before we explore these results, we must describe a preliminary step we took, prior to obtaining our estimates in Table 2. We expected that the student's general quality as measured by GPA, and the course grade (Grade) would be correlated. We found a simple correlation between these variables of .67. However, good students with high GPAs are more likely to make better grades in the course (Grade). To increase the efficiency of our estimates, we ran a regression using GPA as the dependent variable and Grade as the independent variable. We used the residuals from that regression as our measure of overall student quality (GPA Error). These residuals represent the extra information that GPA carries, apart from that which is explained by the course grade—student quality that was not reflected in the economics course grade. GPA Error is used in obtaining our estimates in Table 2. Since they are residuals of a regression, their mean is zero, as is seen in Table 1.

Table 2: Regression Estimates

Variable	(1) Negative Binomial Model: 'Visits' is dependent variable	(2) Probit Model: 'At Least One Visit' is dependent variable
Intercept	-2.160***	-1.561***
	(0.310)	(0.280)
Prof1	-0.803*	-0.795**
	(0.432)	(0.391)
Prof2	-0.692***	-0.417*
	(0.238)	(0.224)
Micro	0.489	0.702**
	(0.315)	(0.305)
Hours	0.0022	0.0015
	(0.0028)	(0.0025)
Grade	0.581***	0.534***
	(0.081)	(0.078)
GPA Error	0.688***	0.552***
	(0.228)	(0.206)
Female	0.186	0.042
	(0.171)	(0.176)

281 Observations Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.10$

Our dependent variable in specification 1, Visits, only takes on positive integer values (i.e. 0, 1, 2, 3). A count data model is typically used with this type of data. We selected the negative binomial model for specification 1 since it assumes the mean of the dependent variable is less than the standard deviation (see Byers et al (2003) for additional explanation). The mean of visits (0.54) is less than its standard deviation (0.79).

For specification 2, we use At Least One Visit as the dependent variable. Since the At Least One Visit variable is dichotomous, we used a probit model to estimate specification 2.

Across both estimates, the student's grade in the course (Grade) was found to be positively related to utilization of extra credit opportunities, and the coefficient was statistically different than zero at the .01 level. Across both estimates, the students GPA (above that which was predicted by the course grade—GPA Error) was found to be positively related to utilization of extra credit opportunities and significantly different than zero at the .01 level.

The point estimate of Female was positive in both estimations, but not significantly different than zero at even the .10 level. In a separate, unreported, estimation we found that Females were more likely than males to take advantage of the first extra credit opportunity with a high positive coefficient that was significant at the .01 level.

The coefficient of the number of hours that the student had accumulated, a measure of maturity, was not significantly different than zero in either estimation, though both coefficients' point estimates were positive.

The dummy variable representing whether the student in question was in a microeconomics course was used as a control variable, but was not of special interest. Its coefficient estimates were positive, with the coefficient on At Least One Visit significantly different than zero at the .05 level.

Finally, the coefficients of the two professors included in the estimation (the third professor's dummy variable was excluded to avoid perfect collinearity) were negative in both estimations and significantly different than zero in both estimations, but with varying degrees of confidence. This is likely due to differences that we cannot measure—perhaps the omitted professor had a reputation for giving lower grades, hence students were more likely to take advantage of his extra credit opportunities.

6. Conclusions

Perhaps the most interesting result we find is that so few students took advantage of extra credit opportunities which could significantly affect their grades. A fully participating student could raise their course grade by three percentage points by asking the professor a question in his office three times. Yet, the average student received 0.18 of the 3.0 possible points. Students put less effort into the extra credit opportunities than into the course work.

Our other empirically strong result was that a student who took advantage of an extra credit opportunity most likely had a high grade and a high GPA. That is, extra credit aids those who least need aid because those who most need aid are unwilling to take advantage of it—after all, a major reason that a student makes a low grade is low engagement with the course, which also seems to apply to extra credit opportunities.

One direction for future research would be to explore how the size of the reward affects student behavior. A professor who increases the extra credit reward may see participation increase. In this way, one could calculate a reward elasticity of participation.

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Smart Blockchain Contracts and Firm Value: An Interrupted Time Series Model

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Abstract

Smart contracts enable automatic transaction processing, depending on certain conditions being satisfied. While smart contracts offer potential benefits such as the elimination of transaction-processing intermediaries, they also entail additional risks related to hostile agents and coding errors. We investigate whether the market perceives smart contracts as value-enhancing for firms. We find that firm value rises immediately upon smart contract announcement and continues to rise for a period following the announcement. Our findings suggest that investors think that the benefits of smart contracts outweigh their potential drawbacks, but that this information is incorporated into prices with some delay. Further research in this area is needed to investigate the cash flow effects of smart contracts and determine whether the perception of the market is correct.

1. Introduction

Smart contracts enable automatic transaction processing for contracts. Smart contracts are embedded into blockchains and programmed to activate depending on the occurrence of conditions specified in their code. There are numerous purported benefits of using smart contracts. First, intermediaries are not needed to process transactions, potentially reducing the operating costs of companies that utilize them. Second, the lack of intermediaries may reduce the possibility of fraud; parties to smart contracts no longer need to trust third parties to act as faithful executors. Third, smart contracts are transparent and resistant to unauthorized changes to the contract, as the contracts are secured by the blockchain network.

However, they carry some risks as well. First, they are vulnerable to attacks; a majority of the blockchain's mining power could successfully fork the chain and alter the contract. Second, users must be wary of errors in the coding. If the smart contract is not programmed properly, it may produce incorrect output. If a dispute arises, the smart contract's legal status becomes unclear. Second, parties to a smart contract are not limited by their geolocation; thus, the issue of legal jurisdiction to settle disputes is murky.

Do the benefits of smart contracts outweigh the risks at their current stage of development? Despite the estimated $6.45 billion in financial losses attributed to attacks targeting smart contracts (Chaliasos et al, 2023), interest in blockchain continues to rise (Macrinici et al, 2018). We investigate this question by observing investor reactions to smart contract announcements by firms.

Our study makes several contributions. To our knowledge, our study is the first to address the effect of smart contracts on firm value. Furthermore, our finding that investors view smart contracts as value enhancing suggests that the benefits of smart contracts outweigh the risks and drawbacks (or at least that the market perceives the benefits of smart contracts to outweigh their risks). Our results also suggest that there is a "post-smart contract announcement drift", where the price continues to rise in the period following the announcement of the smart contract. Investors may be able to earn abnormal returns by investing in companies that have recently announced smart contracts.

2. Literature Review

"Smart contracts" take the form of computer programs that are embedded in a blockchain platform. The activation of such programs depends on the occurrence of conditions that were originally agreed upon in detail by the parties of the contract and then written in the relevant programming codes. These programs automate the execution of the contract without involving third parties and incurring the associated costs. Indeed, the purpose of smart contracts is to negate the need for intermediaries and reduce operating costs and the chances of losses due to fraud. A smart contract can also be considered a procedure that aims to transfer value from entity to entity as long as certain conditions are satisfied, which are uniquely defined and stored on the blockchain network.

The concept of smart contracts was proposed in the 1990s by cryptographer Nick Szabo (www.brickken.com), an American of Hungarian descent. Since then, smart contracts have gained popularity in business practice due to several advantages over contracts made traditionally. According to the concept of their operation, the programmatic algorithmizing of contract terms makes these contracts transparent and significantly resistant to unauthorized changes to the contract. In addition, they are also secure, which is ensured by the blockchain environment in which they operate. A not insignificant part of this is that the execution of the contract (once the conditions are met in advance) is automated, and therefore fast. Smart contracts can be used in variety of industries and walks of life. They are used in financial services (Macrinici et al., 2018), for buy-sell transactions (Song et al., 2021), supply chain tracking (Dietrich et al., 2022; Wang et al., 2021), and to confirm ownership, such as of real estate, including land (Stefanovic et al., 2022). It is also an ideal tool for hospitals to store data for their patients (Sreejith & Senthil, 2023), and develop the so-called Internet of Medical Things (IoMT) to allow patients to track their health problems (Lakhan et al., 2021). Other examples are the Internet of Things (IoT) on other fronts, such as trading data packages (Xiong & Xiong, 2019) and trading data analytics services (Jiang et al., 2019). Smart contracts can also be used to mitigate unprecedented threats to privacy rights and data security (Merlec et al., 2021), or at least in university payment transactions (Gunawan et al., 2021). Smart contracts can also eliminate the risk of fraud during elections (Setia & Susanto, 2019). These are just some examples of the application of smart contracts, showcasing their vast applications.

Generally, a smart contract does not constitute a legally binding contract (Dwivedi et al., 2021). Among the ten reasons highlighted by renowned lawyer Mitch Jackson for this, the first seems to be the most important: "One of the biggest legal challenges facing blockchain and smart contract technology is the issue of jurisdiction. Because these technologies are global in nature, it is difficult to determine which jurisdiction applies when it comes to resolving disputes or enforcing contracts." (Jackson, 2023). Despite the many legal uncertainties, however, Belarus became the first country in history to legalize smart contracts on December 22, 2017 (Belarus, 2017).

Despite this, smart contracts, along with their undoubted advantages, still require caution when it comes to their application. This is because they are a relatively young concept and still pose many challenges faced by their stakeholders (Ayman et al., 2020). For example, Macrinici et al. (2018) identified 16 problems associated with blockchain-based smart contracts but simultaneously noted that, despite everything, smart contracts have become one of the most sought-after technologies owing to the high customization they bring to transactions. In another study, Chen et al. (2021) defined 20 defects for smart contracts, divided them into five groups, and were able to categorize the importance of these defects for determining exposure to, for example, control of the contract by undesirables' persons (referred to by them as attackers). Additionally, they highlighted a paramount issue, i.e., the need to ensure that smart contracts are error-free and well-designed before they are deployed on the blockchain considering that a flaw or defect in a smart contract will cause it to "produce" an incorrect or unexpected result or behave in an undesirable way (Chen et al., 2021).

The dynamic development of ways, areas, and methods of using smart contracts, in view of the various technological changes that may be relevant to their operation, triggers an urgent need to pay attention to the issue of not only programmability (programming languages) (Varela-Vaca & Quintero, 2021; Dwivedi et al., 2021), but also the security of smart contracts. Chaliasos et al. (2023) reported that attacks targeting smart contracts are on the rise and have caused an estimated $6.45 billion in financial losses. Although researchers are proposing various automated tools for detecting threats to these contracts, the effectiveness of these tools/solutions have been proved unsatisfactory thus far (Chaliasos et al., 2023).

It is still noteworthy, at this point that, as observed in the academic world since 2016 (Macrinici et al., 2018), the explosive interest in blockchain invariably persists, and publications of articles on blockchain-based smart contracts are numerous; however, they mainly reflect experiments and present methods (Siddiqui et al., 2023), tools and models (Song et al., 2020). This means that practice will still have to wait for the widespread use of this valuable instrument in business (and not only in business), which, with the imperative of optimizing costs (financial and non-financial) of current operations, can support the implementation of tasks defined by the business model or activities in line with the mission adopted by units of the public sphere, for example. However, there is no doubt that this will happen. While it may not initially happen internationally (if only because of the issues of legal norms for transactions undertaken in this economic dimension), it is likely that "today's" experiments will turn "tomorrow" into practice on the scale of individual countries. Daily observations of the way in which various new technological and technical solutions are implemented, which excellently accelerate or shorten the way in which various processes are carried out, buttress this conclusion.

Smart contracts, today, can be considered an innovative solution to the way business is conducted, and as such, can be a driver of increased market value for a company/unit that successfully applies this solution in its operations. It can also, as it increases in scope, cause changes in the culture and way of doing business on a scale beyond the two parties of the contract.

It should be noted, however, that smart contracts exclude the role of intermediaries in contracting and will contribute to changes in the professional competencies that will be necessary in conducting certain activities. This perspective can be seen simultaneously as a threat to certain professional groups, but also as an opportunity for their further development. Certainly, the ability to communicate clearly in business will be crucial, as the terms on which the smart contract is based must be unambiguous. They cannot leave room for loose interpretations, as they need to be sewn into programming algorithms that require precision.

In improving the features of smart contracts, including their resistance to abuse, machine learning, which is a type of artificial intelligence (AI) that, in the broadest terms, enables a system to learn incrementally from data using various algorithms that describe it, and to predict results by learning from training data that form the basis of precise models, plays an important role.

3. Methodology and Research Hypotheses

To investigate whether the benefits of smart contracts outweigh the risks at their current stage of development, we observed investor reactions to smart contract announcements by firms.
We achieved this by gathering the smart contracts data elements (N = 82 events) from the last five years to investigate its effect on the firm's value. Firms were assigned to the treatment group if they announced a smart contract in the sample year or a previous year. We began our analysis with an interrupted time series model using ordinary least squares regression, regressing firm value on a time dummy variable, a treatment dummy variable (equals to one if the firm has announced a smart contract in the observation year or a prior year), and a continuous time variable indicating the time passed since the announcement of the smart contract. The results of this regression are consistent with smart contracts providing an immediate increase to

firm value and that firm value continues to increase following the smart contract's announcement.

To ensure our results were robust, we ran an additional test using an autoregressive 1 model (AR[1] model). Our dependent variable, firm value, showed evidence of autocorrelation. Therefore, after running autocorrelation tests, we determined that the most appropriate modelling is an autoregressive process with 1 lag value. The results of the AR[1] estimation strengthen the effect of smart contracts on firm value. The immediate effect of the smart contract sharply increases firm value, and firm value continues to increase over time. Overall, we find that investors consider smart contracts to be value-enhancing for the firm.

Below we verify the following hypothesis:

Hypothesis 1 (H1): Firms announcing new smart contracts that are intended to increase firm revenue over time produce higher positive stock returns.

4. Results

4.1 Randomized Controlled Study

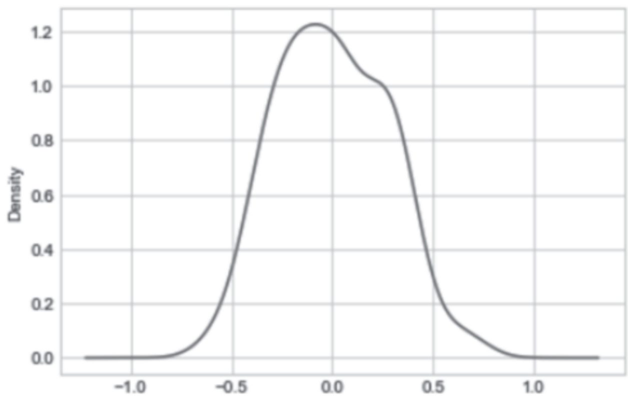
The randomized controlled experiment was conducted using the interrupted time series (ITS) in Python programming tool. In our quasi-experiment research design our selected sample was not divided by a completely random process but by a natural process before and after the smart contract's announcement date. Our research method is ITS, which was used to assess the intervention's effects within our selected sample population for this study. Our time series equation mathematical model came from the innovator John Graunt, a 17^{th}-century London haberdasher, and was used in our smart contracts business analysis:

$$Y = b_0 + b_1 T + b_2 D + b_3 P + \epsilon \qquad (1)$$

Where Y is the outcome variable; T is a continuous variable which indicates the time passed from start of the observational period; D is a dummy variable indicating observation collected before ($D = 0$) or after ($D = 1$) the intervention; P is a continuous variable indicating time passed since the intervention has occurred (before intervention has occurred, $P = 0$); with ϵ representing a zero centered as a Gaussian random error.

We gathered the smart contracts data elements ($N = 82$ events) from the last five years to investigate its effect on the firm's value. We checked whether the ordinary least squares (OLS) regression satisfied the normality of residuals as it is the major assumption to design an interrupted time series model. Our assumptions are a) residuals follow a normal distribution and b) individual observations are independent.

Figure 1: Distribution of Residuals Values



We applied the Jarque-Bera test on all residuals to check whether their skewness and kurtosis match ed the normal distribution; H_0: residual distribution follows a normal distribution. Our ordinary least squares summary output shows a Prob (JB): 0.448, for which a standard α level of 0.05 does not allow us to discard the null hypothesis H_0. We proved that our first assumption for residual follows a normal distribution.

We check the second assumption – the independence of observations with the Durbin-Watson statistic tests whether the residuals are correlated with their immediate predecessor, that is, if they have an autocorrelation at lag 1 or AR (1). We take a look again our OLS summary results, and we observe that the Durbin-Watson statistic has a value of 0.541, which signals a strong positive AR (1).

4.2 An Interrupted Time Series Model

The study implemented an OLS regression to evaluate the impact of the intervention.

Figure 2: OLS Regression Results

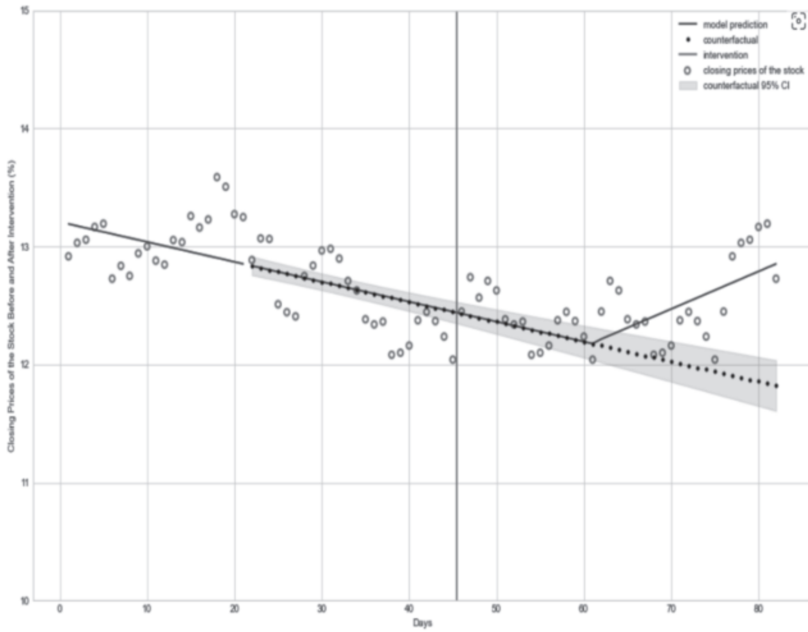
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      Y   R-squared:                       0.525
Model:                            OLS   Adj. R-squared:                  0.507
Method:                 Least Squares   F-statistic:                     28.79
Date:                Sat, 30 Jul 2022   Prob (F-statistic):           1.24e-12
Time:                        20:02:01   Log-Likelihood:                -8.4194
No. Observations:                  82   AIC:                             24.84
Df Residuals:                      78   BIC:                             34.47
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     13.2077      0.071    185.305      0.000      13.066      13.350
T             -0.0169      0.002     -8.449      0.000      -0.021      -0.013
D              0.0067      0.143      0.047      0.962      -0.277       0.290
P              0.0487      0.010      4.821      0.000       0.029       0.069
==============================================================================
Omnibus:                        2.016   Durbin-Watson:                   0.541
Prob(Omnibus):                  0.365   Jarque-Bera (JB):                1.605
Skew:                           0.173   Prob(JB):                        0.448
Kurtosis:                       2.409   Cond. No.                         228.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

The model estimates that our bounce rate increased 0.0067%, and this effect is statistically significant where P > |t| is virtually zero. It is also important to mention that the model estimates on average 0.0487, but significantly increased in bounce rate each week after the intervention, which is unexpected since the firm's value just a few hours after the initiation of the new smart contract.

We evaluate how the model fits before and after intervention and how the smart contracts impact the value of the firm by observing the changes in prices of the book value stocks before and after the intervention moment. This is also known as economic firm value after the smart contract acquisition.

Figure 3: Model Fits Visualization



Our second approach to justify the impact of smart contracts on the firm's value is the autoregressive model approach. The autoregressive model specifies that each observation depends linearly on prior observation. Our model can be written as

$$y_t = c + \phi_1 y_{t-1} + \ldots + \phi_p y_{t-p} + \epsilon_t \qquad (2)$$

where y_t: is the observation at time t; y_{t-1} is the observation at time $t - i$; ϕ_1 is the coefficient of how much observation y_{t-1} correlates to y_t,, and ϵ_t the white noise N $(0, \sigma^2)$ at time t.

Figure 4: Full Autocorrelation

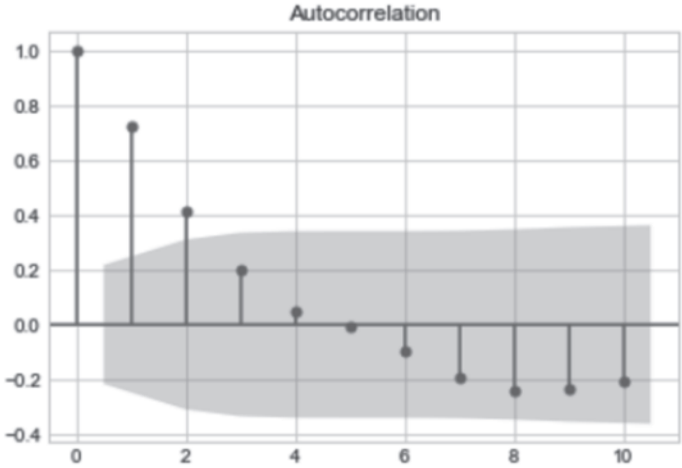


Figure 4 shows that all the observation correlates with past observations from our ITS model. We r an the C partial autocorrelation at lag *p* on all our results after removing the effect of any correlations due to the terms at shorter lags.

Figure 5: Partial Autocorrelation

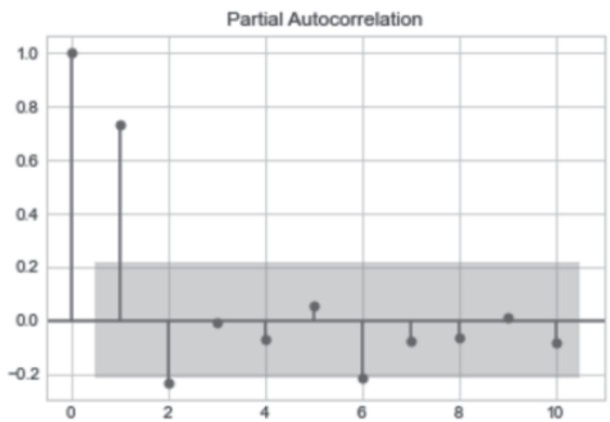


Figure 5 concludes that our model is autoregressive at lag 1, also known as AR (1).

We processed the autoregressive integrated moving average model, as we inferred by the name AR models. We believe that ARIMA (1,0,0) is the best equivalent of AR (1).

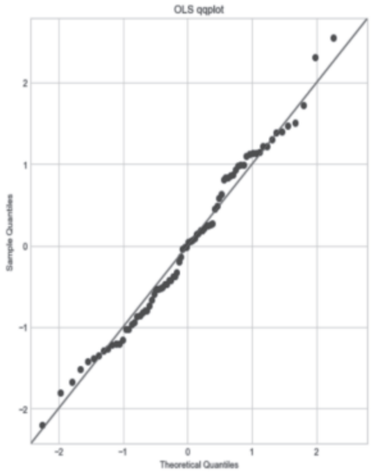
Figure 6: SARIMAX Results

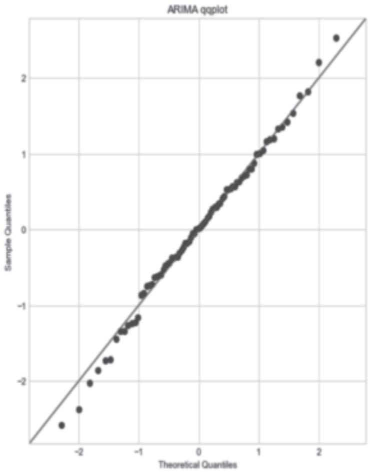
```
                               SARIMAX Results
==============================================================================
Dep. Variable:                      Y   No. Observations:                   82
Model:                 ARIMA(1, 0, 0)   Log Likelihood                  23.223
Date:                Sat, 30 Jul 2022   AIC                            -34.446
Time:                        20:04:05   BIC                            -20.005
Sample:                             0   HQIC                           -28.648
                                 - 82
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const         13.1936      0.184     71.818      0.000      12.834      13.554
T             -0.0175      0.005     -3.323      0.001      -0.028      -0.007
D              0.2916      0.331      0.881      0.379      -0.357       0.941
P              0.0329      0.021      1.573      0.116      -0.008       0.074
ar.L1          0.7483      0.078      9.578      0.000       0.595       0.901
sigma2         0.0329      0.005      6.305      0.000       0.023       0.043
===================================================================================
Ljung-Box (L1) (Q):                   2.57   Jarque-Bera (JB):                 0.27
Prob(Q):                              0.11   Prob(JB):                         0.88
Heteroskedasticity (H):               0.96   Skew:                            -0.13
Prob(H) (two-sided):                  0.91   Kurtosis:                         3.08
===================================================================================
```

The autoregressive model estimates that the bounce rate increased 0.29% on average, and this effect is statistically significant (P > |t| = 3.7%, which is less than our $\alpha = 5\%$).

We found that our OLS model fits best for our event study with abnormal return analysis for all our data elements.
Simultaneously, we observed that the ARIMA (1, 0, 0) model residuals were not only normally distributed in general but were also a good fit for our study (Figure 7).

Figure 7: ARIMA Residual Values





The summary of our autoregressive model shows a Prob (JB): 0.88, which is compatible with the null hypothesis of the normally distributed residuals.

5. Findings & Conclusion

The results of our study indicate that the market views smart contracts as value-enhancing for firms. Firm value rises immediately upon announcement of the smart contract, indicating that the market thinks that the benefits of smart contracts outweigh their risks. Further, we find that the market incorporates the smart contract's value with some delay; the price continues to rise in the period following the smart contract's announcement.

Our study makes several important contributions. First, to our knowledge, our study is the first to examine the association between smart contracts and firm value. Second, the finding that investors value smart contracts as value-enhancing suggests that the benefits of smart contracts exceed the risks and drawbacks. Finally, our results suggest that investors could earn abnormal returns by investing in firms that have recently announced smart contracts, as the price continues to rise following the announcement.

In addition, it is worth noting that this study opens a space for research in a field strongly related to accounting and the methodologies used therein. An interesting area of research relating to smart contracts may also be ascertaining their utility in determining the amount of goodwill in mergers and acquisitions. Such a study can be conducted in two aspects: (1) the impact on goodwill of the mere fact of announcing the use of a new contract (the importance of the "zero moment" of the implementation of this innovative business instrument), and (2) the impact on goodwill (including both the determination of its value at the date of the merger/acquisition and the subsequent impairment testing) with a view to observe the business efficiency of such a contract as its implementation unfolds over time. The above aspects may also be relevant for determining the value of goodwill and testing its impairment for fair presentation of group reporting.

Summa Summorum, our study shows the impact of smart contracts on the market value of a company's shares, which draws attention to the legitimacy of testing whether the use of smart contracts over a longer time horizon is relevant, not only for a short-term investor (share price changes) but also for a long-term investor, making a merger or acquisition of a company involved in such a contract, or forming/expanding its capital group (here the issue of goodwill in individual reporting (for acquisitions) and in consolidated reporting (for the acquisition of ownership rights with the intention of holding them for the long term) is important.

However, our study has a couple limitations. First, our analysis only looks at a certain number of years post-smart contract announcement. It is possible that the long-run value effects could be negative. Second, we do not provide direct evidence of the benefits and costs of smart contracts. Rather, we provide evidence on the market’s perception of the effects of smart contracts.

There are numerous “low-hanging fruit” opportunities for research in this area. Future researchers could examine the effect of other cryptocurrency projects on firm value, for example. More research is also needed to determine whether characteristics of the firm are associated with the market’s reaction to smart contract announcements; it is possible that smart contracts may be more beneficial for some firms than others. Finally, future research could examine the cash flow effects of smart contracts, essentially asking: is the market *correct* that smart contracts provide cash-flow benefits?

We found that the stock market reacts positively to the new smart blockchain contract announcements, thus supporting our hypothesis in this study. Our study has several implications. First, no existing literature investigates the impact of new blockchain contract announcement on stocks. This is the first study to examine the economic firm value’s using a machine learning algorithm and random experiment. The conceptual framework connects the smart contract with their stock return performance. Our findings suggest that investors favor the new smart blockchain announcement when they plan investment project with that specific company or business. Future research could investigate the other digital cryptocurrencies projects and firm characteristics as new signals that impact the stock performance and firm value. Our results suggest that the investors must invest in the new smart contracts once they are implemented for the first time because they reduce time and save costs. We recommend all business investors take a bold step toward exploring the new digital innovations. By understanding smart contracts, all CFOs of companies can better plan their investments to have a greater impact on their firm’s market value. Nonetheless, disregarding long-run stock value reactions to new smart contract’s announcements is still a limitation of this study. Furthermore, we did not investigate the risk effects of new smart contracts, which can be investigated in future studies along with their impacts.

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