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The Valuation Effects of REIT Mergers During the COVID-19 Pandemic

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Abstract

The purpose of this study is to examine the valuation effect of mergers, which generally supports the notion of a synergistic agglomeration. The shock that the COVID-19 pandemic posed upon the real estate industry presented an opportunity for financially stronger REITs to acquire some struggling firms using their free cash flows. This study covers the entire year of 2020, from when COVID-19 was first declared as a public health emergency until the end of the year when the vaccines were approved. By applying a standard event study method, we assess five different return measures of the bidder, target, and their combined outcomes and test them against two competing hypotheses: empire-building versus synergy hypothesis. Contrary to the prevalent finding in the merger literature that mergers are mostly synergistic, our study finds that the COVID-19 pandemic facilitated empire-building mergers. Our study is amongst the first to examine REIT mergers during the COVID-19 pandemic.

Keywords: COVID-19, Event Study, Mergers and Acquisitions, Real Estate Investment Trust (REIT), Valuation Effect.
JEL Classification: G34.
Acknowledgment: Dr. Seongsu David Kim, Ph.D., wants to dedicate this paper to his newborn son.

I Introduction

Most mergers are assumed to create synergy under normal economic conditions. However, in some cases, the bidding firms may overtake target firms without creating the expected synergies or economies of scale. This is known as the empire-building hypothesis (Jensen, 1986). The period of the COVID-19 pandemic presented a different macroeconomic environment. The austere situation of commercial real estate owners and the risk of mortgage insolvency of many residential owners posed a different environment to those negatively affected by the pandemic. However, this situation also allowed financially stable larger companies to expand their empire at a lower cost. Our study explores whether the nature of mergers involving Real Estate Investment Trusts (REITs) during the COVID-19 pandemic has lent support to the empire-building hypothesis instead of the prevalent synergistic merger hypothesis.

II Competing Hypotheses

Studies on mergers from 1980 to 2001 have shown that mergers are generally synergistic and rational, generate efficiencies, and build economies of scale (Moeller, Schlingemann, & Stulz, 2005). By investigating 31 events, Allen and Sirmans (1987) found that REIT mergers among equity/mortgage REIT companies with the same property and geographic focus generated higher

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abnormal returns than unrelated matches. However, regarding the public status of the bidder, Ling and Petrova (2011) found that public acquirers are more disposed to expanding market power.

The empire-building hypothesis is based on Jensen's (1986) argument that managers use excess resources (i.e., free cash flow) to invest in projects that are not necessarily beneficial to the shareholders but still help enhance the firm's prestige and popularity. It is expected that if a merger does not add value, such merger news will negatively affect the stock price of the acquiring firm in the market. The synergy hypothesis pertains to Myers and Majluf's (1984) argument that a way to overcome the lack of financial resources would be to merge with another firm: a strategy with less information asymmetry than relying on external funds. Shareholders perceiving a synergistic merger would then welcome a merger announcement with a positive response.

The hypotheses and expected signs of the target, bidder, and combined outcome are listed in Table 1. The assessed returns in our study are the cumulative abnormal returns (CARs) of five different return measures, evaluated by the *t*-test and Wilcoxon Signed-Rank test on the merger announcement date. Vis-à-vis the expected signs of the statistical tests, a positive test result is notated as *Positive*. A negative test result is notated as *Negative*. A zero or negative outcome is notated as *Non-Positive*. A zero or positive outcome is notated as *Non-Negative*.

Table 1: Competing Hypotheses

	Empire Building	**Synergy**
Target	Positive	Positive
Bidder	Negative	Non-Negative
Combined	Non-Positive	Positive

Andrade, Mitchell, and Stafford (2001) submit that several motivations can drive merger activities: 1) The motivation to create synergy through an economy of scale; 2) The attempt to increase market power by forming monopolies or oligopolies; 3) The motivation to remove incompetent target management through a hostile takeover; 4) An acquirer's self-serving attempt to over-expand at the agency's cost; 5) The motivation to diversify through exploiting internal capital markets. Despite these various motivations, all five intentions can be summarized into two competing hypotheses by Jensen (1986), and, Myers and Majluf's (1984) seminal work.

Regarding REIT mergers, contrary to Jensen's (1986) free cash flow hypothesis that a firm's unnecessary expansion through mergers decreases a firm's value, Ghosh, Petrova, and Xiao (2012) do not find evidence of such mergers. However, Eichholtz and Kok (2007) find evidence of the inefficient management hypothesis in the REIT industry. According to Agrawal and Jaffe (2003), the inefficient management hypothesis posits that a target's inefficient management before the merger motivates a takeover to enhance the target's performance. Such merger motivation is detected if a target's return exhibits a significantly negative performance before the merger, whereby, on the announcement day, both the target and the bidder exhibit positive returns. Observing such inefficient management on the target's side is important because there are only a handful of cases where a REIT merger involves a tender offer due to the target's mismanagement – a hostile takeover. The fact that poor performance prior to the merger is the primary reason for a merger, signals that an acquirer's motivation of building an empire through absorbing a mismanaged target is, in fact, more common than it is explicitly shown in the market, where we define hostile takeovers only by the presence of a tender offer.

Another merger motivation that backs the empire-building hypothesis is the hubris hypothesis. Regarding this hypothesis, Roll (1986) submits that overconfident managers engage in value-destroying acquisitions to disguise their hubris at shareholders' cost. Roll (1986) further argues that overconfident managers tend to overpay the target due to their hubris and miscalculated synergy in the future. The upshot of such a motivation is responded with a negative bidder's return and a positive target's return. Regarding REIT mergers, Lu, Mao, and Shen (2015) find such evidence by observing acquirers that are less transparent and have fewer growth opportunities (i.e., low cash flow). In a public-public merger, the authors (Lu, Mao, & Shen, 2015) find that such acquirers show a statistically significant negative abnormal return on the announcement day.

Regarding the sign conventions of the bidder and target, one of the very first REIT merger studies was conducted by Allen and Sirmans (1987), who found that most of the bidder's returns in a REIT merger were positive during 1977-1983. Sahin (2005), however, found that acquiring firms exhibited a significant negative return, and the target, a positive return, during 1990-1998. Regarding the target's return, McIntosh, Officer, and Born (1989) found that most of the target's returns in REIT mergers were positive during 1962-1986. Even though there are some differences based on different types of mergers and time windows, Ratcliffe and Dimovski (2012) use a meta-analysis and provide evidence that, generally speaking, the target enjoys significantly positive gains in a REIT merger. However, despite their analysis, given the different results based on different waves, it is advised to conduct an examination that includes the combined return.

Regarding the merger of public-public and public-private firms, Chang (1998) finds that the bidder's return is negative in a public-public merger. In contrast, the bidder's return is positive in a public-private merger. Regarding the REIT industry, in a sample of 132 mergers between 1997 and 2006, Campbell, Ghosh, Petrova, and Sirmans (2011) find the same result.

III. Data and Model

Our research observes REIT mergers in 2020 – the first year of the pandemic. This covers the period between the time the Centers for Disease Control and Prevention (CDC) noticed the appearance of the Novel Coronavirus outbreak in Wuhan City, Hubei Province, China (January 9, 2020), and the end of the month when the U.S. Food and Drug Administration (FDA) approved of the first two COVID-19 vaccines: Pfizer-BioNTech (December 11, 2020) and Moderna (December 18, 2020). The primary reason for setting our observation window to this period was to capture the effect of the pandemic before a flurry of merger activities began with the easing of the pandemic-related restrictions in 2021.

We screened our merger cases using Bloomberg Terminal. Table 2 summarizes the conditions that were applied to obtain the merger data. Furthermore, Table 2 shows only completed mergers of U.S.-based publicly listed bidders and targets used in our study. The screening decreased the number of cases to five, significantly lower than the number of mergers in 2021.

As shown in Table 3, the mergers included various types of REITs. While all cases had a REIT company on either the target or bidder's side, only two involved a merger between REITs. Two of the five mergers (i.e., POPE and ANH) involved cash and stock deals, and the remaining three were all cash arrangements.

Two types of data were merged in this study. The stock return data were extracted from the Center for Research in Security Prices (CRSP) database, where firms were traded on the NYSE, NASDAQ, or AMEX. We merged this data with the quarterly financial-accounting information of each firm, which was obtained from the Standard and Poor Global Market Intelligence Compustat database.

Table 2: Sample Restriction

Sample Restriction by Bloomberg	Obs.
Deal Status: Completed	739,675
Dates: 01/01/2020 – 12/31/2020	38,394
Deal Type: M&A	21,413
Exchange: United States (Apply to Target and Acquirer)	220
Index: United States (Apply to Target and Acquirer)	68
Sector/Industry: Include REITs	5
Public/Private: Public (Apply to Target and Acquirer)	5
SIC Code: Finance, Insurance, and Real Estate (Apply to Target and Acquirer)	5

Table 3: Public-Public REIT Mergers in 2020

Date	Target (Ticker)	Type	Bidder (Ticker)	Type	Deal Value (Mil.)
1/15/2020	Pope Resources a Delaware LP (POPE)	Non-REIT	Rayonier Inc. (RYN)	REIT - Diversified	700.26†
2/10/2020	Taubman Centers Inc. (TCO)	REIT-Retail	Simon Property Group Inc. (SPG)	REIT-Malls	6,480.82
10/19/2020	Front Yard Residential Corp. (RESI)	REIT-Residential	Ares Management Corp. (ARES)	Non-REIT	2,491.74
12/7/2020	Anworth Mortgage Asset Corp (ANH)	REIT-Mortgage	Ready Capital Corp. (RC)	REIT-Mortgage	2,145†
12/30/2020	Red Lion Hotels Corp. (RLH)	Non-REIT	Service Properties Trust (SVC)	REIT-Hotel	89.13

†: *Indicates cash-stock deals. The remaining three were all cash arrangements.*

We applied parametric (*t*-test) and nonparametric tests (Wilcoxon Signed-Rank test) to assess the return data. Regarding nonparametric testing methods, MacKinlay (1997) enunciates that they can be used as a robustness test because they do not assume any underlying distributions. Furthermore, nonparametric approaches also apply more stringent test statistics than parametric *t*-tests. Since it removes the assumption of an underlying distribution and uses ranks instead of raw observation values, it can also analyze data with low observation numbers.

In our study, we used five different return measures. Those five return measures are the net market return, abnormal returns based on the Capital Asset Pricing Model (CAPM) (Sharpe, 1964), Carhart's (1997) Four Factor model, Fama-French Three Factor model (Fama & French, 1993), and Fama-French Five Factor model (Fama & French, 2015). The risk-free rate and the market factors were imported from Dr. Kenneth R. French's data library.[1] The net market model return, otherwise called the market-adjusted return, was computed by simply subtracting the market return $R_{m,t}$ (i.e., S&P 500 index return) from the raw return $R_{i,t}$ (i.e., holding period return or buy-and-hold return) of the firm (bidder, target). It is simply the difference between the raw and market index returns and does not involve stochastic components. Here, $R_{i,t}$ is the raw return of firm i on trading day t and $R_{m,t}$ is the market index m of the S&P 500 on trading day t. In the equation below, $R_{i,t}^{NM}$ is the net market return of firm i on trading day t.

$$R_{i,t}^{NM} = R_{i,t} - R_{m,t} \tag{1}$$

The abnormal return based on Sharpe's (1964) CAPM is a model where the excess return of the firm was regressed on the market index excess return. Noted is that in all regression-based abnormal return measures, we ran a regression based on the month when the merger was announced. That is, we used the returns in January for the first merger, February for the second, October for the third, and December for the last two mergers.

$$(R_{i,t} - R_{f,t}) = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) + \varepsilon_{i,t}^{CAPM} \tag{2}$$

In the equation above, Jensen's Alpha (Jensen, 1968) is denoted as α_i, the Beta as β_i, and the risk-free rate is denoted as $R_{f,t}$. The stochastic term $\varepsilon_{i,t}^{AR}$ is the error term, which is asymptotically zero. This residual component is the stochastic disturbance or, simply said, the abnormal return. Thus, the abnormal return is the difference between a firm's excess return and its predicted value.

$$\varepsilon_{i,t}^{CAPM} = \left(R_{i,t} - R_f\right) - \left(\widehat{\alpha}_i + \widehat{\beta}_i\left(R_{m,t} - R_f\right)\right) = (R_{i,t} - R_f) - E[R_{i,t} - R_f] \tag{3}$$

The third return type comes from the Fama-French Three Factor model (Fama & French, 1993). This model includes the SMB (small minus big) and HML (high minus low) factors. Together with the market return premium $(R_{m,t} - R_{f,t})$, these are the three factors in the Fama-French Three Factor model. Here, the residual $\varepsilon_{i,t}^{FF3}$ of this Fama-French Three Factor regression model is the abnormal return that we used in assessing the return outcomes.

$$(R_{i,t} - R_{f,t}) = \alpha_i^{FF3} + \beta_{1,i}^{FF3}\left(R_{m,t} - R_{f,t}\right) + \beta_{2,i}^{FF3} SMB_t + \beta_{3,i}^{FF3} HML_t + \varepsilon_{i,t}^{FF3} \tag{4}$$

The fourth return measure comes from the Carhart Four Factor model (Carhart, 1997). This model adds a fourth factor: the MOM (momentum factor), to the Fama-French Three Factor model. As in the preceding model, the residual $\varepsilon_{i,t}^{C4}$ is the abnormal return.

$$(R_{i,t} - R_{f,t}) = \alpha_i^{C4} + \beta_{1,i}^{C4}\left(R_{m,t} - R_{f,t}\right) + \beta_{2,i}^{C4} SMB_t + \beta_{3,i}^{C4} HML_t + \beta_{4,i}^{C4} MOM_t + \varepsilon_{i,t}^{C4} \tag{5}$$

[1] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

The last return type comes from the Fama-French Five Factor model (Fama & French, 2015). The Fama-French Five Factor model adds the RMW (most minus least profitable) and CMA (conservative minus aggressive) to the Fama-French Three-Factor model (Fama & French, 1993). Again, the residual $\varepsilon_{i,t}^{FF5}$ is the abnormal return.

$$(R_{i,t} - R_{f,t}) = \alpha_i^{FF5} + \beta_{1,i}^{FF5}(R_{m,t} - R_{f,t}) + \beta_{2,i}^{FF5}SMB_t + \beta_{3,i}^{FF5}HML_t + \beta_{4,i}^{FF5}RMW_t + \beta_{5,i}^{FF5}CMA_t + \varepsilon_{i,t}^{FF5} \quad (6)$$

Based on the five return measures discussed so far, we also generated the combined return to assess the characteristics of a merger. This return measure is simply the buy-and-hold (or holding period return) of the sum of the bidder's and target's market capitalizations. This measure was also used in seminal studies by Becher (2000) and Mulherin and Boone (2000).

$$Combined\ Return_{n,t}^{a} = \frac{\left(PrcShr_{n,t}^{Bid} + PrcShr_{n,t}^{Tar}\right) - \left(PrcShr_{n,t-1}^{Bid} + PrcShr_{n,t-1}^{Tar}\right)}{\left(PrcShr_{n,t-1}^{Bid} + PrcShr_{n,t-1}^{Tar}\right)} \quad (7)$$

In the notation above, the superscript (a) indicates the type of abnormal return. $PrcShr_{i,t}^{Bid}$ is the market capitalization of the bidder observed on trading day t. By the same token, $PrcShr_{i,t}^{Tar}$ is the market capitalization of the target observed on day t. The superscripts Bid and Tar each indicate the bidder and the target, whereby n is the merger number, and t is the trading day.

After obtaining the abnormal returns of five return estimations by the bidder, target, and the combined outcome, we computed the cumulative abnormal return (CAR): the sum from the previous trading day up to the announcement day. The primary reason for applying a one-trading day run-up period is because there could have been early reactions in the market. Contrary to event studies that observe events exogenous to the firm, firm endogenous events most likely experience a market reaction before or on the announcement day, and spillovers to post-announcement days are not uncommon.

$$CAR_i^a(-1,0) = \sum_{t=-1}^{0} Abnormal\ Return_{i,t}^{a} \quad (8)$$

In the notation above, superscript a indicates the type of abnormal return. The abbreviations used for each type of return are as follows: NM (Net Market model), CAPM (Capital Asset Pricing Model), FF3 (Fama-French Three Factor model), C4 (Carhart Four factor model), FF5 (Fama-French Five Factor model).

We ran an Ordinary Least Squared (OLS) model and a nonparametric Spearman correlation matrix based on ranks as post-estimation. The OLS model was only based on the target's return, while the Spearman rank correlation table on both. The post-estimation model also applied a nonparametric assessment to address the small sample size limitation of this study.

$$CAR_i^a(-1,0) = \gamma_1 + \gamma_2 MTB_i + \gamma_3 DYR_i + \gamma_4 REIT2_i + \gamma_5 DEALV_i + \gamma_6 PTYPE_i + \varepsilon_i^a \quad (9)$$

Regarding the variables in the OLS model, MTB_i is the market-to-book ratio, and DYR_i is the dividend yield ratio of firm i. These two variables only pertain to the target firm, whereby

$REIT2_i$, $DEALV_i$, and $PTYPE_i$ have the same values in both the target and the bidder's sample. Variables MTB_i and DYR_i were generated by the previous quarter's financial-accounting information. Variable $REIT2_i$ is a binary variable and indicates whether a merger was between two REIT companies. Variable $DEALV_i$ is the deal value in billion dollars. Variable $PTYPE_i$ is a dichotomous variable that switches on when the payment type involves both cash and stock, compared to a cash-only deal, which was coded as zero.

IV. Results

The summary statistics of two trading days by target (t), bidder (b), and combined (c) return are listed in Table 4. Regarding the CAR values, the summary statistics are based on the CAR before and on the announcement day. As for the last five variables in Table 4, there is no variability among the trading days.

Table 4: Summary Statistics: CAR (-1, 0)

	N	*Mean*	*St. Dev.*	*Min.*	*Max.*
(t) CAR (-1, 0) NM	10	0.148	0.194	-0.0108	0.514
(b) CAR (-1, 0) NM	10	-0.00416	0.0317	-0.0843	0.0215
(c) CAR (-1, 0) NM	10	-11.65	41.73	-127.7	16.97
(t) CAR (-1, 0) CAPM	10	0.11	0.171	-0.0558	0.405
(b) CAR (-1, 0) CAPM	10	-0.00303	0.0302	-0.0873	0.0121
(c) CAR (-1, 0) CAPM	10	-10.13	64.14	-174.1	86.95
(t) CAR (-1, 0) FF3	10	0.0925	0.168	-0.0636	0.424
(b) CAR (-1, 0) FF3	10	-0.00773	0.0317	-0.0947	0.012
(c) CAR (-1, 0) FF3	10	-4.027	23.11	-61.94	32.53
(t) CAR (-1, 0) C4	10	0.0867	0.156	-0.0643	0.365
(b) CAR (-1, 0) C4	10	-0.00905	0.0313	-0.0946	0.0123
(c) CAR (-1, 0) C4	10	-2.285	13.57	-29.09	26.85
(t) CAR (-1, 0) FF5	10	0.0898	0.173	-0.0739	0.439
(b) CAR (-1, 0) FF5	10	-0.00687	0.0296	-0.0897	0.0104
(c) CAR (-1, 0) FF5	10	-19.49	70.29	-215.7	40.03
(t) MTB	10	-34.76	79.65	-185.7	9.341
(t) DYR	10	0.00917	0.00892	0	0.0213
REIT2	10	0.4	0.516	0	1
DEALV	10	2.381	2.355	0.0891	6.481
PTYPE	10	0.4	0.516	0	1

The *t*-test and Wilcoxon Signed-Rank test coefficients are listed in Table 5. When interpreting the results, it is noted that the Wilcoxon Signed Rank test is evaluated by the *Z*-test.

Given the sign conventions in both tests, we can conclude that REIT mergers in 2020 support the empire-building hypothesis. Most of the five return measures show a positive result in the target, a negative result in the bidder, and a non-positive result in the combined return columns. These findings suggest that mergers predominantly benefitted the target stockholders (e.g., Andrade, Mitchell, and Stafford, 2001). However, considering that the ultimate assessment of the combined return is what concludes whether a merger's perception is built on a synergistic or expansion-oriented purpose, the non-positive result of the combined return of all five return measures supports the empire-building hypothesis.

Table 5. *T*-Test and Wilcoxon Signed-Rank Test

	Target	Bidder	Combined
T-Test	*T*-Test	*T*-Test	*T*-Test
CAR	(*obs.* = 5)	(*obs.* = 5)	(*obs.* = 5)
Net Market Return	3.135**	-0.733	-0.749
Capital Asset Pricing Model	2.921**	0.645	-0.447
Fama-French 3 Factor	2.462*	-0.886	-0.53
Carhart 4 Factor	2.553*	-0.972	-0.358
Fama-French 5 Factor	2.253*	-0.849	-0.835
Wilcoxon Signed-Rank Test	*Z*-Test	*Z*-Test	*Z*-Test
CAR	(*obs.* = 5)	(*obs.* = 5)	(*obs.* = 5)
Net Market Return	2.023**	-0.405	0.135
Capital Asset Pricing Model	1.753*	0.405	-0.405
Fama-French 3 Factor	1.753*	-0.674	-0.944
Carhart 4 Factor	1.753*	-0.405	-0.944
Fama-French 5 Factor	1.753*	-0.135	-0.674

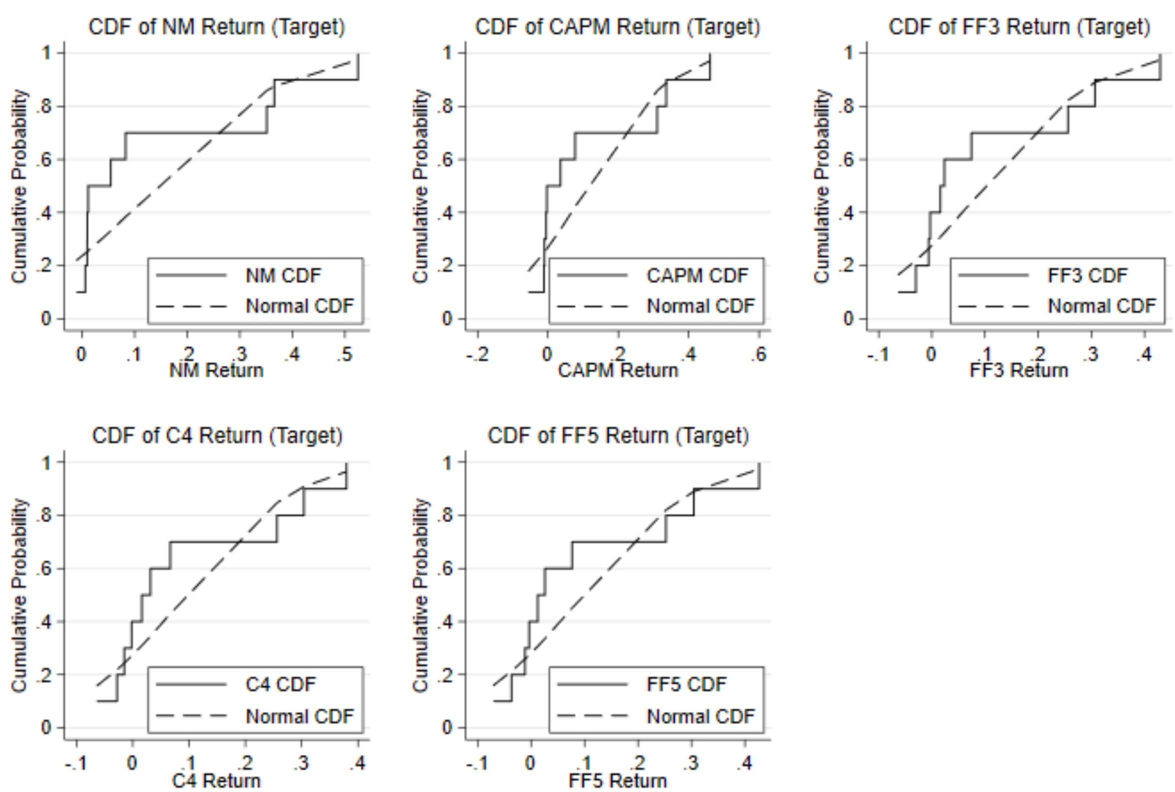
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

One of our study's concerns is the small number of observations. However, given the analysis in MacKinlay’s (1997) seminal paper on event studies, the number of observations is not a big concern as long as the magnitude of the abnormal returns is large and the variance among observations is small. MacKinlay (1997) provides evidence that the power of event study test statistics to reject the null hypothesis that the abnormal return is zero increases in one of the three following conditions: 1) Large number of observations, 2) Large abnormal returns, 3) Small variance among observations (i.e., short time window). His paper (MacKinlay, 1997) demonstrates that the number of observations is not a big concern if the abnormal return is large enough. MacKinlay (1997) demonstrates this by comparing the cumulative probability (i.e., the power of an event study test) of a small sample with large abnormal returns against a large sample with small abnormal returns. The results show that the testing power is growing faster in the former case. These results remain solid even when applying a broader observation window. However, the problem with samples with expansive observation windows is that it introduces more variability into the sample. With more variability, the magnitude of the abnormal return is more difficult to observe. As shown in Figure 1, our return samples increase faster than the Normal distribution. This is evidence that our abnormal returns are large enough to satisfy the condition for a good event study to reject the null hypothesis.

MacKinlay (1997) submits that if the testing power is small, the researcher should increase the sample size, shorten the event window, or apply a more rigorous testing method. Except for the sample size stipulation, our study satisfies the remaining two conditions. Regarding the testing method, as MacKinlay (1997) suggests, we apply both the parametric (*t*-test) and nonparametric (Wilcoxon Signed-Rank test) tests.

In many merger-related event studies, the nonparametric test is used to test robustness (e.g., Kim, 2023). The reason for applying a nonparametric approach also pertains to the small observation number in an event study. Since a nonparametric test does not assume an underlying distribution, it is more rigorous for samples with small observation numbers. By assigning ranks based on the magnitude and signs based on each observation's direction, the nonparametric test used in our study approximates our small sample towards a Normal distribution (and, therefore, the *Z*-test). As shown in Table 5, the test results of the *t*-test and *Z*-test (based on a nonparametric Wilcoxon Signed-Rank test) are nearly identical, which shows evidence of the robustness of our tests – even with a small sample.

Figure 1. Cumulative Distribution Functions (CDFs) of Returns



Based on the results in Table 5, we explore the inferences of the target's return in Table 6. Each model's total number of observations is based on two trading days for each of the five events. Therefore, the ten trading days are based on the merger announcement day and the day before. Despite the low observation number, the *R*-Squared is relatively high, indicating that our regression model exhibits a good fit.

Among the variables added to our estimation model, the DYR shows a statistically significant negative outcome throughout all return types. For tax exemption, a REIT must pay 90% of its taxable income as dividends, and 75% of this income should come from real estate assets. This stipulation pushes REITs towards a low-cash structure with a large amount of debt outstanding. Since REITs are mostly short of cash, during the COVID-19 pandemic, the public found cash losses through dividend payouts would decrease shareholder values.

Such investor sentiment is also found in the positive and significant PTYPE coefficient. This payment type variable was coded as one if the payment was made in cash and stock, compared to a cash-only deal, which was coded as zero. Previous literature documents that a cash-only deal increases shareholder values (e.g., Andrade, Mitchell, and Stafford, 2001; Heron and Lie, 2002). Similarly, regarding REIT mergers, Ratcliffe and Dimovski (2012) find that bidders gain significant wealth in a cash-financed deal. The opposite holds for public-public mergers financed through stock payments, where the bidder is devalued because the target is then recognized to be overvalued (Campbell, Ghosh, & Sirmans, 2001). In conclusion, based on the results from the dividend yield ratio (DYR) and the payment method in the merger deal (PTYPE), we can conclude that the public did not like cash payments during the pandemic.

In Table 6, variable REIT2 exhibits a positive and significant coefficient, which indicates that a merger between REITs increases the target's shareholder values. A merger between similar types of bidders and targets is informationally more transparent than mergers with non-REIT companies. Similar results were found in Ratcliffe and Dimovski's (2012) meta-analysis on REIT mergers. The authors (Ratcliffe & Dimovski, 2012) find that the mean excess return of the acquirer in a REIT-REIT merger was larger than a merger that involved a non-REIT target.

Table 6: Cross-Sectional Regression (Target)

	CAR (-1, 0) **NM**	CAR (-1, 0) **CAPM**	CAR (-1, 0) **FF3**	CAR (-1, 0) **C4**	CAR (-1, 0) **FF5**
(t) MTB	-0.00205	-0.00178	-0.00114	-0.000770	-0.00117
	(0.00172)	(0.00151)	(0.00140)	(0.00141)	(0.00139)
(t) DYR	**-83.16****	**-74.50****	**-66.71****	**-60.44****	**-66.22****
	(26.02)	(22.79)	(21.20)	(21.33)	(20.97)
REIT2	**0.710***	**0.631***	**0.574***	0.509	**0.575***
	(0.327)	(0.286)	(0.266)	(0.268)	(0.263)
DEALV	0.0760	0.0658	0.0863	0.0862	0.0893
	(0.0567)	(0.0497)	(0.0462)	(0.0465)	(0.0457)
PTYPE	**0.920****	**0.845****	**0.732****	**0.673****	**0.734****
	(0.279)	(0.244)	(0.227)	(0.229)	(0.225)
Constant	0.00691	-0.0161	-0.0628	-0.0635	-0.0797
	(0.101)	(0.0887)	(0.0826)	(0.0831)	(0.0817)
Observations	10	10	10	10	10
R-squared	0.777	0.778	0.802	0.767	0.816

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parentheses.

The last analysis in our study uses a nonparametric approach as a robustness check to make up for the limitation of using a small sample size. The Spearman correlation in Table 7 shows significant coefficient results that were insignificant in the previous analysis (i.e., Table 6). The rank-based correlation of the bidder and target's CAR values of five return measures suggests that the deal value positively correlates with the target's share price. This is because a higher deal value makes the public think that the target is valuable (e.g., Andrade, Mitchell, and Stafford, 2001). The positive correlation between the market-to-book ratio and the bidder's return shows that the bidder's growth potential assures a favorable bidder valuation. Here, the Spearman correlation does not show any deviations from findings in previous merger studies under normal macroeconomic circumstances.

Table 7: Spearman Rank Correlation Coefficients

	(t) MTB (b) MTB	(t) DYR (b) DYR	REIT2	DEALV	PTYPE
(t) CAR NM	0.172	0.125	0.142	0.197	0.213
(t) CAR CAPM	0.271	0.2	0.142	0.172	0.355
(t) CAR FF3	0.123	0.288	0.355	**0.615***	0.142
(t) CAR C4	0.123	0.288	0.355	**0.615***	0.142
(t) CAR FF5	0.049	0.356	0.426	**0.64****	0.142
(b) CAR NM	**0.615***	0.309	0.142	**0.64****	-0.213
(b) CAR CAPM	**0.591***	-0.042	-0.142	0.394	0
(b) CAR FF3	0.492	-0.236	-0.426	0.32	-0.355
(b) CAR C4	**0.714****	-0.139	-0.355	0.492	-0.355
(b) CAR FF5	0.443	-0.103	-0.142	0.394	-0.426

*** p<0.01, ** p<0.05, * p<0.1

V. Conclusions

In this study, we investigated the valuation effects of mergers involving REITs. Contrary to the prevalent finding that mergers create synergy, we found that during the COVID-19 pandemic, mergers advocated the empire-building hypothesis. This was found in the non-positive combined return of five different return types on the merger announcement day. Anomalies of the pandemic were also observed in the dividend yield ratio and the payment type in the merger, where shareholders exhibited an aversion towards cash spending.

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The Effect of Cross-Listing, Institutional Ownership, External Monitoring, and Capital Stringency Regulation on Bank Performance: A Comparison of Developed and Developing Economies

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Abstract

A bank listed on a single exchange must endure complex rules and high compliance costs. Those rules and costs are magnified when a bank decides to cross-list on multiple exchanges especially when the exchanges are in countries with varying degrees of development. We study the impact of cross-listing, institutional ownership, external monitoring, and capital stringency regulation on banks' performance in developed and developing economies. The effect of cross-listing from a more developed to a less developed country differs in the opposite direction. We find that cross-listing results in higher profit and lower asset quality in banks from developed economies and lower profit and higher asset quality in banks from developing economies due to higher regulations and compliance costs. Cross-listing is associated with higher capital in banks from developed countries and higher asset growth and loan growth in banks from developing economies, especially after the 2008 crisis period. Higher institutional ownership results in higher profit, better asset quality, higher growth in banks from both developed and developing economies, and higher tier-1 capital in banks from developed countries. Higher external monitoring results in lower profit, better asset quality, and higher tier-1 capital but lower growth of assets and loans in banks from developing economies. Higher capital stringency regulation results in lower profit and higher tier-1 capital in developing countries and higher profit and better asset quality but lower growth in banks from developed countries. During the financial crisis, US listed banks were positively associated with asset quality when compared to non-US listed banks, and US listed banks were positively associated with tier-1 capital. After the Dodd-Frank Act was implemented, banks with higher capital stringency regulation and investor protection are associated lower profit due to increased regulatory requirements and cost.

JEL Classification: G15, G21, G28, G38, 057
Keywords: Cross-listing, External monitoring, Capital stringency regulation, Institutional ownership, performance, capital, growth

I Introduction

Banks play an important and unique role in economic growth and financial stability (Demirgcu-Kunt *et al*., 2011). Though many industries are subjected to strict regulation, banks are also highly leveraged when compared to non-bank firms. Their business model naturally includes savings, lending, investment, and real estate, with their two major sources of income being interest income where the bank is taking risk on its own behalf and provision earnings where the bank is taking risk on behalf of investors (Jeucken and Bouma, 1999). Their critical role in the economy coupled with their enhanced leverage require that banks be highly regulated and supervised (Barth *et al*., 2004 and 2008). Hirtle *et al*. (2020) distinguish between regulation and supervision. According to their analysis, regulation specifies the activities the bank can or cannot perform and the minimum financial standards such as capital and liquidity requirements. In contrast, supervision identifies a bank's regulatory compliance and the issues that threaten its immediate or long-term health. Due

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to the significant differences between banks and other corporations and the extensive compliance requirements by regulators and supervisors, cross-listing of bank stock has an impact on a bank's performance and risk.

Vast literature find the cross-listing of non-banking firms has numerous benefits such as higher value (King and Segal 2004; Foucault and Gehrig 2008), growth (Khurana *et al*., 2008), better corporate governance (Lel and Miller, 2008 and Berkman and Nguyen, 2010), and increased shareholder protection (Coffee, 1999 and Stulz, 1999). Non-banking firms that are listed in a strong investor protection country such as the United States adhere to the regulations in that country (Coffee, 1999; Stulz, 1999; and Lel and Miller, 2008). Despite all the literature on non-banking firms, there is limited literature on cross-listing in banking firms. While most studies in banking literature focus on the effect of cross-listing on economic development and growth of the country (Bhattacharya, 1993; Bruno et al., 2014 and Demirguc-Kunt et al., 1998), Claessens *et al*. (2001) study the effect of foreign banks on domestic banks in developed and developing countries for the 1988-1995 period and find that foreign banks in developing countries have higher profitability when compared to domestic banks. Our paper contributes to the literature by providing insight to the effects of cross-listing, institutional ownership, external monitoring, and capital stringency in banking firms for the period 2004-2018. We analyze how the bank's profitability, asset quality, capital maintenance and growth differ in banks in developed and developing countries.

In analyzing the general operation of foreign banks in poor countries one study found those banks struggle to overcome distance and cultural issues to monitor their subsidiaries (Detragiache *et al*., 2008). This struggle results in a reduction in overall efficiency and welfare of the bank. When a bank from a less developed country desires to be cross-listed in a more developed country, we expect that bank to adhere to regulations of the more developed country resulting in both lower profit due to higher compliance costs and higher asset quality due to greater monitoring. Alternatively, when a bank from a more developed country desires to be cross-listed in a less developed country, we expect that bank to experience higher profit due to lower compliance costs but lower asset quality due to less monitoring. Each country may have different requirements for banking operations; therefore, the study of the cross-listing effect on banks' performance is important.

We use a sample of banks from 98 countries and classify them into banks from developed and developing countries. If the bank lists its stock in multiple exchanges, we consider such banks as cross-listed banks. We test the effect of cross-listing in multiple stock exchanges, institutional ownership, external monitoring, and capital stringency regulation on bank performance and risk. To analyze a bank's performance and risk we use four factors: (1) its profitability, (2) its asset quality, (3) its capital maintenance and (4) its growth.

We use return on assets (ROA) and return on equity (ROE) as proxies for profitability of the bank. We measure the banks' asset quality using several variables including non-performing loans (NPL), bad loans to deposits ratio (BLOAND) and bad loans to total loans ratio (BLOANP). Our methodology is like Liang *et al*. (2013) who use ROA and ROE as proxies for bank performance and who use NPL and NCO (Net charge offs) as proxies for asset quality. To measure the banks' capital maintenance, we use tier-1 and total capital percentages (Tier-1 + Tier-2 capital). Tier-1 capital consists of the banks' core capital (mostly equity) and tier-2 capital is supplementary capital both of which are regulatory requirements. Bank regulators impose a minimum amount of capital and recommend that a bank operates at above minimum levels to protect debtholders and to reduce the possibility of failure. Barth *et al*. (2004) note that capital serves as a buffer against bank failure and asset losses. To measure the growth of the bank we analyze the growth of assets, loans, and deposits. One of the banks' main businesses is lending, and loans are typically the largest component of the banks' asset. Deposit growth defines a core source of funding that banks can obtain to lend and continue growing.

When comparing banks in developed countries with banks in developing countries, we find significant differences in the impact of cross-listing, capital stringency, and increased external monitoring from institutional ownership. Banks from developed countries that cross-list are more profitable but have lower asset quality due to listing in other exchanges where regulations are not as stringent. Comparatively, banks from developing countries that cross-list in more developed countries experience a higher level of compliance requirements; therefore, they are less profitable due to an increased compliance cost but have better asset quality due to increased compliance requirements. These findings are consistent with research on non-banking firms by Ribstein (2005), Coffee (1999), and Stulz (1999). We further find that banks from developing countries that specifically cross-list on US stock exchanges have better asset quality (i.e., lower NPL and bad loans).

We find that capital levels are consistent among cross-listed firms regardless of whether the firm originates from a developed or a developing country. Studies find that non-US firms that are listed in the US can access higher equity capital (Reese and Weisbach, 2002) and have higher liquidity (Berkman and Nguyen, 2010). We also find that larger firms have lower profit and capital and higher quality of assets. While Hakenes and Isabel (2011) find that large banks have a competitive advantage under the IRB Basel II approach and hence require less capital, Avramidis *et al.* (2018) finds larger banks have higher levels of monitoring over smaller banks.

The presence of high levels of institutional ownership in banks located in both developed and developing countries also has a positive and significant impact. Banks with high levels of institutional ownership (which creates an increased amount of external monitoring in both developed and developing countries) have higher profit and better asset quality; however, those from developed countries also have higher capital and higher loan growth. Banks from developing countries with high external monitoring experience better asset quality but lower profit due to compliance costs. If that same category of banks have higher capital regulation stringency, they will also experience higher capital levels.

Investor protection variable (ADRI) is a country-based variable to indicate the strength of that country's protection of investors. In banks from developing economies, the ADRI variable is positively associated with asset quality and negatively associated with profit. These positive and negative relationships imply that higher protection countries have both higher compliance requirements and greater transparent operations of the bank which increase compliance costs.

We conduct additional tests by dividing the sample into crisis-period only (2008-2009) and post-crisis period and into before and after the Dodd-Frank Act (2010) implementation period. Due to several bank failures during the financial crisis, the Dodd-Frank Act was implemented which imposed more stringent regulations on financial institutions.

The results in the post-crisis period are similar to the full sample with the exceptions listed below. US listing was positively associated with profit implying that only profitable firms remained listed on US stock exchanges. Banks from developed countries with low external monitoring that are listed on US exchanges were negatively associated with profitability. The capital stringency regulation and ADRI (investor protection variable) were positively associated with profitability in banks from developed countries and negatively associated with profitability in banks from developing countries. Banks from developed countries that are listed in US are positively associated with tier-1 capital due to greater regulations and risk reduction requirements.

In the crisis-period sample, banks from high external monitoring countries and high capital stringency were negatively associated with profitability, and banks with higher investor protection were positively associated with tier-1 and total capital.

In the post-Dodd-Frank Act sample, banks from developing countries that list in multiple exchanges are negatively associated with profitability due to higher compliance costs. Banks that have higher tier-1 capital are positively associated with profitability. After the Dodd-Frank Act, US listed firms are positively associated with profitability implying that only profitable banks chose to be listed in US. DiSalvo (2019) mentions that regulatory changes since the Dodd-Frank Act have resulted in tighter post-crisis regulation and higher costs which led to some banks withdrawing from US.

The remainder of the paper proceeds as follows. Section 2 discusses the literature and Hypotheses. Section 3 describes and discusses the data sources and variables used in our empirical analysis. Section 4 provides our methodology and discusses the results of our analysis. Section 5 concludes.

II Literature and Hypotheses

In a theory known as the "Bonding Hypothesis," Coffee (1999) and Stulz (1999) proposed that a foreign firm that bonds itself to a major US stock exchange through cross-listing will increase the protection for its minority shareholders. That theory encouraged Huang *et al*. (2013) to study firms that cross-listed using American Depository Receipts (ADRs). They discovered that the Bonding Hypothesis created a higher cash reserve when compared to other firms. In a related study, Lel and Miller (2008) find that firms from weak investor protection countries are more likely to terminate poorly performing CEOs when they cross-list in a major US exchange.

When examining the banking industry, Siddique *et al*. (2020) compare the performance of commercial banks in India and Pakistan (developing countries) with those of banks in Japan and Saudi Arabia (developed countries). They find non-performing loans and cost efficiency ratios have a negative relationship with ROA and ROE in both pools while the capital adequacy ratio is positively related to the ROA and ROE. Since Asian banks in general have higher non-performing loans, their study recommends the banks enhance their loan approval process and monitoring. Aebi *et al*. (2011) find that banks with better risk management strategies such as having a chief risk officer who reports to the board of directors have better stock performance and ROE during the 2008 financial crisis. Using a sample of US banks, Hirtle *et al*. (2020) find that banks with higher supervision hold higher quality loans and experience less volatility of earnings and market returns. Using a sample of Chinese banks, Liang *et al.* (2013) test the effect of board characteristics on bank performance (ROA and ROE) and asset quality (non-performing loans and net charge offs). They find stronger bank performance and asset quality occur in banks with a larger number of board meetings and the presence of independent directors while weaker bank performance and asset quality occur in banks with a larger board size and a greater number of political connections. With the lower level of compliance efforts and related cost, Claessens *et al*. (2001) find that foreign banks in developing countries have higher profitability when compared to domestic banks.

Typically, developed countries have more stringent regulatory requirements and higher monitoring when compared to developing countries. Hence, we hypothesize

Hypothesis 1: Cross-listing increases profit but decreases asset quality for banks from developed countries, and decreases profit but increases asset quality for banks from developing countries.

Reese and Weisbach (2002) find that non-US firms cross-list in the US to increase minority shareholder protection. This cross-listing increases equity issues. They find that equity issue increases (a) from outside the US in firms from weak protection countries and (b) from inside the US in firms from strong protection countries. In a similar study that focused on non-banking firms, Berkman and Nguyen (2010) find that firms that are cross-listed in US have higher stock liquidity as compared with firms that are not cross-listed.

Banks that are cross-listed are expected to have higher tier-1 capital since they can raise more equity capital from multiple countries. Hence, we hypothesize:

Hypothesis 2: Banks that are cross-listed have a higher capital when compared to banks that are not cross-listed.

Elyasiani and Jia (2010) find that a bank holding company's performance is positively associated with institutional ownership stability. They also mention that institutional owners monitor the bank which reduces information asymmetry. By disclosing information more readily, management can attract more Wall Street coverage which increases demand for shares and increases liquidity of stock. Deng *et al*. (2013) find that large and stable institutional ownership is associated with higher diversification and lower risk among bank holding companies.

Several studies focus on institutional ownership in non-banking firms. Chung and Wang (2014) find that a firm's leverage decreases when institutional ownership increases. They also find that institutions effectively monitor the firm's capital structure. Using a sample of Chinese firms, Lin and Fu (2017) find that foreign and large institutional ownership increases firm performance. Duggal and Millar (1999) find a positive relationship between institutional ownership and bidder gains in takeovers. Examining a sample of Indian firms, Nashier and Gupta (2016) find that institutional ownership has a positive impact on firm performance and managerial actions and decisions. Higher institutional ownership also increases liquidity and analyst coverage because of the increase in monitoring.

Banks with higher institutional ownership can generate higher profit, improve asset quality, increase growth, and maintain higher tier-1 capital. Hence, we hypothesize:

Hypothesis 3: Banks with higher institutional ownership have better performance and higher capital.

Barth *et al*. (2013b) make three findings: (a) tighter restrictions on bank activities is negatively associated with bank efficiency, (b) greater capital regulation stringency is positively associated with bank efficiency, and (c) market-based monitoring of banks is positively associated with efficiency. While capital regulation, official supervision, and restrictions on bank activity policies are positively related to bank performance, Ly (2015) finds that deposit insurance and private monitoring are negatively related to bank performance. Additionally, Lee and Lu (2015) find that bank development is improved with higher capital regulatory requirements and supervisory monitoring.

Anginer and Demirguc-Kunt (2014) find that higher forms of capital (tier-1 capital) reduce systematic risk in banks whereas lower forms of capital (tier-2 capital) have a negative effect especially during the financial crisis. The negative effect is less prominent in smaller banks, countries and higher monitoring. Their findings also support existing research that capital acts as a buffer to absorb liquidity risk and information and economic shocks and acts to reduce defaults. Kim and Sohn (2017) find that bank capital is positively related to lending growth in large banks that have retained sufficient liquid assets. They also mention that recent regulations require banks to maintain sufficient capital, liquid assets, and stable funding sources to reduce risk from negative economic shocks.

The effect of monitoring is more pronounced in banks from developing countries. While higher monitoring results in higher compliance costs (thus lower profit), it increases asset quality and tier-1 capital levels. Also, stringent capital requirements require banks to maintain more tier-1 capital which is predominantly equity capital.

Banks with higher tier-1 capital are expected to experience higher cost of capital. Hence, we hypothesize:

Hypothesis 4: Banks from developing countries with higher monitoring and higher capital stringency regulations have lower profit, better asset quality and higher tier-1 capital.

III Data and Variables

3.1 Data

The banks' accounting and cross-listing data is collected from Capital IQ (CIQ) for the period 2004–2018. We restrict our sample to depositary institutions, by requiring that (a) the bank's primary SIC code be in the range 6000–6099 and (b) the bank is classified as "Diversified Banks" or "Regional Banks" when using CIQ industry descriptions. Banks are also excluded from the sample if they have zero deposits or loans such as non-depositary brokerages and insurance companies. With the exception of country-level controls, we winsorize all of our continuous variables at 1.0% in each tail to reduce the impact of outliers. This method results in 2,019 unique banking firms in 98 countries. The final sample consists of an unbalanced panel data with a total of 16,407 observations.

To develop our sample, we use a variety of sources. The World Bank Regulation Surveys and Barth, Caprio, and Levine (2013) provided bank regulatory and monitoring indexes, and Spamann Anti-Director Rights Index (ADRI) (Spamann, 2010) provided the investor protection variable. We also utilized the United Nations Development Programme's classification of countries to divide the sample based on the bank's headquarters being in a developed economy (including G7 countries) or developing economy. This classification uses various factors and combines them into a single score called Human Development Index (HDI).

3.2 Variables

3.2.1. Dependent variables

Our dependent variables are classified into four categories: financial performance, asset quality, capital maintenance, and growth. Financial performance is measured by the variables ROA (net income divided by total assets) and ROE (net income divided by common equity). Asset quality is measured by non-performing loans (problem loans to loans ratio, bad loans to deposits (BLOAND) and bad loans percentage (BLOANP). Capital maintenance is measured by regulatory requirements for Tier-1 capital (CAP1) and total capital to risk adjusted assets. Finally, growth is measured by asset growth (AGRTH), loan growth (LGRTH) and deposit growth (DGRTH).

3.2.2 Independent variables

We incorporate several independent variables in our analysis. DEV is a dummy variable to indicate if the bank is from developing country. US is a dummy variable to indicate if a bank is listed in the US exchanges. NUM is the number of exchanges in which a bank is listed. ASSET is the natural logarithm of assets. LOAN is the ratio of loans/ total assets. DEBT is the total debt scaled by total assets. DIV, dividend payment scaled by total assets to measure dividend payments. RISK is the standard deviation of monthly returns over the fiscal year.

We also include variables to measure regulatory pressure. CAPSTRIN is the level of regulatory pressure to maintain the required capital levels. EXTMOR is the level of external monitoring in a country. ADRI is anti-director rights index defined as the level of shareholder protection in the country. Finally, INSTPER is the bank's institutional ownership defined as the percentage ownership by institutions like pension funds, mutual funds, insurance companies, etc.

Table 1: Summary of statistics and country origin of observations

Variables	Num. of Obs.	Mean	Median	Q1	Q3	Std. Dev.
ADRI	16,407	3.186	3	2	4	1.194
AGRTH	16,320	0.108	0.074	0.009	0.173	0.169
ASSET	16,407	8.710	8.508	7.070	10.082	2.091
BLOAND	16,407	2.954	1.421	0.902	3.072	4.601
BLOANP	16,407	2.994	1.634	1.068	3.402	3.666
CAP1	13,232	1.136	0.280	0.043	1.157	3.990
CAP12	7,776	2.152	1.763	1.069	2.674	3.196
CAPSTRIN	16,256	4.051	4.125	2.875	4.75	1.049
DEBT	16,407	0.125	0.090	0.038	0.174	0.122
DEV	16,407	0.409	0	0	1	0.492
DGRTH	16,303	0.116	0.075	0.008	0.178	0.196
DIV	16,407	0.003	0.002	0.000	0.004	0.004
DODD	16,407	0.521	1	0.000	1	0.499
EXTMOR	15,929	4.781	4.800	4.500	5.500	1.019
INSTPER	16,407	0.220	0.141	0.026	0.326	0.242
LEX	15,929	0.087	0	0	0	0.282
LGRTH	16,312	0.119	0.084	0.008	0.188	0.192
LOAN	16,407	0.651	0.666	0.575	0.745	0.143
NPL	16,407	1.978	0.913	0.263	2.240	4.298
NUM	16,407	1.600	1	1	2	1.821
RISK	16,407	0.084	0.069	0.048	0.101	0.136
ROA	16,407	0.822	0.833	0.415	1.208	0.997
ROE	16,407	8.343	9.279	5.327	13.486	11.395
US	16,407	0.568	1	0	1	0.495

Table 1 presents the summary statistics for the variables used in our analysis. The average ROA in our sample is about 0.82% and the average ROE is 8.34%. On average, 56.80% of the banks in our sample were listed in US exchanges, and 41% of the sample banks are from developing countries.

Table 2 presents pairwise correlations of the variables used in our analysis. We find that assets are highly correlated with number of exchanges on which the bank is listed, and loan growth is positively correlated with the growth of both deposits and assets.

IV Method and Results

We use OLS regression to test the impact of cross-listing, institutional ownership, regulation and monitoring on three areas: the banks' performance, their capital maintenance, and their growth. We include year fixed effects in all regression models.

Panel A of Table 3 reports OLS regression results for bank profitability and asset quality as the dependent variables using the full sample. The results show a significantly negative relationship between the variable US indicating if a bank is listed in a US exchange and the variables of ROA, BLOAND and BLOANP. The coefficients of US are -0.132 with t-stat of -2.14, -1.999 with t-stat of -5.24, -2.118 with t-stat of -6.25, and – 1.665 with t-stat of -6.13 in the models for ROA, NPL, BLOAND, and BLOANP, respectively. These coefficients are negative and significant at the five percent level for the models of ROA and at the one percent level for the models of NPL, BLOAND and BLOANP, suggesting that banks listed in US have a lower profitability (lower ROA) and higher asset quality (lower non-performing loans and bad loans). The coefficient on dummy variable to indicate if the bank is from developing country (DEV) is significant and positive for the models of ROA, ROE, NPL and BLOAND. This result implies that when compared to banks from developed countries, the banks from developing countries report higher profitability (coefficient = 1.281 with t-stat = 12.22 for the model of ROA, coefficient = 15.37 with t-stat = 11.70 for the model of ROE) but lower quality assets (coefficient = 2.638 with t-stat = 5.50 for the model of NPL, coefficient = 3.703 with t-stat = 8.71 for the model of BLOAND, coefficient = 2.460 with t-stat = 7.03 for the model of BLOANP). The coefficients of the variable measuring the number of exchanges a bank is listed, NUM, are positive and significant at 1% for the models of both ROA and ROE (coefficient = 0.0721 with t-stat = 6.06 for the model of ROA, coefficient = 0.691 with t-stat = 5.34 for the model of ROE) implying that as the number of exchanges a firm is listed increases, its profitability increases. Conversely, the evidence shows that the coefficients of NUM are positive and significant in the models of bad loans, implying that listing in multiple exchanges reduces asset quality (coefficient = 0.401 with t-stat = 5.41 for the model of NPL, coefficient = 0.406 with t-stat = 6.15 for the model of BLOAND, coefficient = 0.3 with t-stat = 5.68 for the model of BLOANP). The coefficient on interaction variable Developing and Multiple exchanges (NUMDEV) is negative and significant in the model for ROA (coefficient = -0.0597 with t-stat = -2.66). This result implies that for every additional exchange on which the bank is cross-listed, banks from developing countries experience a reduction of 0.0597% in ROA compared to banks from developed countries that are cross-listed. This reduction directly relates to the compliance cost to the bank from a developing country to list in a greater number of exchanges. Because banks from developed countries already have higher regulations in their home country, fewer additional compliance costs are incurred by these banks when listing in an additional exchange. Our results support Ribstein (2005) documenting that firms cross-listing in other countries are pressured to incur excessive compliance costs to meet that country's legal

Table 2. Correlation matrix

	US	DEV	LEX	NUM	ASSET	LOAN	CAP1	AGRTH	LGRTH	DGRTH	DIV	RISK	DEBT	INSTPER	CAPSTRIN	EXTMOR	ADRI	DODD
US	1																	
DEV	-0.5733*	1																
LEX	-0.1221*	0.1742*	1															
NUM	0.2209*	0.0508*	0.1834*	1														
ASSET	-0.0565*	0.1820*	0.2211*	0.6446*	1													
LOAN	0.0713*	-0.1563*	-0.1122*	-0.2540*	-0.2356*	1												
CAP1	0.0889*	-0.0992*	-0.0628*	-0.1432*	-0.3526*	0.0234*	1											
AGRTH	-0.0287*	0.0858*	0.0921*	-0.0454*	-0.0933*	-0.0196*	0.1021*	1										
LGRTH	-0.0201*	0.0792*	0.0899*	-0.0423*	-0.1038*	0.0241*	0.1107*	0.8452*	1									
DGRTH	-0.0314*	0.0751*	0.0886*	-0.0327*	-0.0909*	-0.0158*	0.1021*	0.8511*	0.7452*	1								
DIV	-0.0292*	0.1842*	0.0038	0.0223*	0.0016	-0.0969*	0.0274*	0.0174*	0.0185*	0.0245*	1							
RISK	-0.0551*	0.0683*	0.0483*	-0.0088	-0.0008	-0.0240*	0.0187*	-0.0041	-0.0139	0.0095	-0.0456*	1						
DEBT	0.0822*	0.0276*	0.1472*	0.2862*	0.3015*	-0.0279*	-0.1270*	-0.0212*	-0.0218*	-0.0447*	-0.0151	0.0198*	1					
INSTPER	0.3514*	-0.2547*	-0.0545*	0.2557*	0.2774*	-0.0055	-0.1399*	-0.0074	-0.0079	-0.0054	0.0082	-0.0262*	0.1154*	1				
CAPSTRIN	0.0188*	0.1764*	-0.0581*	0.0192*	-0.0453*	-0.0115	-0.0240*	-0.0491*	-0.0519*	-0.0448*	0.0319*	-0.0096	-0.1019*	0.0422*	1			
EXTMOR	0.3091*	-0.2244*	-0.6952*	-0.1511*	-0.2774*	0.0773*	0.0603*	-0.0490*	-0.0517*	-0.0406*	0.0348*	-0.0616*	-0.1341*	0.2092*	0.3231*	1		
ADRI	-0.5287*	0.3966*	0.1423*	0.1968*	0.4913*	-0.1335*	-0.1594*	-0.0488*	-0.0663*	-0.0361*	-0.0688*	0.0213*	0.1389*	-0.2020*	-0.2338*	-0.3602*	1	
DODD	-0.0778*	0.1239*	-0.1198*	0.1181*	0.1716*	-0.0603*	-0.0906*	-0.1928*	-0.1878*	-0.1740*	-0.0035	-0.0689*	-0.0885*	0.1356*	0.4027*	0.3145*	0.0601*	1

Table 3. Baseline Regression Results
Panel A.

This panel reports regression results of bank performance with several proxies for the performances of the banks: ROA, ROE, NPL, BLOAND, and BLOANP. The dependent variables, AGRTH, and LGRTH are winsorized at the one percent level. All models include the robust option to obtain robust standard errors. Numbers in parentheses represent the t-statistics. The superscripts, ***, **, and * denote the 1%, 5%, and 10% levels of significance, respectively. Please refer Appendix 1 for the definitions of variables.

VARS	ROA	ROA	ROE	ROE	NPL	NPL	BLOAND	BLOAND	BLOANP	BLOANP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
US	-0.132**	-0.132**	0.281	0.322	-1.999***	-2.010***	-2.118***	-2.125***	-1.665***	-1.670***
	(-2.14)	(-2.14)	(0.41)	(0.47)	(-5.24)	(-5.29)	(-6.25)	(-6.26)	(-6.13)	(-6.15)
DEV	1.281***	1.249***	15.37***	14.80***	2.638***	2.994***	3.703***	3.954***	2.460***	2.720***
	(12.22)	(11.88)	(11.70)	(11.20)	(5.50)	(6.24)	(8.71)	(9.27)	(7.03)	(7.75)
USDEV	0.258**	0.257**	0.643	0.591	2.316***	2.273***	3.083***	3.056***	3.054***	3.021***
	(2.54)	(2.53)	(0.58)	(0.53)	(3.59)	(3.54)	(5.38)	(5.33)	(6.67)	(6.60)
NUM	0.0721***	0.0659***	0.691***	0.638***	0.401***	0.435***	0.406***	0.419***	0.300***	0.313***
	(6.06)	(5.55)	(5.34)	(4.91)	(5.41)	(5.89)	(6.15)	(6.35)	(5.68)	(5.93)
NUMDEV	-0.0597***	-0.0544**	-0.245	-0.176	-0.584***	-0.604***	-0.595***	-0.608***	-0.574***	-0.584***
	(-2.66)	(-2.43)	(-1.01)	(-0.72)	(-4.07)	(-4.23)	(-4.67)	(-4.76)	(-5.63)	(-5.74)
EXTMOR	0.100***	0.100***	0.918***	0.899***	0.184***	0.206***	0.144***	0.161***	0.0492	0.0679
	(6.13)	(6.11)	(4.29)	(4.19)	(3.04)	(3.40)	(2.69)	(3.01)	(1.08)	(1.50)
DEVEXT	-0.151***	-0.146***	-2.067***	-1.970***	-0.200***	-0.253***	-0.251***	-0.290***	-0.0305	-0.0707
	(-8.20)	(-7.88)	(-8.54)	(-8.10)	(-2.94)	(-3.72)	(-4.19)	(-4.83)	(-0.60)	(-1.38)
ASSETS	-0.0413***	-0.0385***	-0.0413	-0.0515	-0.278***	-0.292***	-0.268***	-0.260***	-0.224***	-0.218***
	(-4.07)	(-3.77)	(-0.36)	(-0.44)	(-5.19)	(-5.44)	(-5.65)	(-5.46)	(-5.75)	(-5.60)
LOAN	0.175**	0.0337	-0.407	-1.955**	4.520***	5.381***	5.410***	5.954***	-0.400*	0.104
	(2.29)	(0.44)	(-0.43)	(-2.07)	(14.26)	(16.93)	(19.29)	(21.15)	(-1.69)	(0.44)
CAP1	-0.0120***	-0.00910***	-0.157***	-0.172***	-0.0380***	-0.0434***	0.0632***	0.0782***	0.0234***	0.0330***
	(-5.28)	(-3.57)	(-5.70)	(-5.54)	(-3.62)	(-3.76)	(6.80)	(7.64)	(3.03)	(3.88)
AGRTH	0.638***		9.652***		-2.427***		-1.575***		-1.443***	
	(15.64)		(17.82)		(-16.47)		(-12.09)		(-13.03)	

LGRTH		0.501***		8.071***		-2.400***		-1.544***		-1.526***
		(13.59)		(16.50)		(-18.04)		(-13.12)		(-15.27)
DIV	85.72***	85.22***	664.9***	660.7***	-55.34***	-53.78***	-18.62**	-19.04**	-13.70**	-13.81**
	(36.08)	(35.84)	(22.00)	(21.79)	(-6.08)	(-5.92)	(-2.31)	(-2.37)	(-2.01)	(-2.03)
RISK	-2.725***	-2.714***	-41.58***	-41.17***	9.796***	9.602***	5.922***	5.770***	5.185***	5.020***
	(-21.57)	(-21.43)	(-24.87)	(-24.54)	(21.46)	(21.04)	(14.68)	(14.30)	(15.10)	(14.64)
DEBT	-0.324***	-0.331***	-0.600	-0.707	-0.0807	-0.0755	5.430***	5.470***	-0.921***	-0.912***
	(-3.50)	(-3.57)	(-0.53)	(-0.63)	(-0.21)	(-0.19)	(15.62)	(15.74)	(-3.15)	(-3.13)
INSTPER	0.328***	0.340***	2.672***	2.769***	-1.133***	-1.119***	-0.521***	-0.520***	-0.509***	-0.495***
	(6.58)	(6.83)	(4.41)	(4.55)	(-5.40)	(-5.34)	(-2.80)	(-2.80)	(-3.26)	(-3.17)
CAPSTRIN	-0.0601***	-0.0597***	-0.366***	-0.364***	0.143***	0.134***	0.0857**	0.0793**	0.0409	0.0344
	(-5.66)	(-5.62)	(-2.68)	(-2.66)	(3.56)	(3.33)	(2.41)	(2.23)	(1.36)	(1.14)
ADRI	-0.0621***	-0.0638***	-0.122	-0.115	0.130	0.136	-0.203*	-0.203*	-0.141	-0.143*
	(-3.13)	(-3.22)	(-0.55)	(-0.52)	(1.08)	(1.13)	(-1.89)	(-1.89)	(-1.64)	(-1.66)
Year FF	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squares	0.221	0.218	0.286	0.279	0.111	0.114	0.101	0.105	0.0691	0.0748
Obs.	12883	12877	12883	12877	12883	12877	12883	12877	12883	12877

Panel B.

This panel reports regression results of bank performance measured in CAP1 CAP12, asset growth, loan growth and deposit growth. All dependent variables are winsorized at the one percent level. All models include the robust option to obtain robust standard errors. Numbers in parentheses represent the t-statistics. The superscripts, ***, **, and * denote the 1%, 5%, and 10% levels of significance, respectively. Please refer Appendix 1 for the definitions of variables.

VARS	CAP1	CAP12	AGRTH	LGRTH	DGRTH
	(1)	(2)	(3)	(4)	(5)
US	0.629	0.0921	-0.0115	-0.0173	-0.0137
	(0.97)	(0.19)	(-1.00)	(-1.33)	(-1.03)
DEV	-2.246***	0.551	0.195***	0.291***	0.185***
	(-3.52)	(1.03)	(10.34)	(13.73)	(8.34)
USDEV	-0.433	-0.0306	-0.0337*	-0.0377*	-0.0206
	(-0.39)	(-0.04)	(-1.75)	(-1.74)	(-0.93)
NUM	0.343***	0.292***	-0.00540**	0.00328	0.00231
	(2.84)	(3.39)	(-2.30)	(1.24)	(0.86)
NUMDEV	0.237	-0.0915	0.0110**	0.00530	0.00331
	(0.95)	(-0.57)	(2.51)	(1.08)	(0.66)
EXTMOR	-0.184***	-0.0903	0.0312***	0.0376***	0.0285***
	(-4.66)	(-1.59)	(10.31)	(11.05)	(7.92)
DEVEXT	0.369***	-0.0267	-0.0330***	-0.0478***	-0.0292***
	(8.32)	(-0.37)	(-9.34)	(-12.04)	(-6.96)
ASSETS	-1.326***	-0.831***	-0.0000859	-0.00218	-0.00210
	(-26.78)	(-15.46)	(-0.05)	(-1.07)	(-1.00)
LOAN	-0.200	0.236	-0.0839***	0.137***	-0.0688***
	(-0.91)	(0.76)	(-5.95)	(8.63)	(-4.14)
DIV	64.12***	35.95***	-0.414	-0.150	-0.261
	(10.65)	(4.56)	(-0.96)	(-0.31)	(-0.51)
RISK	1.228***	0.286	-0.0255**	-0.0368***	-0.00980
	(4.17)	(0.67)	(-2.53)	(-3.24)	(-0.82)
DEBT	-1.994***	1.275***	-0.0472***	-0.0657***	-0.269***
	(-7.18)	(3.68)	(-2.80)	(-3.46)	(-13.53)
INSTPER	0.955***	0.144	0.0766***	0.0835***	0.0816***
	(6.51)	(0.73)	(7.95)	(7.71)	(7.21)
CAPSTRIN	0.0971***	0.256***	-0.00453**	-0.00814***	-0.00294
	(3.68)	(8.56)	(-2.38)	(-3.80)	(-1.30)
ADRI	0.474**	0.284**	-0.00289	-0.00488	0.00166
	(2.37)	(2.03)	(-0.79)	(-1.18)	(0.39)
Year FF	Yes	Yes	Yes	Yes	Yes
R-squares	0.107	0.0754	0.0466	0.0533	0.0997
Obs.	12925	7509	15842	15835	15825

requirements. The coefficients of NUMDEV are negative and significant in all models of bad loans (models 6 through 10 for NPL, BLOAND and BLOANP) implying banks from developing countries that cross-list on multiple exchanges have better asset quality.

The variable "ASSETS" has a negative coefficient in the ROE and ROA models implying that larger banks have a lower profitability (Aladwan, 2015 and Goddard *et al*., 2004) and have better asset quality (coefficient on NPL = -0.278 with t-stat = -5.19 and BLOAND = -0.268 with t-stat = -5.65). Coefficient on variable LOAN is positively and significantly related to NPL (coefficient = 4.52 with t-stat = 14.26) and bad loans (coefficient = 5.410 with t-stat = 19.29) since banks with higher loans (when compared to their other assets) are expected to have higher percentage of bad loans. Because tier-1 capital (i.e., equity capital and retained earnings) is more expensive as compared with other forms of capital, banks with higher tier-1 capital tend to have a lower profitability (ROA). but have a negative and significant relation with non-performing loans (NPL) and a positive and significant relation with bad loans. Banks with higher asset growth (AGRTH) experienced higher ROA and lower NPL and bad loans. Banks that pay more dividends are more profitable and have lower NPL and bad loans. Banks with higher standard deviation (RISK) on stocks have monthly returns that are negatively and significantly related to ROA and ROE and that are positively related to NPL and bad loans. This relationship implies that banks with higher risk experience lower profit and asset quality. The coefficient on the variable DEBT has similar results as the variable RISK implying a higher debt ratio will lower the banks' profit and asset quality.

Variable "INSTPER" that measures the bank's level of institutional ownership is positively related to ROE (coefficient 0.328) and ROA (coefficient 2.672) and is negatively related to NPL (coefficient = -1.133) and bad loans (coefficient = -0.521). Every 1% increase in institutional ownership increases the ROA by 0.328% and reduces NPL by 1.133%. Variables "CAPSTRIN" and "ADRI" represent capital regulation and investor protection, respectively. These variables are negative and significantly affect the ROA implying that banks from countries with greater regulation and investor protection will experience a lower profit (Ribstein 2005). Higher capital stringency did not result in better asset quality (positive and significant coefficient in the models with NPL and BLOAND as the dependent variables). Banks from higher investor protection countries (ADRI) show a reduction in the percentage of bad loans. Coefficients on interaction of variables DEV and external monitoring (DEVEXT) is negative and significant for ROA and ROE as dependent variables. Such a relationship implies that if the bank is from a developing country with high external monitoring, the ROA will decrease by 0.151% and ROE by 2.067%, respectively when compared to banks from developed countries with high external monitoring. The coefficient on DEVEXT is negative and significant in models with NPL and bad loans as dependent variables resulting in better asset quality for banks in developing countries compared to banks from developed countries when both have high external monitoring.

Table 3B reports OLS regression results for banks' capital maintenance, asset growth, loan growth and deposit growth as the dependent variables using the full sample. Regarding capital maintenance, the variable for developing countries (DEV) is negatively associated with tier-1 capital which shows that banks from developing countries have 2.246% lower tier-1 capital when compared to banks from developed countries. Coefficient on variable NUM implies that for every additional exchange on which the bank is listed, the bank would have a 0.343% increase in tier-1 capital and 0.292% increase in total capital.

When analyzing asset growth, interaction variable "NUMDEV" is positively and significantly associated implying that for each additional exchange, banks from developing economies experienced an increase in asset growth of 0.0110%. Banks with greater institutional ownership are positively and significantly associated with tier-1 capital and asset growth, loan growth and deposit growth. Elyasiani and Jia (2010) mention that institutional ownership increases firm performance, stock demand, and liquidity. Chung and Wang (2014) mention that institutional ownership can substitute for monitoring.

Although banks with greater capital stringency are associated with higher tier-1 and total capital, they have lower asset and loan growth. Jonghe and Oztekin (2015) mention that banks with higher capital stringency have lower risk as verified by supervisors. They also mention that such banks can quickly adjust (increase) equity capital. The coefficient on ADRI is positive and significant implying that Banks with higher shareholder protection tend to have higher tier-1 and total capital. Interaction variable DEVEXT (Banks from developing countries with higher external monitoring) is positively and significantly associated with tier-1 capital implying that higher monitoring increases the level of tier-1 capital among banks in developing countries but negatively associated with asset growth, loan growth and deposit growth.

In table 4A we divide the sample into banks from developed and developing countries and compare each using five proxies: ROA, ROE, NPL, BLOAND, and BLOANP. Banks from developed countries listed in US had better asset quality when compared to banks from developing countries (NPL and bad loans as dependent variable). For banks from developed countries with low external monitoring (LEX), the profitability increased by 0.216% when compared to banks from low external monitoring countries listed in US. If the bank is from a low external monitoring country, the asset quality improved (negative and significant coefficient on NPL and BLOANP). If the bank is from a high external monitoring country listed in multiple exchanges (variable NUM), the ROA increases by 0.0580% when compared with banks from developed and low external monitoring countries (variable NUMLEX). If banks from developing economies with low external monitoring are listed in the multiple exchanges (variable NUMLEX), the percentage of NPL decreases by 0.403% when compared to banks from high monitoring countries listed in multiple exchanges (Bonding hypothesis by Coffee 1999 and Stulz 1999).

The bank's asset size has a negative effect on ROA, BLOAND and BLOANP in developed countries. Larger banks in developing countries have a positive effect on ROE and a negative effect on NPLs and bad loans implying that larger banks have higher profit and better asset quality. The variable "LOAN" is positively and significantly associated with ROA for banks in developed economies and is negatively and significantly associated with ROA for banks in developing economies. Higher institutional ownership positively and significantly affects profit and increases asset quality (significant and negative coefficient on NPL, BLOAND and BLOANP) in banks from both developed and developing economies. Higher capital stringency and shareholder protection (ADRI) decrease ROA in banks from developing countries due to higher compliance costs.

Table 4B reports OLS regression results where banks' capital, asset growth, loan growth and deposit growth are the dependent variables. Models 1, 3, 5, 7 and 9 report results for developed economies and the remaining models report results for developing economies. Low external monitoring is positively associated with total capital in banks from developing economies (coefficient on variable ROE = 0.856 and significant at 1%) and negatively (insignificant) associated with tier-1 capital. Interaction variable "USLEX" is negative and significant in the "loan growth" model for developing countries implying that banks from developing countries with low external monitoring have restricted loan growth due to higher regulations in US which require higher tier-1 capital maintenance to generate additional loans. The variable "NUM" is positively associated with tier-1 and total capital in banks from developed economies and higher tier-1

Table 4
Panel A.

This panel reports regression results of bank performance with several proxies for the performances of the banks: ROA, ROE, NPL, BLOAND, and BLOANP. The dependent variables, AGRTH, and LGRTH are winsorized at the one percent level. Columns 1, 3, 5, 7, 9 report results for banks from developed economies and columns 2, 4, 6, 8, 10 report results for banks from developing economies. All models include the robust option to obtain robust standard errors. Numbers in parentheses represent the t-statistics. The superscripts, ***, **, and * denote the 1%, 5%, and 10% levels of significance, respectively. Please refer Appendix 1 for the definitions of variables.

VARS	ROA	ROA	ROE	ROE	NPL	NPL	BLOAND	BLOAND	BLOANP	BLOANP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
US	-0.0697	0.171*	0.226	0.982	-0.317***	0.830	-1.065***	2.124***	-1.213***	2.200***
	(-1.15)	(1.67)	(0.33)	(0.97)	(-2.60)	(1.35)	(-5.06)	(3.19)	(-6.81)	(4.07)
LEX	0.216***	-0.0963	0.803	0.0189	-1.536***	1.306***	-0.301	1.697***	-0.533***	1.646***
	(2.99)	(-1.58)	(0.83)	(0.03)	(-10.03)	(3.85)	(-1.61)	(6.27)	(-3.42)	(7.09)
USLEX	-0.121	-0.00632	-0.933	-2.592**	0.406	0.258	-1.528***	-0.686	-0.630**	0.203
	(-0.91)	(-0.06)	(-0.55)	(-2.03)	(1.45)	(0.44)	(-4.18)	(-1.51)	(-2.07)	(0.52)
NUM	0.0580***	0.00632	0.541***	0.178	-0.0205	0.328*	0.197***	0.0608	0.206***	-0.0661
	(5.11)	(0.22)	(4.27)	(0.63)	(-0.90)	(1.95)	(4.95)	(0.34)	(6.13)	(-0.46)
NUMLEX	0.00742	0.0117	0.769***	0.852***	0.00586	-0.403***	0.126**	-0.186	0.0593	-0.316***
	(0.33)	(0.43)	(2.64)	(2.65)	(0.12)	(-2.64)	(2.11)	(-1.53)	(1.19)	(-3.03)
ASSETS	-0.0431***	0.00658	-0.130	0.648***	0.171***	-0.668***	-0.195***	-0.826***	-0.122***	-0.693***
	(-3.72)	(0.38)	(-0.94)	(3.63)	(7.18)	(-6.62)	(-5.42)	(-8.47)	(-4.05)	(-8.55)
LOAN	0.315***	-0.379***	0.343	-3.567***	1.534***	9.350***	3.620***	11.98***	0.294	1.980***
	(3.72)	(-3.27)	(0.32)	(-2.73)	(8.62)	(14.35)	(15.93)	(22.20)	(1.56)	(4.30)
DIV	88.45***	70.59***	777.3***	521.1***	-58.16***	-51.11***	-3.465	-30.83**	-16.44**	-26.12**
	(26.09)	(25.40)	(17.09)	(15.87)	(-8.06)	(-3.33)	(-0.40)	(-2.55)	(-2.28)	(-2.52)
RISK	-0.374***	-0.749***	-5.009***	-7.545***	0.661***	7.611***	0.572***	6.782***	0.543***	5.496***
	(-8.27)	(-4.21)	(-8.40)	(-3.52)	(6.95)	(7.77)	(4.34)	(8.91)	(4.92)	(8.39)
DEBT	-0.215**	-0.441***	-1.181	0.118	-0.702***	3.564***	4.776***	7.212***	-0.694***	-1.911***
	(-2.19)	(-3.00)	(-0.93)	(0.07)	(-3.39)	(4.31)	(18.30)	(10.59)	(-3.20)	(-3.29)
INSTPER	0.399***	0.274***	3.384***	3.456***	-1.120***	-1.737***	-0.359**	-1.742***	-0.457***	-1.160***

	(7.10)	(3.11)	(4.77)	(3.36)	(-9.54)	(-3.55)	(-2.33)	(-4.46)	(-3.57)	(-3.47)
CAPSTRIN	0.00774	-0.0358***	0.134	-0.231	0.283***	0.100	-0.142***	0.115**	-0.154***	0.0854*
	(0.52)	(-2.77)	(0.65)	(-1.52)	(8.87)	(1.40)	(-3.84)	(2.04)	(-5.02)	(1.76)
ADRI	-0.0176	-0.147***	0.142	-0.836***	0.270***	-0.544***	0.0932	-0.739***	-0.0797	-0.229
	(-0.68)	(-4.52)	(0.47)	(-2.60)	(5.10)	(-2.79)	(1.07)	(-3.50)	(-1.09)	(-1.34)
Year FF	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squares	0.250	0.0998	0.210	0.0618	0.187	0.0630	0.0884	0.134	0.0892	0.0583
Obs.	9563	6366	9563	6366	9563	6366	9563	6366	9563	6366

Panel B.

This panel reports regression results of bank performance measured in CAP1, CAP12, asset growth, loan growth and deposit growth. All dependent variables are winsorized at the one percent level. Columns 1, 3, 5, 7, 9 report results for banks from developed economies and columns 2, 4, 6, 8, 10 report results for banks from developing economies. All models include the robust option to obtain robust standard errors. Numbers in parentheses represent the t-statistics. The superscripts, ***, **, and * denote the 1%, 5%, and 10% levels of significance, respectively. Please refer Appendix 1 for the definitions of variables.

VARS	CAP1	CAP1	CAP12	CAP12	AGRTH	AGRTH	LGRTH	LGRTH	DGRTH	DGRTH
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
US	1.096	0.229	0.400	0.327	-0.00818	-0.0356**	-0.00791	-0.0319*	-0.0153	-0.0295*
	(1.42)	(0.30)	(1.25)	(0.43)	(-0.57)	(-2.57)	(-0.50)	(-1.93)	(-0.95)	(-1.73)
LEX	-0.360	-0.0843	0.00351	0.856***	-0.00935	0.00785	-0.0135	0.0322**	0.0939***	0.0258*
	(-0.84)	(-0.43)	(0.01)	(3.02)	(-0.57)	(0.71)	(-0.74)	(2.50)	(4.92)	(1.89)
USLEX	0.114	-0.152	-0.183	-0.169	-0.0248	-0.0143	0.0163	-0.0760***	-0.112***	-0.0150
	(0.19)	(-0.44)	(-0.45)	(-0.32)	(-0.81)	(-0.71)	(0.48)	(-3.26)	(-3.16)	(-0.60)
NUM	0.452***	0.422**	0.271***	0.259	-0.00831***	0.00463	0.000651	0.00630	-0.00109	0.0114**
	(3.45)	(2.12)	(5.12)	(1.29)	(-3.09)	(1.17)	(0.22)	(1.34)	(-0.36)	(2.35)
NUMLEX	-0.00188	-0.0776	0.0320	-0.0895	0.0175***	0.00533	0.00866	0.0107*	0.00905	-0.00424
	(-0.03)	(-0.92)	(0.75)	(-0.81)	(3.41)	(1.07)	(1.53)	(1.85)	(1.52)	(-0.69)
ASSETS	-1.723***	-1.015***	-0.840***	-0.944***	0.000574	-0.00100	-0.00364	-0.00182	0.00733**	-0.00760**
	(-29.59)	(-11.20)	(-18.11)	(-9.13)	(0.21)	(-0.40)	(-1.22)	(-0.61)	(2.37)	(-2.44)

LOAN	-1.472***	2.163***	-0.199	0.792	0.0173	-0.180***	0.241***	0.0316	0.0438*	-0.176***
	(-6.20)	(4.92)	(-0.77)	(1.45)	(0.89)	(-9.13)	(11.23)	(1.37)	(1.94)	(-7.25)
DIV	73.31***	59.93***	-27.90***	51.98***	-2.871***	0.0462	-3.094***	0.393	-1.736*	-0.136
	(8.91)	(6.44)	(-2.93)	(4.48)	(-3.72)	(0.09)	(-3.62)	(0.66)	(-1.93)	(-0.21)
RISK	1.973***	1.200**	0.401	0.198	-0.0293***	-0.0912***	-0.0372***	-0.131***	-0.0205*	-0.0814*
	(6.03)	(2.07)	(1.06)	(0.28)	(-2.82)	(-2.63)	(-3.24)	(-3.30)	(-1.71)	(-1.92)
DEBT	-0.931***	-3.614***	0.484*	1.798***	0.00779	-0.0664***	0.0171	-0.118***	-0.315***	-0.208***
	(-2.96)	(-7.01)	(1.76)	(2.78)	(0.35)	(-2.66)	(0.69)	(-4.03)	(-12.04)	(-6.77)
INSTPER	1.768***	0.436	0.696***	-0.112	0.0856***	0.0450***	0.0986***	0.0404**	0.0683***	0.0380*
	(11.01)	(1.40)	(4.48)	(-0.29)	(6.62)	(2.79)	(6.90)	(2.17)	(4.57)	(1.92)
CAPSTRIN	-0.201***	0.263***	-0.0377	0.311***	-0.00283	-0.000279	-0.0107***	-0.000304	-0.00921**	0.00111
	(-5.00)	(6.49)	(-1.24)	(6.52)	(-0.84)	(-0.12)	(-2.86)	(-0.11)	(-2.32)	(0.38)
ADRI	1.092***	0.207	0.305***	0.186	-0.0187***	-0.00198	-0.0207***	-0.00756	-0.0295***	0.00544
	(3.91)	(0.78)	(2.58)	(0.70)	(-3.06)	(-0.45)	(-3.07)	(-1.44)	(-4.24)	(1.00)
Year FF	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squares	0.173	0.0838	0.169	0.0713	0.0869	0.224	0.122	0.213	0.0730	0.185
Obs.	8463	4462	3900	3609	9527	6315	9523	6312	9519	6306

capital in banks from developing economies implying that banks listed in multiple exchanges have access to higher capital when compared to banks that are not listed in multiple exchanges. Reese and Weisbach (2002) find that non-US firms cross-list in US to increase minority shareholder protection. This action increases equity issue following cross-listing. They find that firms from weak protection countries receive more equity issue from non-US sources and firms from strong protection countries receive more equity issue from the US. Interaction variable "NUMLEX" is positive and significant in the model where "asset growth" is the dependent variable implying that low monitoring banks listed in multiple exchanges are associated with greater asset growth when compared to banks listed on a single exchange. The variable "ASSETS" is negatively associated with capital. Hakenes and Isabel (2011) find that large banks have a competitive advantage under the IRB Basel II approach and hence require less capital. The variable "Institution ownership" (INSTPER) is positively and significantly associated with dependent variables tier-1 capital, asset growth, loan growth and deposit growth in banks from developed economies. Institutional ownership positively influences the growth variables in developing economies. Higher capital stringency requirement is positively and significantly associated with tier-1 and total capital in developing economies. Higher ADRI (shareholder protection) is associated with higher tier-1 and total capital in developed countries. Caprio *et al*. (2007) find a positive relationship between shareholder protection and firm valuation.

Tables 5A and 5B are like tables 3A and 3B except that we include only observations after the 2008 financial crisis period. The variable for the level of external monitoring in a country (EXTMOR) is negative and significant in the models with NPL and Bad loans as the dependent variables. This result supports the hypothesis that firms with higher external monitoring have better asset quality. Hirtle *et al*. (2020) find that banks with higher supervision hold less-risky loans and have less volatile earnings and market returns. Higher tier-1 capital is positively and significantly associated with ROA and ROE implying that maintenance of tier-1 capital increased profitability of banks in the post-crisis period. Other variables' coefficients are similar in sign but have a different magnitude when compared to the entire time period in table 3A and 3B.

Tables 6A and 6B are like tables 4A and 4B except that they report regression results for only the post-crisis period. We divide the sample into banks from developed and developing countries. Table 6A shows that since the crisis period, banks from developed countries experience an increase of 0.146% in ROA if they are listed in the US (in model (1), the coefficient of US = 0.146 with t-stat = 1.96). In developed economies, banks from low external monitoring countries listed in the US experience a 0.396% decrease in ROA when compared to banks from high external monitoring countries (in model (1), the coefficient of the interaction variable, USLEX = -0.369 with t-stat = -2.04). An increase in investor protection (ADRI) by 1 in developed countries results in a 0.108% increase in ROA (in model (1), the coefficient of the interaction variable, USLEX = -0.369 with t-stat = -2.04).

In table 6B, US listed banks in developed countries have a 1.075% increase in tier-1 capital following the crisis period (in model (1), the coefficient of US = 1.075 with t-stat = 3.83). The remaining variables show similar results for the entire sample.

Tables 7A and 7B include results for the crisis period (2008-2009) only. Table 7A shows that interaction variable USDEV is positively associated with ROA implying that banks from developing countries and listed in the US outperform banks from developing countries but do not list in the US markets. Further, the coefficient is much larger when compared to the full sample implying the benefits listing in the US for developing countries' banks during the crisis period.

Table 5
Panel A

This panel reports regression results for the post-crisis period of bank performance with several proxies for the performances of the banks: ROA, ROE, NPL, BLOAND, and BLOANP. The dependent variables, AGRTH, and LGRTH are winsorized at the one percent level. All models include the robust option to obtain robust standard errors. Numbers in parentheses represent the t-statistics. The superscripts, ***, **, and * denote the 1%, 5%, and 10% levels of significance, respectively. Please refer Appendix 1 for the definitions of variables.

VARS	ROA	ROA	ROE	ROE	NPL	NPL	BLOAND	BLOAND	BLOANP	BLOANP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
US	-0.0777	-0.0699	0.720	0.840	-1.706***	-1.740***	-2.256***	-2.272***	-1.595***	-1.610***
	(-0.95)	(-0.86)	(0.68)	(0.79)	(-3.34)	(-3.41)	(-5.19)	(-5.22)	(-4.59)	(-4.63)
DEV	2.073***	1.983***	26.41***	25.07***	1.120*	1.535**	3.116***	3.348***	1.757***	2.030***
	(14.54)	(13.87)	(14.05)	(13.27)	(1.74)	(2.39)	(5.68)	(6.08)	(3.92)	(4.52)
USDEV	0.276**	0.275**	0.974	0.984	2.160***	2.116***	3.096***	3.073***	2.939***	2.898***
	(2.21)	(2.21)	(0.61)	(0.61)	(2.71)	(2.65)	(4.56)	(4.52)	(5.42)	(5.34)
NUM	0.0923***	0.0836***	1.182***	1.081***	0.478***	0.513***	0.422***	0.441***	0.342***	0.358***
	(6.28)	(5.71)	(6.26)	(5.70)	(5.23)	(5.63)	(5.43)	(5.67)	(5.50)	(5.75)
NUMDEV	-0.0975***	-0.0895***	-0.770**	-0.676**	-0.627***	-0.647***	-0.564***	-0.574***	-0.572***	-0.580***
	(-3.68)	(-3.39)	(-2.26)	(-1.98)	(-3.70)	(-3.83)	(-3.91)	(-3.98)	(-4.97)	(-5.03)
EXTMOR	0.209***	0.196***	2.150***	1.968***	-0.286***	-0.229***	-0.0503	-0.0180	-0.224***	-0.185***
	(8.99)	(8.45)	(6.98)	(6.36)	(-3.29)	(-2.64)	(-0.68)	(-0.24)	(-3.61)	(-2.98)
DEVEXT	-0.291***	-0.275***	-4.001***	-3.761***	0.136	0.0676	-0.192**	-0.232***	0.0837	0.0383
	(-11.25)	(-10.59)	(-11.65)	(-10.91)	(1.43)	(0.71)	(-2.34)	(-2.82)	(1.22)	(0.56)
ASSETS	-0.0378***	-0.0380***	-0.456***	-0.468***	-0.448***	-0.451***	-0.344***	-0.348***	-0.332***	-0.330***
	(-2.92)	(-2.94)	(-2.72)	(-2.78)	(-6.46)	(-6.52)	(-5.81)	(-5.88)	(-6.91)	(-6.87)
LOAN	-0.00186	-0.195**	-1.858	-4.268***	5.516***	6.360***	6.425***	6.893***	-0.153	0.340
	(-0.02)	(-1.99)	(-1.45)	(-3.31)	(13.49)	(15.49)	(18.33)	(19.57)	(-0.53)	(1.17)
CAP1	0.0183***	0.0201***	0.0278	0.0292	-0.212***	-0.214***	0.123***	0.125***	0.0387***	0.0411***
	(4.86)	(5.31)	(0.57)	(0.59)	(-12.04)	(-12.11)	(8.17)	(8.26)	(3.12)	(3.31)
AGRTH	0.721***		9.840***		-1.977***		-1.162***		-1.152***	
	(13.84)		(14.16)		(-10.70)		(-7.33)		(-8.70)	

LGRTH		0.564***		8.499***		-1.921***		-1.084***		-1.263***
		(12.10)		(13.66)		(-11.62)		(-7.63)		(-10.66)
DIV	88.73***	88.28***	679.5***	674.0***	-53.32***	-52.01***	-1.046	-0.700	-2.071	-1.459
	(29.07)	(28.93)	(16.83)	(16.66)	(-4.55)	(-4.44)	(-0.10)	(-0.07)	(-0.25)	(-0.17)
RISK	-2.688***	-2.666***	-39.40***	-38.78***	7.570***	7.383***	4.652***	4.559***	4.144***	3.994***
	(-17.97)	(-17.78)	(-19.77)	(-19.41)	(14.00)	(13.65)	(10.03)	(9.81)	(10.70)	(10.32)
DEBT	-0.528***	-0.547***	-2.443	-2.548	-0.315	-0.299	7.169***	7.198***	-0.585	-0.603
	(-4.37)	(-4.53)	(-1.54)	(-1.60)	(-0.61)	(-0.58)	(16.12)	(16.19)	(-1.59)	(-1.64)
INSTPER	0.365***	0.389***	4.073***	4.247***	-1.839***	-1.858***	-0.577**	-0.579**	-0.490**	-0.476**
	(5.75)	(6.13)	(4.91)	(5.10)	(-6.55)	(-6.62)	(-2.40)	(-2.40)	(-2.47)	(-2.40)
CAPSTRIN	-0.0741***	-0.0758***	-0.442**	-0.463**	0.289***	0.288***	0.169***	0.170***	0.153***	0.152***
	(-4.99)	(-5.11)	(-2.26)	(-2.36)	(4.92)	(4.92)	(3.36)	(3.37)	(3.66)	(3.65)
ADRI	0.0168	0.0108	1.066***	0.998***	0.000691	0.0218	-0.168	-0.153	-0.0820	-0.0717
	(0.67)	(0.43)	(3.28)	(3.06)	(0.00)	(0.14)	(-1.30)	(-1.18)	(-0.79)	(-0.69)
Year FF	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squares	0.174	0.171	0.411	0.406	0.0993	0.101	0.115	0.117	0.0663	0.0709
Obs.	9224	9220	9224	9220	9224	9220	9224	9220	9224	9220

Panel B

This panel reports regression results for the post-crisis period of bank performance measured in CAP1 CAP12, asset growth, loan growth and deposit growth. All dependent variables are winsorized at the one percent level. All models include the robust option to obtain robust standard errors. Numbers in parentheses represent the t-statistics. The superscripts, ***, **, and * denote the 1%, 5%, and 10% levels of significance, respectively. Please refer Appendix 1 for the definitions of variables.

VARS	CAP1	CAP12	AGRTH	LGRTH	DGRTH
	(1)	(2)	(3)	(4)	(5)
US	0.627	0.129	0.00166	-0.0117	0.00775
	(1.34)	(0.25)	(0.14)	(-0.88)	(0.60)
DEV	-0.324	1.721**	0.124***	0.252***	0.0728***
	(-0.67)	(2.48)	(5.28)	(9.52)	(2.68)
USDEV	-0.496	-0.282	-0.0487***	-0.0464**	-0.0516***
	(-0.67)	(-0.36)	(-2.73)	(-2.29)	(-2.63)
NUM	0.328***	0.264***	-0.00601***	0.00372	0.00120
	(4.07)	(2.97)	(-2.72)	(1.48)	(0.49)
NUMDEV	-0.0761	-0.144	0.0129***	0.00528	0.00902**
	(-0.49)	(-0.89)	(3.29)	(1.19)	(2.10)
EXTMOR	-0.152***	0.00305	0.0187***	0.0363***	0.0119**
	(-3.35)	(0.03)	(4.65)	(8.04)	(2.53)
DEVEXT	0.175***	-0.184	-0.0177***	-0.0396***	-0.00529
	(3.52)	(-1.63)	(-3.86)	(-7.66)	(-0.98)
ASSETS	-0.784***	-0.654***	0.000909	0.00164	-0.00139
	(-16.79)	(-10.60)	(0.49)	(0.78)	(-0.67)
LOAN	0.0859	1.277***	-0.0782***	0.130***	-0.0745***
	(0.38)	(3.46)	(-5.04)	(7.44)	(-4.21)
DIV	22.62***	25.19***	-0.157	0.196	-0.859
	(3.66)	(2.75)	(-0.31)	(0.35)	(-1.47)
RISK	0.768***	0.194	-0.250***	-0.343***	-0.231***
	(2.75)	(0.40)	(-9.12)	(-11.13)	(-7.14)
DEBT	-3.473***	1.899***	-0.107***	-0.139***	-0.269***
	(-12.11)	(4.53)	(-5.62)	(-6.48)	(-12.44)
INSTPER	0.272*	-0.368	0.0719***	0.0729***	0.0725***
	(1.72)	(-1.49)	(6.83)	(6.15)	(6.09)
CAPSTRIN	0.172***	0.216***	-0.00282	-0.00379	-0.00408
	(5.53)	(5.28)	(-1.17)	(-1.40)	(-1.47)
ADRI	0.296**	0.201	-0.00666*	-0.00422	-0.00609
	(2.19)	(1.37)	(-1.81)	(-1.01)	(-1.49)
Year FF	Yes	Yes	Yes	Yes	Yes
R-squares	0.0664	0.0403	0.0386	0.0427	0.0759
Obs.	9239	6035	11269	11265	11257

Table 6
Panel A.

This panel reports regression results for the post-crisis period of bank performance with several proxies for the performances of the banks: ROA, ROE, NPL, BLOAND, and BLOANP. The dependent variables, AGRTH, and LGRTH are winsorized at the one percent level. Columns 1, 3, 5, 7, 9 report results for banks from developed economies and columns 2, 4, 6, 8, 10 report results for banks from developing economies. All models include the robust option to obtain robust standard errors. Numbers in parentheses represent the t-statistics. The superscripts, ***, **, and * denote the 1%, 5%, and 10% levels of significance, respectively. Please refer Appendix 1 for the definitions of variables.

VARS	ROA	ROA	ROE	ROE	NPL	NPL	BLOAND	BLOAND	BLOANP	BLOANP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
US	0.146**	0.138	2.988***	0.664	-0.668***	0.782	-1.564***	1.942***	-1.639***	2.205***
	(1.96)	(1.23)	(2.68)	(0.58)	(-3.16)	(1.18)	(-6.88)	(2.71)	(-7.66)	(3.88)
LEX	0.466***	-0.136	2.796	0.334	-1.063***	1.876***	0.766**	2.140***	0.484*	1.940***
	(3.81)	(-1.50)	(1.58)	(0.32)	(-3.85)	(3.62)	(2.53)	(5.50)	(1.87)	(6.01)
USLEX	-0.396**	0.0971	-6.866**	-3.097	0.154	0.629	-0.600	-0.502	-0.0130	-0.373
	(-2.04)	(0.55)	(-2.40)	(-1.51)	(0.31)	(0.63)	(-1.10)	(-0.71)	(-0.03)	(-0.63)
NUM	0.0817***	0.00523	1.059***	0.266	0.0136	0.362*	0.257***	0.199	0.309***	0.0205
	(6.21)	(0.16)	(5.39)	(0.80)	(0.37)	(1.92)	(6.47)	(1.00)	(8.32)	(0.13)
NUMLEX	0.0266	0.0200	1.554***	0.906*	0.0121	-0.710***	-0.143	-0.409**	-0.114	-0.387**
	(0.70)	(0.45)	(2.81)	(1.83)	(0.13)	(-2.80)	(-1.42)	(-2.08)	(-1.29)	(-2.38)
ASSETS	-0.0990***	0.0180	-1.182***	0.587***	0.164***	-0.574***	-0.267***	-0.863***	-0.286***	-0.757***
	(-6.44)	(0.92)	(-5.20)	(2.85)	(4.11)	(-5.03)	(-6.16)	(-7.98)	(-7.31)	(-8.66)
LOAN	-0.225**	-0.401***	-5.440***	-3.948**	2.441***	8.512***	3.905***	11.81***	0.480**	1.483***
	(-2.06)	(-2.87)	(-3.43)	(-2.50)	(9.57)	(10.61)	(13.95)	(19.37)	(1.99)	(2.93)
DIV	89.07***	69.96***	794.1***	511.6***	-44.44***	-55.52***	11.15	-0.0603	0.662	-7.654
	(17.22)	(21.38)	(10.67)	(13.39)	(-3.90)	(-2.99)	(0.89)	(-0.00)	(0.06)	(-0.70)
RISK	-3.951***	-1.469***	-60.10***	-15.90***	6.975***	9.433***	5.310***	7.159***	4.910***	5.915***
	(-22.00)	(-6.78)	(-23.45)	(-6.19)	(18.31)	(7.69)	(12.60)	(8.41)	(13.98)	(8.31)
DEBT	-0.430***	-0.513***	-2.916	2.927	-0.486	3.699***	5.635***	6.358***	-0.228	-2.570***
	(-3.17)	(-2.97)	(-1.48)	(1.50)	(-1.55)	(3.73)	(16.39)	(8.47)	(-0.77)	(-4.13)
INSTPER	0.417***	0.525***	4.870***	5.590***	-1.455***	-2.894***	-0.154	-2.034***	-0.0703	-1.417***
	(5.94)	(4.51)	(4.74)	(4.20)	(-8.55)	(-4.34)	(-0.83)	(-4.11)	(-0.43)	(-3.44)

CAPSTRIN	0.0766***	-0.0655***	0.980**	-0.361*	0.0192	0.311***	-0.234***	0.215***	-0.182***	0.207***
	(2.77)	(-3.96)	(2.44)	(-1.89)	(0.30)	(3.30)	(-3.33)	(3.17)	(-3.03)	(3.64)
ADRI	0.108***	-0.157***	2.134***	-0.907**	-0.0619	-0.441**	-0.0821	-0.599**	-0.122	-0.108
	(3.14)	(-4.25)	(4.17)	(-2.39)	(-0.67)	(-2.02)	(-0.82)	(-2.54)	(-1.34)	(-0.58)
Year FF	0	1.707***	7.752**	0	-1.429***	2.010	2.272***	0	5.344***	0
R-squares	0.215	0.0876	0.176	0.0533	0.169	0.0526	0.0920	0.130	0.0952	0.0677
Obs.	6301	4993	6301	4993	6301	4993	6301	4993	6301	4993

Panel B.

This panel reports regression results for the post-crisis period of bank performance measured in CAP1 CAP12, asset growth, loan growth and deposit growth. All dependent variables are winsorized at the one percent level. Columns 1, 3, 5, 7, 9 report results for banks from developed economies and columns 2, 4, 6, 8, 10 report results for banks from developing economies. All models include the robust option to obtain robust standard errors. Numbers in parentheses represent the t-statistics. The superscripts, ***, **, and * denote the 1%, 5%, and 10% levels of significance, respectively. Please refer Appendix 1 for the definitions of variables.

VARS	CAP1	CAP1	CAP12	CAP12	AGRTH	AGRTH	LGRTH	LGRTH	DGRTH	DGRTH
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
US	1.075***	0.0600	0.330	-0.0143	0.00791	-0.0396***	0.0132	-0.0334**	-0.000388	-0.0346**
	(3.83)	(0.08)	(1.31)	(-0.02)	(0.56)	(-2.86)	(0.87)	(-2.00)	(-0.03)	(-2.07)
LEX	-0.0751	-0.0101	-0.405	1.329***	-0.0207	0.0301**	-0.0259	0.0585***	0.0797***	0.0246
	(-0.23)	(-0.03)	(-0.92)	(2.62)	(-0.84)	(2.00)	(-0.96)	(3.34)	(2.85)	(1.35)
USLEX	0.335	0.0985	0.136	0.0726	-0.0341	-0.00956	-0.0394	-0.0898**	-0.0797**	-0.0545
	(0.50)	(0.16)	(0.19)	(0.05)	(-0.90)	(-0.31)	(-0.96)	(-2.52)	(-1.96)	(-1.46)
NUM	0.356***	0.129	0.218***	0.163	-0.00956***	0.00782*	-0.00346	0.0101**	-0.00198	0.0144***
	(8.24)	(0.60)	(5.37)	(0.72)	(-3.81)	(1.92)	(-1.29)	(2.06)	(-0.76)	(2.93)
NUMLEX	-0.00670	-0.0679	0.0322	-0.100	0.00886	-0.00227	0.0121	0.00612	-0.000401	-0.00171
	(-0.08)	(-0.44)	(0.42)	(-0.38)	(1.19)	(-0.33)	(1.50)	(0.75)	(-0.05)	(-0.20)
ASSETS	-1.074***	-0.491***	-0.611***	-0.722***	0.00585**	-0.00122	0.00502	-0.00326	0.00769**	-0.00640**
	(-32.25)	(-4.76)	(-15.12)	(-6.03)	(1.96)	(-0.46)	(1.56)	(-1.04)	(2.42)	(-2.02)
LOAN	-0.810***	1.430***	0.288	2.180***	0.0000650	-0.184***	0.186***	0.0580**	0.0146	-0.197***
	(-5.49)	(2.81)	(1.27)	(3.37)	(0.00)	(-8.26)	(7.91)	(2.22)	(0.61)	(-7.32)

DIV	17.86***	24.46**	-32.42***	40.03***	-1.537	-0.296	-1.462	0.143	-1.889	-1.057
	(3.10)	(2.31)	(-3.96)	(2.95)	(-1.48)	(-0.51)	(-1.28)	(0.21)	(-1.60)	(-1.49)
RISK	0.499***	1.300**	-0.00352	-0.0170	-0.344***	-0.138***	-0.466***	-0.215***	-0.291***	-0.169***
	(2.63)	(2.13)	(-0.01)	(-0.02)	(-9.40)	(-3.40)	(-11.51)	(-4.62)	(-6.78)	(-3.43)
DEBT	-0.202	-6.917***	0.559**	3.052***	-0.0499*	-0.0999***	-0.0284	-0.170***	-0.248***	-0.265***
	(-1.02)	(-11.50)	(2.24)	(3.98)	(-1.85)	(-3.62)	(-0.97)	(-5.27)	(-8.31)	(-7.96)
INSTPER	0.600***	0.171	0.116	-0.995*	0.0507***	0.0677***	0.0610***	0.0571**	0.0413***	0.0563**
	(5.81)	(0.42)	(0.84)	(-1.94)	(3.67)	(3.46)	(4.07)	(2.50)	(2.76)	(2.39)
CAPSTRIN	0.0245	0.221***	0.00289	0.185***	0.00490	-0.00377	0.0150**	-0.00491	0.00516	-0.00744**
	(0.66)	(4.31)	(0.08)	(2.98)	(0.90)	(-1.33)	(2.51)	(-1.49)	(0.85)	(-2.17)
ADRI	0.726***	0.171	0.130	0.131	-0.0156**	-0.00739	-0.00771	-0.0104*	-0.0211***	-0.000188
	(7.21)	(0.61)	(1.39)	(0.45)	(-2.34)	(-1.59)	(-1.07)	(-1.86)	(-2.99)	(-0.03)
Year FF	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squares	0.200	0.0682	0.115	0.0478	0.0657	0.153	0.0920	0.143	0.0593	0.141
Obs.	5536	3703	2973	3062	6292	4977	6289	4976	6285	4972

Table 7 - Bank Performance During the Crisis Period
Panel A.

This panel reports regression results of bank performance with several proxies for the performances of the banks: ROA, ROE, NPL, BLOAND, and BLOANP during the financial crisis period, 2008-2009. The dependent variables, AGRTH, and LGRTH are winsorized at the one percent level. All models include the robust option to obtain robust standard errors. Numbers in parentheses represent the t-statistics. The superscripts, ***, **, and * denote the 1%, 5%, and 10% levels of significance, respectively. Please refer Appendix 1 for the definitions of variables.VARS

	ROA	ROA	ROE	ROE	NPL	NPL	BLOAND	BLOAND	BLOANP	BLOANP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
US	-0.0215	-0.00449	2.564	2.790	-0.749*	-0.768*	-1.537***	-1.535***	-1.252***	-1.260***
	(-0.16)	(-0.03)	(1.33)	(1.43)	(-1.67)	(-1.70)	(-2.88)	(-2.88)	(-3.09)	(-3.10)
DEV	0.549	0.592	17.95**	18.27**	0.310	0.302	-2.791	-2.939	-1.607	-1.666
	(1.01)	(1.07)	(2.29)	(2.32)	(0.17)	(0.17)	(-1.29)	(-1.36)	(-0.98)	(-1.01)
USDEV	0.477**	0.437*	3.800	3.408	0.169	0.212	0.986	1.041	1.794***	1.831***
	(2.16)	(1.95)	(1.19)	(1.06)	(0.23)	(0.28)	(1.12)	(1.19)	(2.69)	(2.74)
NUM	0.108***	0.104***	1.573***	1.527***	0.122	0.147*	0.319***	0.323***	0.227***	0.235***
	(4.33)	(4.10)	(4.36)	(4.20)	(1.45)	(1.74)	(3.20)	(3.25)	(2.98)	(3.10)
NUMDEV	-0.152***	-0.141***	-1.721**	-1.609**	-0.117	-0.140	-0.143	-0.151	-0.311**	-0.322**
	(-3.09)	(-2.82)	(-2.41)	(-2.24)	(-0.72)	(-0.85)	(-0.73)	(-0.77)	(-2.10)	(-2.17)
EXTMOR	-0.222*	-0.215*	-2.238	-2.155	-0.0161	-0.0303	-0.00304	-0.0180	0.254	0.244
	(-1.91)	(-1.82)	(-1.33)	(-1.28)	(-0.04)	(-0.08)	(-0.01)	(-0.04)	(0.72)	(0.69)
DEVEXT	0.0930	0.0847	-0.934	-1.003	0.228	0.238	1.300***	1.327***	0.927**	0.940**
	(0.75)	(0.67)	(-0.52)	(-0.56)	(0.55)	(0.57)	(2.63)	(2.69)	(2.47)	(2.50)
ASSETS	-0.0209	-0.0213	-0.421	-0.440	-0.246***	-0.257***	-0.238**	-0.254**	-0.238***	-0.245***
	(-0.75)	(-0.75)	(-1.05)	(-1.09)	(-2.71)	(-2.80)	(-2.21)	(-2.36)	(-2.88)	(-2.96)
LOAN	-0.112	-0.289	-0.767	-2.847	3.186***	3.868***	5.750***	5.629***	-0.724	-0.520
	(-0.47)	(-1.19)	(-0.22)	(-0.81)	(4.78)	(5.80)	(7.46)	(7.34)	(-1.16)	(-0.83)
CAP1	0.0651***	0.0631***	0.378	0.350	-0.190***	-0.183***	0.173***	0.174***	0.0856*	0.0881*
	(4.01)	(3.83)	(1.61)	(1.48)	(-3.81)	(-3.64)	(2.95)	(2.96)	(1.86)	(1.91)
AGRTH	0.974***		12.08***		-1.205***		-0.0914		-0.514**	
	(6.96)		(5.68)		(-4.77)		(-0.32)		(-2.06)	

LGRTH		0.537***		8.081***		-0.683***		0.419		-0.108
		(4.14)		(4.14)		(-2.86)		(1.57)		(-0.46)
DIV	145.6***	144.3***	1188.6***	1168.7***	-121.3***	-119.7***	31.12	27.22	-47.54**	-48.50**
	(17.87)	(17.45)	(10.00)	(9.76)	(-5.64)	(-5.52)	(1.26)	(1.10)	(-2.33)	(-2.37)
RISK	-3.573***	-3.754***	-56.39***	-58.49***	5.341***	5.511***	3.978***	4.091***	4.678***	4.800***
	(-9.58)	(-10.02)	(-10.09)	(-10.47)	(7.30)	(7.56)	(4.85)	(5.00)	(6.51)	(6.69)
DEBT	0.168	0.116	3.958	3.460	-1.653**	-1.658**	4.190***	4.252***	-0.313	-0.281
	(0.66)	(0.45)	(1.07)	(0.93)	(-2.22)	(-2.21)	(4.84)	(4.91)	(-0.45)	(-0.41)
INSTPER	0.186	0.192	3.945*	4.089*	-0.649	-0.606	0.999**	1.063**	0.786**	0.816**
	(1.30)	(1.33)	(1.90)	(1.96)	(-1.59)	(-1.48)	(2.11)	(2.25)	(2.06)	(2.13)
CAPSTRIN	-0.117***	-0.123***	-1.002*	-1.049*	0.479***	0.484***	-0.0411	-0.0404	0.158	0.162
	(-2.95)	(-3.05)	(-1.75)	(-1.82)	(3.66)	(3.66)	(-0.26)	(-0.26)	(1.34)	(1.36)
ADRI	-0.0376	-0.0469	0.282	0.180	0.222	0.247	-0.0713	-0.0602	0.0271	0.0381
	(-0.83)	(-1.02)	(0.43)	(0.27)	(1.50)	(1.64)	(-0.40)	(-0.34)	(0.20)	(0.28)
Year FF	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squares	0.141	0.126	0.401	0.396	0.233	0.230	0.122	0.122	0.145	0.143
Obs.	1663	1662	1663	1662	1663	1662	1663	1662	1663	1662

Panel B.

This panel reports regression results of bank performance measured in CAP1 CAP12, asset growth, loan growth and deposit growth during the financial crisis period, 2008-2009. All dependent variables are winsorized at the one percent level. All models include the robust option to obtain robust standard errors. Numbers in parentheses represent the t-statistics. The superscripts, ***, **, and * denote the 1%, 5%, and 10% levels of significance, respectively. Please refer Appendix 1 for the definitions of variables.

VARS	CAP1	CAP12	AGRTH	LGRTH	DGRTH
	(1)	(2)	(3)	(4)	(5)
US	0.750***	0.459	0.0136	-0.00914	-0.00001
	(2.79)	(0.96)	(0.72)	(-0.43)	(-0.00)
DEV	-0.777	3.304*	0.193***	0.242***	0.0274
	(-0.71)	(1.71)	(2.77)	(3.06)	(0.34)
USDEV	-0.232	-0.125	-0.0627**	-0.0624*	-0.0628*
	(-0.52)	(-0.16)	(-2.07)	(-1.81)	(-1.77)
NUM	0.291***	0.209**	-0.00242	0.00306	-0.000396
	(6.13)	(2.35)	(-0.64)	(0.72)	(-0.09)
NUMDEV	-0.0153	-0.0709	0.0122*	0.0104	0.0171**
	(-0.16)	(-0.38)	(1.77)	(1.33)	(2.13)
EXTMOR	-0.0955	0.244	0.0126	0.0173	-0.0152
	(-0.40)	(0.61)	(0.86)	(1.04)	(-0.89)
DEVEXT	0.203	-0.630	-0.0347**	-0.0434**	0.00116
	(0.81)	(-1.44)	(-2.14)	(-2.36)	(0.06)
ASSETS	-0.826***	-0.712***	-0.000711	0.00157	-0.00201
	(-17.97)	(-7.87)	(-0.20)	(0.39)	(-0.48)
LOAN	-0.815***	0.272	-0.147***	0.0179	-0.101**
	(-3.14)	(0.49)	(-4.41)	(0.48)	(-2.56)
DIV	-11.31	18.75	1.656	4.195***	-0.298
	(-1.39)	(1.24)	(1.36)	(3.09)	(-0.20)
RISK	-0.107	0.705	-0.380***	-0.269***	-0.308***
	(-0.47)	(1.39)	(-6.31)	(-4.04)	(-4.22)
DEBT	-0.933***	2.663***	-0.0728**	-0.0798*	-0.112***
	(-2.93)	(4.37)	(-1.98)	(-1.93)	(-2.59)
INSTPER	0.306*	1.044***	0.00190	-0.0271	0.0210
	(1.83)	(2.60)	(0.09)	(-1.08)	(0.80)
CAPSTRIN	-0.0115	0.00194	-0.0148***	-0.0194***	-0.0122**
	(-0.15)	(0.01)	(-2.86)	(-3.32)	(-2.02)
ADRI	0.406***	0.509***	-0.00779	-0.00435	-0.0107
	(4.66)	(3.21)	(-1.27)	(-0.62)	(-1.49)
Year FF	Yes	Yes	Yes	Yes	Yes
R-squares	0.106	0.0911	0.0852	0.105	0.0685
Obs.	1671	844	2018	2017	2011

Table 8. The Effect of Dodd-Frank Act
Panel A.

This panel reports regression results of bank performance after the Dodd-Frank Act became effective in 2010 with several proxies for the performances of the banks: ROA, ROE, NPL, BLOAND, and BLOANP. The sample period of this table starts after 2010. The dependent variables, AGRTH, and LGRTH are winsorized at the one percent level. All models include the robust option to obtain robust standard errors. Numbers in parentheses represent the t-statistics. The superscripts, ***, **, and * denote the 1%, 5%, and 10% levels of significance, respectively. Please refer Appendix 1 for the definitions of variables.

VARS	ROA	ROA	ROE	ROE	NPL	NPL	BLOAND	BLOAND	BLOANP	BLOANP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
US	0.0517	0.0433	1.195	1.097	-1.568***	-1.509***	-1.561***	-1.514***	-1.092**	-1.053**
	(0.63)	(0.52)	(1.31)	(1.20)	(-3.19)	(-3.07)	(-2.83)	(-2.75)	(-2.54)	(-2.45)
DEV	0.553**	0.534*	5.643*	5.458*	2.945*	3.147*	3.074*	3.224*	7.033***	7.199***
	(1.99)	(1.90)	(1.83)	(1.77)	(1.77)	(1.89)	(1.65)	(1.73)	(4.83)	(4.95)
USDEV	0.177	0.192*	0.694	0.847	1.374**	1.254*	1.828**	1.741**	1.877***	1.781***
	(1.55)	(1.67)	(0.55)	(0.67)	(2.00)	(1.83)	(2.37)	(2.25)	(3.12)	(2.96)
NUM	0.0240*	0.0217	0.164	0.127	0.450***	0.469***	0.376***	0.394***	0.413***	0.422***
	(1.77)	(1.58)	(1.09)	(0.84)	(5.61)	(5.85)	(4.25)	(4.45)	(5.94)	(6.09)
NUMDEV	-0.0455*	-0.0436*	-0.150	-0.116	-0.314**	-0.328**	-0.301*	-0.313*	-0.447***	-0.455***
	(-1.89)	(-1.80)	(-0.57)	(-0.44)	(-2.16)	(-2.26)	(-1.84)	(-1.91)	(-3.50)	(-3.56)
EXTMOR	-0.0110	-0.0109	-0.287	-0.258	-0.114	-0.120	-0.340	-0.348	0.165	0.167
	(-0.24)	(-0.23)	(-0.56)	(-0.50)	(-0.41)	(-0.43)	(-1.08)	(-1.11)	(0.67)	(0.68)
DEVEXT	-0.00994	-0.00796	-0.399	-0.390	-0.191	-0.211	0.00213	-0.0128	-0.789***	-0.807***
	(-0.18)	(-0.14)	(-0.65)	(-0.64)	(-0.57)	(-0.63)	(0.01)	(-0.03)	(-2.70)	(-2.77)
ASSETS	-0.0104	-0.0120	0.0596	0.0566	-0.317***	-0.316***	-0.353***	-0.357***	-0.421***	-0.414***
	(-0.83)	(-0.95)	(0.42)	(0.40)	(-4.66)	(-4.65)	(-5.14)	(-5.22)	(-7.66)	(-7.58)
LOAN	0.102	-0.00230	-0.402	-1.517	4.654***	5.389***	6.079***	6.651***	-0.410	0.121
	(1.05)	(-0.02)	(-0.36)	(-1.34)	(10.36)	(11.97)	(15.49)	(16.89)	(-1.27)	(0.37)
CAP1	0.0160***	0.0160***	-0.0200	-0.0249	-0.110***	-0.107***	0.105***	0.107***	0.00922	0.0112
	(4.75)	(4.72)	(-0.52)	(-0.64)	(-6.64)	(-6.48)	(7.01)	(7.15)	(0.75)	(0.91)
AGRTH	0.403***		5.777***		-1.734***		-1.139***		-0.942***	

	(7.49)		(8.68)		(-8.60)		(-7.04)		(-7.00)	
LGRTH		0.371***		5.454***		-1.932***		-1.211***		-1.250***
		(7.63)		(9.06)		(-10.58)		(-8.27)		(-10.27)
DIV	80.55***	79.86***	602.6***	602.6***	-57.10***	-56.99***	-6.004	-5.998	-11.08	-10.97
	(26.47)	(26.26)	(16.58)	(16.59)	(-4.57)	(-4.57)	(-0.58)	(-0.58)	(-1.30)	(-1.29)
RISK	-1.625***	-1.552***	-27.50***	-26.57***	6.246***	5.843***	3.239***	2.993***	3.053***	2.773***
	(-9.45)	(-9.03)	(-13.05)	(-12.58)	(9.47)	(8.85)	(6.09)	(5.62)	(6.90)	(6.27)
DEBT	-0.680***	-0.690***	-2.071	-2.116	-1.139**	-1.150**	7.278***	7.297***	-1.080***	-1.108***
	(-5.53)	(-5.60)	(-1.45)	(-1.48)	(-2.02)	(-2.04)	(14.83)	(14.89)	(-2.68)	(-2.76)
INSTPER	0.307***	0.318***	2.438***	2.466***	-1.368***	-1.360***	-0.304	-0.300	-0.353	-0.331
	(4.95)	(5.11)	(3.42)	(3.46)	(-4.61)	(-4.59)	(-1.15)	(-1.13)	(-1.63)	(-1.53)
CAPSTRIN	-0.0335	-0.0361*	0.425*	0.391*	-0.531***	-0.514***	-0.708***	-0.696***	-0.704***	-0.692***
	(-1.57)	(-1.68)	(1.80)	(1.65)	(-4.16)	(-4.02)	(-4.95)	(-4.86)	(-6.30)	(-6.20)
ADRI	-0.0868***	-0.0872***	-0.145	-0.142	-0.217	-0.214	-0.643***	-0.635***	-0.149	-0.150
	(-3.12)	(-3.11)	(-0.47)	(-0.46)	(-1.31)	(-1.28)	(-3.47)	(-3.42)	(-1.03)	(-1.03)
Year FF	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squares	0.0666	0.0684	0.323	0.324	0.0460	0.0520	0.105	0.109	0.0457	0.0550
Obs.	6702	6700	6702	6700	6702	6700	6702	6700	6702	6700

Panel B.

This panel reports regression results of bank performance measured in CAP1 CAP12, asset growth, loan growth and deposit growth after the Dodd-Frank Act became effective in 2010. Consequently, the sample period starts after 2010. All dependent variables are winsorized at the one percent level. All models include the robust option to obtain robust standard errors. Numbers in parentheses represent the t-statistics. The superscripts, ***, **, and * denote the 1%, 5%, and 10% levels of significance, respectively. Please refer Appendix 1 for the definitions of variables.

VARS	CAP1	CAP12	AGRTH	LGRTH	DGRTH
	(1)	(2)	(3)	(4)	(5)
US	1.066*	0.531	0.000514	0.0162	0.00311
	(1.83)	(0.89)	(0.04)	(1.08)	(0.21)
DEV	1.336	2.802	0.0177	0.0306	0.0296
	(0.68)	(1.39)	(0.39)	(0.59)	(0.58)
USDEV	-0.998	-0.476	-0.0313*	-0.0511**	-0.0357*
	(-1.22)	(-0.56)	(-1.71)	(-2.43)	(-1.74)
NUM	0.330***	0.329***	-0.00674***	-0.000215	0.00263
	(3.61)	(3.37)	(-2.94)	(-0.08)	(1.02)
NUMDEV	-0.0896	-0.196	0.00958**	0.00398	0.00474
	(-0.52)	(-1.09)	(2.40)	(0.87)	(1.06)
EXTMOR	-0.161	-0.0833	0.00471	-0.00236	0.00826
	(-0.48)	(-0.24)	(0.60)	(-0.26)	(0.94)
DEVEXT	-0.0446	-0.254	0.00125	0.00394	0.00206
	(-0.11)	(-0.63)	(0.14)	(0.37)	(0.20)
ASSETS	-0.718***	-0.744***	-0.00154	-0.00258	-0.00405*
	(-11.82)	(-10.33)	(-0.77)	(-1.12)	(-1.79)
LOAN	0.617**	0.289	-0.0525***	0.121***	-0.0569***
	(2.00)	(0.70)	(-3.13)	(6.34)	(-2.97)
DIV	31.05***	18.19*	-0.906	-1.186*	-1.155*
	(3.97)	(1.92)	(-1.64)	(-1.92)	(-1.81)
RISK	1.471***	0.508	-0.160***	-0.327***	-0.171***
	(3.69)	(0.96)	(-4.61)	(-8.43)	(-4.20)
DEBT	-4.578***	-0.515	-0.0648***	-0.0804***	-0.224***
	(-12.02)	(-1.11)	(-3.05)	(-3.34)	(-9.20)
INSTPER	-0.0118	0.254	0.0832***	0.0920***	0.0802***
	(-0.06)	(0.93)	(7.41)	(7.22)	(6.27)
CAPSTRIN	-0.156	-0.116	0.00758**	0.0118***	0.00170
	(-1.03)	(-0.73)	(2.18)	(2.98)	(0.44)
ADRI	0.189	0.136	-0.0107**	-0.0133***	-0.00870*
	(0.97)	(0.67)	(-2.40)	(-2.61)	(-1.74)
Year FF	Yes	Yes	Yes	Yes	Yes
R-squares	0.0627	0.0257	0.0735	0.0980	0.0625
Obs.	6708	4722	8226	8224	8223

Higher institutional ownership is not significantly associated with ROA and is negatively associated with the asset quality in the crisis-period.

Table 7B shows that US listing is positively associated with a 0.75% increase in tier-1 capital during the crisis period. The presence of institutional ownership and high investor protection (ADRI) banks are positively associated with tier-1 capital and total capital, but their effect is insignificant on asset growth, loan growth, and deposit growth. Capital stringency regulation is negatively associated with asset growth, loan growth and deposit growth (coefficient on asset growth = -0.0148, loan growth = -0.0194, deposit growth = -0.0122).

Tables 8A and 8B report regression results for post Dodd-Frank Act. In table 8A, the results indicate that banks from higher capital stringency countries are associated with 0.425% increase in ROE and 0.531% decline in NPLs and 0.708% decline in bad loans after the Dodd-Frank Act. During the pre-Dodd-Frank Act higher capital stringency is associated with higher profits and lower asset quality before the Dodd-Frank Act (untabulated results). Post-Dodd-Frank sample also reports that higher ADRI is associated with 0.0868% decline in ROA and 0.643% decline in bad loans.

Table 8B reports that a US listing increases the tier-1 capital by 1.066%. Cross-listing (variable NUM) is associated with a 0.330% increase in tier-1 capital and 0.329% increase in total capital. Cross-listing is associated with a 0.00674% decline in asset growth. Higher capital stringency banks experienced a 0.00758% increase in asset growth and 0.0118% increase in loan growth. Whereas higher ADRI (investor protection) is associated with a 0.0107% decline in asset growth, 0.0133% decline in loan growth and 0.0087% decline in deposit growth, the higher ADRI protects shareholders but not the rights of depositors or creditors.

V Conclusion

Overall, we find that cross-listing, institutional ownership, external monitoring, and capital stringency have different impacts on banks from developed and developing countries. Banks from developed countries that cross-list in multiple exchanges have higher ROA and ROE but lower asset quality whereas banks from developing countries that cross-list have lower ROA due to higher compliance costs. Conversely, cross-listing improves the asset quality and loan growth of banks from developing countries while it is also associated with higher tier-1 capital in banks from developed countries. This effect implies that cross-listing benefits banks from developed countries with the raising of more tier-1 capital and banks from developing countries with attaining higher asset and loan growth.

Institutional ownership has a positive impact on bank profitability, asset quality, asset growth, loan growth and deposit growth in all banks. Institutional ownership is associated with higher tier-1 capital in banks from developed countries. Institutional ownership increases monitoring which helps banks access more capital and increases analyst coverage.

Higher external monitoring is positively associated with ROA and ROE in banks from developed countries since they are already subjected to stringent regulations but negatively associated with ROA in banks from developing countries due to higher compliance costs. Higher external monitoring is positively associated with asset quality in banks from developing countries. Banks from low external monitoring countries that cross-list in multiple exchanges are associated with better asset quality especially after the post-crisis period. During the crisis-period, most variables are negatively associated with profitability, asset quality, asset growth, loan growth and deposit growth. US listed banks are positively associated with asset quality when compared to non-US listed banks, and US listed banks were positively associated with tier-1 capital.

Higher capital stringency regulation is negatively associated with profitability and positively associated with capital maintenance in banks from developing countries due to higher compliance costs and higher regulations respectively. Higher capital stringency is associated with lower profit and better asset quality after the Dodd-Frank Act was implemented due to increased regulations and costs. Banks from high investor protection countries (ADRI) had lower profits after the Dodd-Frank Act. Our findings are important to investors, depositors, and bank regulators.

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Appendix 1. Definition of Variables

Variables	Descriptions
ADRI	Investor protection variable from Spamann Anti-Director Rights Index (Spamann, 2010). Country level variable where a high value indicates higher investor protection.
AGRTH	Growth of assets when compared to the previous year
ASSET	Natural Logarithm of total assets
BLOAND	Bad loans to deposits ratio. Bad loans are defined as loans that are no longer considered redeemable.
BLOANP	Bad loans to total loans
CAP1	Tier-1 capital percentage
CAP12	Total capital percentage (i.e., sum of tier-1 and tier-2 capital)
CAPSTRIN	Capital Stringency variable from Barth *et al*. (2006). Country level variable which measures the stringency of banks' capital requirements based on amount and source of capital and if it incorporates certain risk elements and deducts certain market value losses from capital adequacy.
DEBT	Total Debt scaled by total assets
DEV	Dummy Variable to indicate if the bank is from developing country
DGRTH	Growth of deposits when compared to the previous year
DIV	Total Dividends to Assets
DODD	Dummy variable equal 1 for the year after the Dodd-Frank Act became effective, zero otherwise
EXTMOR	Index that measures the degree of incentivized bank monitoring by private sector
INSTPER	Percentage of institutional ownership in the bank
LEX	Dummy variable for low external monitoring in a country
LGRTH	Growth of loans when compared to the previous year
LOAN	Total loans scaled by total assets
NPL	Non-performing loans to total loans. Non-performing loans are loans on which scheduled payments have not been paid over 90 days.
NUM	Number of exchanges on which the bank is listed
RISK	Standard deviation of stock's monthly returns over the fiscal year
ROA	Return on Assets
ROE	Return on Equity
US	Dummy variable to indicate if the bank is listed in US stock exchange

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The Impact of ESG on Bank Performance and Risk Around the COVID-19 Pandemic

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Abstract

Financial institutions' focus on using ESG (environmental, social, and governance) criteria in decisions has grown significantly over time despite growing controversy over its use. Prior papers have not solved the controversy as they have found mixed results of the benefits of ESG activity. Further, there may have been structural changes that accompanied the pandemic's period of economic stress. The paper examines the relation between ESG ratings and financial institutions' risk and performance measures. Lagged values of ESG and its components are significantly and negatively related to subsequent market performance measures during the pandemic period. During that period, there also appears to be a significant negative relation between accounting performance and higher ESG rated firms. There is also some evidence of a positive relation between risk and ESG ratings during the pandemic period. Overall, it appears that higher ESG financial institutions tended do less well during the pandemic period.

JEL CLASSIFICATION: G01, G21, L25, M14
KEYWORDS: Bank, Pandemic, ESG, Performance

I Introduction

The concept of investing based on the criteria of environmental, social, and governance (ESG) factors has seen a rapid growth in popularity since the term ESG was coined in 2005 and now more than 90% of S&P 500 companies providing ESG information. (Perez, et al., 2022). On October 14, 2021 the Employee Benefits Security Administration published a proposed regulation "Prudence and Loyalty in Selecting Plan Investments and Exercising Shareholder Rights" to allow investments that consider ESG factors (Schultz, 2022). The growth in the focus on ESG criteria has also occurred in financial institutions which interact both through their internal operations and through their credit decisions.

Although ESG has long been in the investment lexicon, using those criteria for financial purposes has become quite controversial recently. For instance, 19 states are investigating large financial companies like Blackrock and Morningstar (Kerber, 2022), for potentially violating consumer-protection laws by using ESG criteria. Cheek and Jones (2022) also discuss anti-ESG legislation in various states addressing discrimination, exclusion, or special treatment due to ESG status. The question of whether pursing ESG activities increases firm value lies at the crux of much of the discussion. It is potentially of even greater import for financial institutions since they interact with ESG considerations both through internal operations and their credit decisions.

This question may be even more challenging given potential structural shifts around the pandemic's economic crisis. Looking at the prior financial crisis of 2007-2008, various papers found systematic changes in financial institutions (Nippani and Ling, 2021), particularly related to ESG-type activities (Cornett, et al., 2016; Miralles, et al., 2019a). It is an open question how the

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most recent economic crisis may have changed the relation between ESG and financial institution risk and performance.

To determine if ESG ratings are informative of future performance, as is suggested by some literature, (Neitzert and Petras, 2021; Usman, et al., 2020), the paper examines 89 medium and large US-listed financial institutions. To provide greater detail, the ESG ratings are also broken into its three component factors. The evidence addresses to what degree the ESG performance of the financial institutions is associated with better performance and risk taking by financial institutions in the two following years that spanned the pandemic.

The remainder of the paper is organized as follows. Section 2 encompasses the literature review of ESG ratings related to firm performance and risk. Section 3 discusses the data used in the analyses. Section 4 provides the empirical methodology for the paper. Section 5 provides the results of the analysis, and Sections 6 covers the conclusions of the paper.

II Literature Review

A major focus of ESG research has been examining whether firm value is created by ESG-based investments (Huang, 2022). Understanding the value implications is of great practical import since American trust fiduciary law allows investing based on ESG criteria tied to firm performance but generally does not support investing on the purely stakeholder grounds (Schanzenbach and Sitkoff, 2020).

Schanzenbach and Sitkoff (2020) argue there are two different categories of ESG investment, risk-return ESG and collateral benefits ESG. Under risk-return, ESG investments are undertaken to create shareholder wealth through activities that either improve the firm's return or lower its risk. These benefits might be directly caused by the ESG investment, or may be indirect. For example, Cornell (2021) argues investors who value ESG criteria as a nonfinancial investment benefit, will prefer firms with strong ESG ratings and will tend to lower the cost of capital of those firms. Shareholders valuing implicit returns can generate an equilibrium where the firm sees lower financial required returns. Ahmed, et al. (2021) model where investors value both wealth and ESG investment. They find those investors appear to benefit from firms' investments in ESG.

The ESG investment decision may also generate indirect benefits that more than cover the costly investment (Albuquerque, et al., 2019; Huang, 2022). In this paradigm there may be benefits accruing to a variety of stakeholders, but stockholders are a net beneficiary of the activities. Cornell and Shapiro (2021) indicate that valuation increase may be explained through considering implicit claims, in addition to the explicit (or contractual) claims, on corporate operations. Implicit claims have minimal legal standing but companies still have an incentive to respect those claims as the ability to issue implicit claims for more than their cost can add value to the firm. Defaulting on such claims could impact the ability to issue valuable claims in the future. Thus, firms have a strong incentive, regardless of legal standing, to not only honor implicit claims but to expand them and increase firm value. Firms engaging in corporate social responsibility (CSR) may indirectly be benefitting shareholders through the creation of such claims.

Providing concrete examples, Albuquerque, et al. (2019) discuss using ESG investment as product differentiation leading to higher margins. Huang (2022) also argues that ESG considerations may be part of a firm strategy giving competitive advantage – attracting customers, retaining employees, reducing information asymmetry, etc. This suggests benefits are derived from signaling reputation to stakeholders. That can induce behavioral changes which lead to improved financial value to the company.

There has been a great deal written on the empirical relation between CSR and company financial performance (Ahmed, et al., 2021; Albuquerque, et al., 2019; Barnea and Rubin, 2010; Cornell, 2021; Davis and Lescott, 2019; Yoon, et al., 2018). These works generally show a positive connection between company accounting-based performance and ESG performance (Henisz and McGlinch, 2019), though the results are somewhat mixed. Huang (2021) finds the ESG-performance relation for a broad range of firms is stronger for accounting-based measures such as return on assets (ROA) and return on equity (ROE) in the literature. Although the broad literature provides insight into the ESG-performance relation, there is some evidence that the significance of ESG may differ between industrial firms and financial intermediaries (Brogi and Lagasio, 2018; Carnevale, et al., 2012).

Papers examining the ESG-performance relation in financial institutions are scarcer. Brogi and Lagasio (2018) find that a significant positive association between ESG performance and ROA with the results appearing to be stronger using a lagged ESG ratings. This is consistent with other works like Cornett, et al., (2016) who find a relation between performance and CSR activities. Other papers report results that vary by country (Buallay, et al., 2021; Carnevale, et al., 2012)

Multiple studies have also looked at the component pieces of ESG and have found mixed relations to performance. Some find a positive relation between performance and ESG ratings, but a negative relation for the social component (Bually, et al., 2020; Miralles-Quiros, et al., 2019a; Miralles-Quiros, et al., 2019b). Shakil, et al., (2019) examine developing markets and finds a positive association with the social and environmental factors but no relation to governance.

Considering the relation between ESG performance and risk, Drago, et al. (2019) argue management teams more concerned about other company stakeholders would engage in lower risk-taking. More recently, Jones (2022) finds evidence supporting socially responsible investments being less risky during times of economic crisis. Fahlenbrach, et al. (2012) examines bank risk culture persistence. Their results suggest that the relation between risk and ESG is a signal of the underlying risk-taking culture in the bank. Neitzert and Petras (2022) use a sample of 582 banks worldwide to confirm a risk-mitigation association with corporate social responsibility behaviors. They find that the risk-reduction relates to ratings on the environmental category. Others also find a risk reduction effect (DiTommaso and Thornton, 2021; Gontarek and Belghitar, 2018; Henisz and McGlinch, 2019) associated with ESG ratings.

In contrast to the works above is the literature that finds the relations between ESG, performance, and risk, not significant or even reversed. Such findings are consistent with the collateral benefits of ESG theory which related CSR investment to externalities not tied to shareholder wealth maximization (Fama, 2021). Low, et al. (2021) discusses the concept as firms having responsibilities and obligations to all its stakeholders in excess of legal requirements. These obligations exist as corporate decisions impact stakeholders. Unlike the risk-return explanation, the collateral benefits framework of ESG may lead to lower firm valuation as resources may be allocated to activities not leading to improved financial performance or risk profile.

If pursing collateral benefits, managers have wide discretion in the allocation of resources without the typical measuring stick of stockholder value. Cespa and Cestone (2007) argue that managers (themselves stakeholders in the firm) control over stakeholder protection can serve as an entrenchment strategy. There is an incentive for management to overinvest in ESG opportunities as now stakeholders would have an interest in retaining the current management team despite poor performance. Some papers find (Barnea and Rubin, 2010; DiTommaso and Thornton, 2020) evidence of overinvestment associated with CSR strategies. Consistent with that argument, Grougiou, et al. (2014) find that bank managers who are active in manipulating earnings are also more involved in ESG-related activities. They argue managers may use these activities to divert attention from their questionable accounting methods.

Empirically, Buallay, et al. (2021) look at banks in 80 countries and find a negative impact of ESG ratings on accounting performance. La Torre, et al. (2021) looks at 44 European banks and compares ESG against a range of performance variables. They find no relation between ESG ratings and accounting performance, and a negative relation with market performance. DiTommaso and Thornton (2021) also find a negative relation to performance. Bhattacharyya, et al. (2021) examine mandatory CSR expenditures in 61 Indian banks but find no relation between accounting performance and CSR expenditures. They do find a significant negative relation to stock market returns. Forgione, et al. (2020) finds higher ratings for environmental or social tend to be associated with lower efficiency in banks in some countries and higher in others.

Many of the banking papers have faced data challenges. Some banking studies look across a large range of countries and over time. This provides more observations but may be a challenge given that some papers (Cornett, et al., 2016; Miralles-Quiros, et al., 2019b) found that the relation between ESG and financial performance changed after the last US financial crisis. The authors suggest there is value in examining shorter and more current periods. Too, the cross-country studies benefit from greater samples size, but there is evidence that the ESG-performance relation differs depending on the nature of the country considered (Caporale, et al., 2022; Carnevale, et al., 2012; Forgione, et al., 2020). These results suggests potential value in examining financial institutions' relation between ESG and performance over the pandemic period in a single market.

III Data

The paper assesses the potential relation between ESG ratings of financial institutions and future performance using data from 2015-2021. The initial sample included 101 mid-sized and large financial institutions with stock traded in the US markets that had ESG data reported. Six financial institutions that underwent Merger and Acquisition activity during the period were dropped, as were six missing necessary financial information. That left 89 financial institutions with 445 observations. Financial data was collected from Capital IQ and from call reports available from the Federal Financial Institutions Examination Council (ffiec.gov).

ESG rating data is taken from the Refinitiv Eikon ESG database which calculates scores based on more than 600 metrics and is widely employed in the literature (Miralles-Quiros, et al. 2019b).. Consistent with prior literature (Aevoae, et al., 2022; Forgione, et al., 2020; Miralles-Quiros, et al., 2019b), the paper also examines each of the component ratings. The ratings are transformed to range between zero and one.

Usman, et al., (2020) argue that there may be a time lag between ESG ratings and that information being reflected in the financial markets. Brogi and Lagasio (2018) used lagged values of ESG to predict future ROA. Serafeim and Yoon (2022) find that ESG ratings can predict future ESG news, with positive market reaction to positive ESG news and negative market reaction to negative news. Davis and Lescott, (2019) also emphasizes the long-term nature of potential competitive advantages derived from ESG-related activities. Given this evidence, lagged ESG values are used.

When evaluating firm performance, the literature widely uses ROA and ROE (Cornett, et al., 2016; Gontarek and Belghitar, 2018; Nippani and Ling, 2021; Shakil, et al., 2019) for accounting performance. The literature also frequently uses market measures of performance (DiTommaso and Thornton, 2020; LaTorre, et al., 2021; Fahlenbrach, et al., 2012).

Beta is used as a measure of risk estimated by using a rolling 60-month average. In addition to beta, three other risk measures are used. The first is the book-to-market (B/M) ratio. Balasubramnian, et. al, (2019), among others, reports the B/M ratio provides insight into future bank loan delinquencies, charge-offs, earnings volatility, and z-scores, four to nine quarters prior to the realization. To ensure a range of risk measures, another considered is the loan-to-deposit (LD) ratio used in LaTorre, et. al. (2021) as a measure of liquidity risk. Other papers, like Buallay, et al., (2020), also uses the LD ratio as a risk measure. The third is the provision for credit losses as a proportion of the total loan portfolio (PCL/TL). Papers such as Bikker and Vervliet (2017) use that variable as an estimator for credit risk.

The analysis also uses a set of control variables based on the characteristics of financial institutions that may explain performance or risk-taking. The natural log of total assets (LnTA), as a measure of size, is very common in the literature (Aevoae, et al., 2022; Albuquerque, et al., 2019; Miralles, et al., 2019b; Shakil, et al., 2019; Usman, et al., 2020). To account for the potential of different lending strategies with different risk profiles, the loan to asset ratio (TL/TA) is included (Aevoae, et al., 2022; Neitzert and Petras, 2022). Banks better able to attract deposits may have improved performance potential moving forward so the regressions also incorporate the ratios of deposits to assets (TD/TA) (Gontarek and Belghitar, 2018; Neitzert and Petras, 2022). Bank leverage has potential risk effects, so the regressions look at long-term debt to total assets ratio (LTD/TA) (Albuquerque, et al., 2019; Shakil, et al., 2019). Another factor that might impact risk, loan quality, is measured by the ratio of non-performing loans to total loans (NPL/TL) (Aevoae, et al., 2022; Bually, et al., 2020). The credit loss reserve ratio, the allowance for credit loss divided by the total loans (ACL/TL) is also included (Christianson, et al., 2008) as it measures institutional actions to manage loan issues. The Federal Funds rate is use as an interest rate control variable, and the control variable for inflation is estimated using the GDP Price Deflator.

Table 1: Descriptive Statistics

Variable	Mean	Std. Dev.	Minimum	Maximum
ESG	0.444	0.149	0.083	0.833
Environmental	0.236	0.275	0.083	1.000
Societal	0.471	0.214	0.083	1.000
Governance	0.570	0.194	0.083	1.000
Market Value	23.902	60.147	0.292	459.587
Total Assets	194.382	506.805	2.593	3743.567
Total Loans	87.114	192.044	1.970	1052.640
Total Deposits	128.753	313.906	1.917	2462.303
Allowance for Loss	1.174	3.150	0.015	28.328
Provision for Loss	0.411	1.727	-9.256	17.480
Long-Term Debt	13.899	45.486	0.000	286.557
Non-Performing Assets	0.693	1.841	0.000	15.549

Note: * indicates significance at the 5% level, ** indicates significance at the 1% level. Financial data is in billions of dollars. ESG ratings are rescaled to vary between 0 and 1.

The first panel of Table 1 includes descriptive statistics averaged across the sample period with the ESG factors were converted on a scale of 0 to 1. It appears that the social and overall ESG ratings appear to have very similar means. The environmental factor appears to be much smaller, though having more dispersion. The minimum in each category is quite low, while the maximum for all but the overall ESG rating is at the maximum possible. The institutions in the sample tend to be large, with mean total assets of $194.38 billion, and a minimum of $2.593 billion. In addition, the mean market value in the sample is $23.902 billion.

The correlation coefficients reported in Table 2 suggest that the ESG rating, and its components, are all significantly related. They all appear to be negatively related to the ROA but exhibit a positive relation to ROE for all but governance. The ESG ratings are also negatively related to the loan/deposit ratio, though not the other measures of risk. This suggests higher ESG banks may meet more of the financing needs of their loan portfolio through deposits. Interestingly there is a significant negative relation between the market performance measures and the ROA suggesting a potential divergence in market and accounting measures.

IV Methodology

The purpose of the study is to examine the ESG ratings of medium and large financial institutions listed in the United States immediately prior to the onset of the pandemic. That will be compared to the financial information of those institutions from two years later to determine if the changes to ESG ratings were associated with superior performance or risk reduction.

> H1: The pre-pandemic levels of ESG and its components predicts subsequent performance of financial institutions

Consistent with the literature, the first hypothesis uses both accounting and market performance measures. The accounting variables are ROA, ROE while the market data used is the natural log of the market value (MV) of the financial institution. The literature has provided mixed evidence on the sign of the relation between these and ESG ratings.

> The second hypothesis examines the ESG changes related to risk.
> H2: The pre-pandemic levels of ESG and its components predicts subsequent changes to the risk of financial institutions

The second hypothesis uses four measures. Beta measures systematic risk, the B/M ratio relates to default risk, the loan/deposit ratio provides insight into liquidity risk, and the provision of credit losses to total loans informs credit risk. A negative coefficient on the beta suggests lower systematic risk associated with a higher ESG rating while a negative coefficient on the B/M ratio suggests a lower future default risk. Similarly, a negative coefficient on the LD ratio and the PCL/TL ratio suggest higher ESG rated financial institutions tend to have lower liquidity risk and credit risk.

To estimate the relation between ESG ratings and financial institutions' risk and performance the paper uses a fixed effects panel data model. The model includes clustering standard deviations by firm. Each uses the equation.

$$V_{i,t} = \beta_0 + \beta_1 * ESG_{i,t-2} + \beta_{2,j*} Controls_{i,t} + OtherFE + \varepsilon_{i,t}$$

Table 2: Correlation Coefficients

Variable	1	2	3	4	5	6	7	8	9	10	11
ESG	—										
E	0.66**	—									
S	0.79**	0.85**	—								
G	0.64**	0.31**	0.33**	—							
MV	0.60**	0.82**	0.81**	0.35**	—						
ROA	-0.31**	-0.33**	-0.36**	-0.12*	-0.28**	—					
ROE	0.11*	0.11*	0.10*	0.01	0.14**	0.37**	—				
Beta	-0.05	-0.15**	-0.13*	0.12*	-0.05	0.07	-0.19**	—			
B/M	-0.04	0.00	0.05	0.00	-0.06	-0.13	-0.21**	0.10*	—		
LD	-0.29**	-0.43**	-0.42**	-0.14**	-0.39**	0.15**	-0.12**	-0.10*	0.12**	—	
PCL/TL	0.09	0.04	0.08	0.07	0.11**	-0.28**	-0.31**	0.03	0.21**	0.14**	—

Note: * indicates significance at the 5% level, ** indicates significance at the 1% level.

The equation is used for all the regressions used in the paper. In the equation, $V_{i,t}$ is the chosen performance or risk variable for financial institution i in period t. The main dependent variable, $ESG_{i,t-2}$ is the lagged chosen ESG measure for financial institution. The ESG measures may either be the full ESG rating, the environmental rating, the social rating, or the governance rating. The lag relation is consistent with the literature and ensures that the effects of the pandemic do not impinge directly on the ESG ratings. The control variables, include the ratios created by scaling non-performing loans, total loans, deposits, and long-term debt by total assets. Also included are the natural log of total assets, ratio of the allowance for credit loss over total loans, the rate of inflation, and interest rates. They control for future changes in performance based on external conditions or current operations, separate from ESG. OtherFE includes firm and time fixed effects.

Table 3: Regression Results of the ESG and Environmental Factors on Bank Performance

Variable	MV	ROA	ROE	MV	ROA	ROE
Intercept	24.192**	-0.031	-0.267	29.591**	0.141	2.790
	2.947	-0.285	-0.116	3.763	1.306	1.234
ESG	0.120	-0.004*	-0.021			
	0.946	-2.331	-0.598			
ESG*PAND	-0.179**	-0.003**	-0.034*			
	-2.904	-4.144	-1.993			
Environment(E)				0.160	0.002	0.008
				1.356	1.406	0.228
E*PAND				-0.169**	-0.002**	-0.021
				-3.487	-3.312	-1.485
TL/TA	0.901**	0.014**	0.127	0.881**	0.015**	0.137*
	3.669	4.367	1.839	3.623	4.541	1.964
LnTA	0.885**	-0.001	0.021	0.823**	-0.002**	-0.006
	14.478	-0.905	1.252	14.711	-3.212	-0.395
TD/TA	0.008	0.004	0.103	-0.127	-0.002	0.024
	0.024	0.885	1.057	-0.373	-0.469	0.245
ACL/TL	5.411	-0.084*	-1.492	3.633	-0.157**	-2.640**
	1.927	-2.278	-1.884	1.435	-4.519	-3.630
LTD/TA	-1.158*	-0.006	-0.049	-1.148*	-0.007	-0.062
	-2.578	-1.083	-0.388	-2.571	-1.102	-0.480
NPL/TA	-2.551	0.000	0.511	-1.595	0.017	0.667
	-0.651	-0.007	0.465	-0.408	0.319	0.593
Interest Rate	-0.102**	-0.001**	-0.015**	-0.097**	-0.001**	-0.018**
	-7.333	-6.844	-4.488	-7.310	-5.927	-4.720
Inflation	22.096**	-0.477**	-7.661**	20.909**	-0.349**	-4.758**
	4.204	-7.289	-5.475	3.974	4.815	-3.146
R^2	0.993	0.761	0.521	0.993	0.741	0.504

Note: * indicates significance at the 5% level, ** indicates significance at the 1% level. Each estimate also includes a t-statistic below it.

V Results

Table 3 reports the results of analyzing performance measures on ESG and the environmental factor. Across the full period, the market value is unrelated to ESG. However, during the pandemic subperiod, the relation becomes negative and significant. It appears that financial institutions with stronger ESG ratings tended to see reductions in their market values, which is consistent with LaTorre, et. al, (2020).

Examining ESG in the context of the ROA, it appears there is a negative relation before the pandemic, and the relation is stronger during the pandemic. The ROE is also significantly negatively related to the ESG rating during the pandemic period. These results are consistent with some of the literature, such as Buallay, et al., (2021), that reports stronger ESG is negatively related to accounting performance. There appears to be consistency between the market-based relation to ESG during pandemic and the accounting-based results. This suggests the market price changes reflect the underlying performance changes of the financial institutions. However, the greater drop in market value of higher ESG firms appears inconsistent with the argument that market values of high-ESG financial institutions are greater than others who do not allocate the same level of resources to those activities.

The rest of the table evaluates performance relative to the environmental factor. Consistent with the ESG results the change in market value is negatively related to the environmental factor during the pandemic period. The results of ROA is also consistent with the findings on ESG during that period. In contrast, the ROE is not significantly related to the environmental factor. The results for the environmental factor again suggest lesser valuations, on average during the pandemic, for those financial institutions which had more actively cultivated a reputation for environmental performance.

Table 4 related measures of bank performance to the social and governance factors. For the social factor, the results are consistent with those of the ESG rating. The market value and the ROA are negatively related to performance during the pandemic period. Interestingly, the ROE was positively related to the social factor during the full period, but that was reversed during the pandemic. It appears that financial institutions with a greater focus on activities tied to the social rating did worse during the recent economic disruptions.

The results of the estimation for the governance factor is shown in the last three columns of Table 4. Consistent with the other performance results, there is a negative relation between performance, accounting and market-based, during the pandemic period and the governance factor rating. This may be somewhat surprising as the governance factor is, presumably, tied to factors associate with improved corporate governance of the institution. Indeed, the governance factor for the full period is positively related to market value but that effect was reversed during the pandemic. A strong governance factor would suggest that the company is better managed, and therefore would be expected to be more adaptable in minimizing the impact of the pandemic period. However, Table 2 shows a significant and positive relation between the governance factors and the other ESG-related factors. It may be these other factors, in institutions with a higher governance factor rating, which drives the results.

The measures of performance suggest that banks, which had earned higher ESG ratings, tended to do more poorly during the pandemic when controlling for other factors. It may be that the decisions of such firms tended to, on average, make them more sensitive to negative economic conditions. This is consistent with the collateral benefits model where financial institution risk-adjusted return is not the sole motivation of the firm.

Table 4: Regression Results of The Social and Governance Factors on Bank Performance

Variable	MV	ROA	ROE	MV	ROA	ROE
Intercept	25.572**	0.060	1.573	24.428**	-0.043	0.837
	3.212	0.554	0.699	2.955	-0.387	0.356
Social(S)	0.004	-0.002	0.028**			
	0.031	-0.888	3.180			
S*PAND	-0.168**	-0.003**	-0.038**			
	-3.354	-4.548	-2.705			
Governance(G)				0.159*	0.000	0.027
				1.989	0.171	1.167
G*PAND				-0.136**	-0.003**	-0.035*
				-2.811	-3.990	-2.567
TL/TA	0.915**	0.016**	0.135	0.933**	0.015**	0.143*
	3.748	4.720	1.958	3.793	4.455	2.048
LnTA	0.876**	-0.001	0.007	0.890**	-0.001	0.012
	14.895	-1.821	0.447	14.336	-0.770	0.706
TD/TA	0.083	0.002	0.087	0.030	0.002	0.064
	0.237	0.450	0.881	0.087	0.483	0.645
ACL/TL	5.753*	-0.103**	-1.865*	5.384	-0.086*	-1.898*
	2.092	-2.785	-2.399	1.913	-2.289	-2.372
LTD/TA	-1.068*	-0.005	-0.036	-1.129*	-0.007	-0.067
	-2.387	-0.876	-0.287	-2.513	-1.171	-0.524
NPL/TA	-2.025	0.008	0.443	-3.361	-0.002	0.401
	-0.515	0.151	0.399	-0.858	-0.029	0.360
Interest Rate	-0.104**	-0.001**	-0.021**	-0.100**	-0.001**	-0.020**
	-7.527	-6.840	-5.373	-7.366	-6.532	-5.141
Inflation	20.625**	-0.386**	-5.208**	22.474**	-0.425**	-4.342**
	3.927	-5.193	-3.507	4.307	-6.503	-2.926
R^2	0.993	0.750	0.519	0.993	0.754	0.512

Note: * indicates significance at the 5% level, ** indicates significance at the 1% level. Each estimate also includes a t-statistic below it.

The other consideration is the level of risk associated with the ESG ratings. Table 5 reports the results of ESG ratings related to four risk measures. Examining systematic risk, beta does not appear related to the usage of ESG. In contrast, the B/M analysis, with a positive coefficient, finds an increase in risk during the pandemic period. The LD ratio results also suggest greater risk during the pandemic period. However, this last effect appears to be offset by the results during the full period where the ESG rating are associated with lower liquidity risk. That full period result is consistent with the literature, but it appears that the existing relation is mitigated during the pandemic period. Finally, the PCL/TL exhibits a positive coefficient for both the full estimation period and the pandemic. That suggests the potential for higher credit risk in firms assigned higher ESG ratings. Across the four measures, the results are mixed, but it appears that most suggest greater risk in high ESG financial institutions during the pandemic. This is consistent with the idea of banks engaging in the generation of collateral benefits less focused on ensuring the financial institution is organized to be robust to negative economic conditions.

Table 5: Regression Results of the ESG Factor on Bank Risk

Variable	Beta	B/M	LD	PCL/TL
Intercept	8.140	-23.308**	5.521*	-0.403**
	0.732	-4.879	2.168	-3.902
ESG	0.290	-0.094	-0.133**	0.005**
	1.664	-1.273	-3.459	2.973
ESG*PAND	0.009	0.071*	0.068*	0.003**
	0.070	1.986	2.287	3.699
TL/TA	-0.072	-0.128		0.003
	-0.226	-0.894		0.815
LnTA	0.058	0.005	-0.080**	0.003**
	0.683	0.127	-4.331	3.891
TD/TA	1.773**	-0.131		0.001
	3.720	-0.642		0.221
ACL/TL	19.130**	-0.514	-6.064**	0.179**
	5.114	-0.315	-7.374	5.063
LTD/TA	0.688	0.538*	0.874**	0.008
	1.104	2.058	7.173	1.343
NPA/TA	0.994	2.095	-2.619*	-0.009
	0.196	0.919	-2.254	-0.190
Interest Rate	0.024	0.066**	0.060**	0.002**
	0.654	8.175	7.962	15.214
Inflation	-40.266**	-20.376**	-2.856	0.882**
	-2.602	-6.663	-0.820	14.483
R^2	0.610	0.850	0.945	0.707

Note: * indicates significance at the 5% level, ** indicates significance at the 1% level. Each estimate also includes a t-statistic below it.

The evidence from estimating the relation between the environmental factor and firm risk is shown in Table 6. The beta appears to be positively related to the environmental factor during the full period with some reversal during the pandemic. This would suggest that a higher environmental rating is associated with greater systematic risk, but that the level was, at least in part, moderated during the pandemic period. It may be that managerial commitments tied to environmental-related issues saw a reduction given the greater risk in the economy. The B/M results are consistent with those of the ESG ratings, but the other two risk measures are not significant. Consistent with collateral benefits, financial institutions with strong environmental scores also appear not to be well positioned, relative to their peers, to manage the risk challenges brought on by the pandemic.

Table 7 reports coefficients for the social factor. Again, consistent with the ESG results, the B/M ratio is significant and positively related to the social factor during the pandemic. Across the full period, the loan-to-deposit ratio is negatively related to the social factor. However, unlike the ESG analysis, there is no significant jump in the risk during the pandemic. The results are consistent with firms having higher social rating being managed to have less liquidity risk.

Table 6: Regression Results of the Environmental Factor on Bank Risk

Variable	Beta	B/M	LD	PCL/TL
Intercept	6.547	-24.389**	5.696*	-0.530**
	0.574	-4.658	2.133	-5.213
E	0.351*	-0.140	0.000	-0.001
	2.233	-1.778	0.009	-0.412
E*PAND	-0.148*	0.081*	0.017	0.000
	-2.166	2.521	1.049	0.397
TL /TA	-0.138	-0.109		0.001
	-0.436	-0.681		0.407
LnTA	0.035	0.028	-0.080**	0.004**
	0.400	0.746	-4.226	5.878
TD/TA	1.735**	-0.080		0.006
	3.675	-0.350		1.455
ACL/TL	19.145**	0.200	-5.990**	0.245**
	5.177	0.119	-7.221	7.412
LTD/TA	0.584	0.532	0.861**	0.007
	0.983	1.791	7.034	1.148
NPA/TA	1.969	1.558	-2.609*	-0.025
	0.388	0.599	-2.206	-0.501
Interest Rate	0.006	0.064**	0.049**	0.002**
	0.237	7.272	10.205	14.261
Inflation	-33.859**	-20.077**	2.758	0.824**
	-3.017	-5.730	1.072	12.968
R^2	0.608	0.848	0.943	0.688

Note: * indicates significance at the 5% level, ** indicates significance at the 1% level. Each estimate also includes a t-statistic below it.

Table 7: Regression Results of the Social Factor on Risk

Variable	Beta	B/M	LD	PCL/TL
Intercept	7.503	-23.576**	5.577*	-0.487**
	0.673	-5.075	2.166	-4.732
S	0.330	-0.029	-0.088*	0.002
	1.939	-0.393	-2.270	1.424
S*PAND	-0.024	0.073*	0.037	0.001
	-0.265	2.512	1.773	1.915
TL/TA	-0.086	-0.128		0.001
	-0.270	-0.901		0.458
LnTA	0.054	0.006	-0.079**	0.004**
	0.636	0.183	-4.206	4.824
TD/TA	1.796**	-0.179		0.004
	3.796	-0.492		0.832
ACL/TL	19.014**	-0.789	-6.003**	0.210**
	5.082	1.933	-7.233	5.881
LTD/TA	0.397	0.504	0.867**	0.006
	0.572	0.787	7.142	1.059
NPA/TA	1.958	1.805	-2.995*	-0.013
	0.381	0.025	-2.532	-0.266
Interest Rate	0.019	0.068**	0.054**	0.865**
	0.617	8.363	8.354	13.641
Inflation	-37.513**	-19.682**	-0.061	0.002
	-2.841	-6.423	-0.020	1.424
R^2	0.608	0.849	0.944	0.693

Note: * indicates significance at the 5% level, ** indicates significance at the 1% level. Each estimate also includes a t-statistic below it.

Table 8: Regression Results of the Governance Factor on Risk

Variable	Beta	B/M	LD	PCL/TL
Intercept	7.316	-23.359**	5.615*	-0.409**
	0.657	-4.858	2.194	-3.844
G	-0.126	-0.097*	-0.074**	-0.001
	-1.138	-2.085	-3.029	-0.626
G*PAND	-0.002	0.058*	0.033	0.002**
	-0.020	2.053	1.397	3.210
TL/TA	-0.191	-0.144		0.001
	-0.595	-1.009		0.436
LnTA	0.061	0.000	-0.083**	0.003**
	0.717	0.005	-4.527	3.800
TD/TA	1.857**	-0.160		0.003
	3.919	-0.792		0.779
ACL/TL	18.919**	-0.623	-6.108**	0.186**
	5.029	-0.381	-7.377	5.127
LTD/TA	0.668	0.517*	0.863**	0.008
	1.098	1.978	7.011	1.330
NPA/TA	0.785	2.555	-2.285	-0.011
	0.154	1.122	-1.951	-0.216
Interest Rate	0.023	0.066**	0.055**	0.002**
	0.657	8.359	7.591	14.889
Inflation	-40.372*	-20.287**	-0.040	0.831**
	-2.537	-6.685	-0.011	13.611
R^2	0.609	0.850	0.945	0.696

Note: * indicates significance at the 5% level, ** indicates significance at the 1% level. Each estimate also includes a t-statistic below it.

Table 8 reports the relation to the governance factor. The evidence on risk is mixed, but is broadly consistent with the ESG-related results. There is evidence of greater risk in the B/M ratio and in the PCL/TL. The loan-to-deposit ratio, again, has a significant negative coefficient suggesting lower liquidity risk across the full period.

It appears that firms with higher ESG, and component, ratings tend to have greater overall risk during the pandemic period. However, consistent with prior literature, there is evidence of lower liquidity risk across the full period including the pandemic.

VI Conclusion

This study evaluated how the performance and riskiness of financial institutions relate to ESG ratings across the economic disruption caused by the pandemic. Using panel data for banks, the relations were analyzed both for the sample period and the pandemic subperiod. Consistent with prior literature (Brogi and Lagasio, 2018; Usman et al., 2020), performance and risk measures were related to lagged changes in an ESG rating and its components to determine potential relations. The relations were controlled for many of the important operating characteristics of financial institutions including size, focus on loans, relative use of deposits, and others.

The results match the literature suggesting weaker performance by firms with stronger ESG ratings, but that relation predominantly occurred during the pandemic period. Looking specifically at banks through the pandemic period, it appears there is a negative relation of ESG and its components to both market and accounting estimates of performance during the pandemic period. It appears that firms, which had used resources to enhance their ESG ratings, had greater challenges in maintaining performance compared to peer institutions. It may be that banks took higher risk loans to support a stronger ESG ratings. In a market of elevated risk that is likely not an optimal strategy.

The results on risk across the full period is mixed, with the B/M value coefficients suggesting greater risk during the pandemic period. However, there is evidence of greater liquidity by higher ESG banks across the full period, which would be consistent with prior literature showing an inverse relation between ESG and risk (Drago, et. al., 2019; Neitzert and Petras, 2022).

Broadly speaking, the data suggests that banks that had higher ESG ratings saw a greater decline in value, both operationally and in the financial markets. It is an open question whether this effect may be temporary and tied to a period of serious economic distress, or whether it reflects a permanent change to the performance of such financial institutions as was observed during the prior financial crisis.

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Herding Behavior in Security Market and Portfolio Management

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Abstract

This study will examine the herding behavior in security market and its impact on the security pricing and overall market return as well as individual returns. In behavioral finance, herding is known as an excessive irrational tendency of investors ignoring the fundamental information presented to them that act together in the markets (Gębka & Wohar 2013). Herding can directly lead to the security market distress and to the increase in trading volatility. In this study, we have conducted an empirical study, focusing on the Dow Jones Industrial Average over a twenty-year period (2000-2020), to examine the herding behavior in the security market. We have adopted the modeling framework used by Christie & Huang (1995), Cheng et al. (2000), and Dang & Lin (2016) to measure the herding index of the DJIA. We have used the Cross-Sectional Absolute Deviation (CSAD) to measure the absolute return dispersion of each individual market security that makes up the DJIA, and the Cross-Sectional Standard Deviation (CSSD). Based on the findings in this study, it is reasonable to conclude that the market behaves in a rationale sense, ignoring the signals of the market and its' largest influencers. In other words, the Efficient Market Hypothesis stands, and individual investors are able to look past their natural human biases and heuristics. This is not to say that spurious herding does not still occur in today's markets, but there is no evidence that intentional herding is a consistent phenomenon that occurs in the market.

Keywords: Behavioral Finance, Herding behavior, Portfolio Management, Cross-Sectional Standard Deviation (CSSD), Cross-sectional absolute deviation (CSAD).

I Introduction

The term "herd behavior" is referred to a phenomenon where people join the crowd and follow their actions, assuming that other individuals have already done their research. They are largely influenced by emotion and instinct, rather than by their own independent analysis. For example, one may imagine a fire in a building that would often cause herd behavior, with people often suspending their individual reasoning and fleeing together in a pack. In Economics, herding can be defined as the phenomenon when individuals decide to follow others and imitate group behaviors rather than deciding independently and critically on the basis of their own, private information. In behavioral finance, particularly, the herd mentality refers to investors' tendency who follow what they perceive other investors are doing, rather than relying on their own analysis.

Herding behavior has received much attention in finance and security market, where a group of investors tends to trade in the same direction over a period, leading to observed behavior patterns that are correlated across individuals (Bikhchandani et al., 1992). In financial market, particularly, herding behaviors happen when investors face uncertain information, and therefore, they tend to follow the stock-investing decisions and actions of others or depend too much on

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public information without paying sufficient attention to their own private information. In behavioral finance, herd mentality bias refers to investors' tendency to follow and copy what other investors are doing. In this study, we will examine the financial phenomenon of herding and its impact on the security pricing and overall market return as well as individual returns.

In the literature, herding is generally known as an excessive irrational tendency of investors ignoring the fundamental information presented to them that would act together in the markets (Gębka & Wohar 2013). According to Erdenetsogt and Kallinterakis (2016), the practice of herding assumes that individuals follow others' behavior disregarding their own private signals or prevailing market fundamentals. Herding can directly lead to market distress and led to the increase in trading volatility. There is a distinction between two different types of herding: (1) spurious, or unintentional, herding which is commonly a result of publicly known news being interpreted similarly and assumed causing efficient price corrections; but this is not usually a cause of excess volatility in the markets. (2) Intentional herding, when investors possess knowledge of other investors' decisions and knowledge and this in turn affects their investment decisions. The securities market is a very large and complex market that is traded nearly every day on a domestic and international level. There is a constant flow of information to each and every investor that comes from different sources, ideologies, and credibility. The two dimensions of financial decisions, cognitive psychology (how people think) and the limits to arbitrage (when markets will be inefficient) affect the herd behavior. It is our human nature to take what we are given and interpret it in our own light. This very nature is what led to Behavioral Finance and the study of its effects on the market.

Christie and Roger D. Huang (1995), argue that in a market setting, herds are characterized by individuals who suppress their own beliefs and base their investment decisions solely on the collective actions of the market, even when they disagree with its predictions. Accordingly, they believe that traditional herd exist when investors are drawn to the consensus of the market, implying that individual returns would move in harmony with the market return. According to Igual and Santamaria (2017) one of the main theories that dominate the Behavioral Finance field is the irrational phenomena of herding. It is the intention of this study to examine how the market under this irrational tendency would directly affect the prices of securities, and returns on individual's portfolios. More specifically, in this study, we plan to analyze and answer the following questions: (1) Is the return dispersion of individual assets from the market return a significant indicator of herding in financial markets? And (2) What affects does herding have on security pricing and overall market return as well as individual returns?

II Literature Review

According to the literature, the average investors have difficult time removing their emotions from their investing activity (Qawi 2010). This issue has been studied extensively in the literature and received much attention. In this study, we plan to analyze a number of deeper implications that would bring light to the direct effects of the individual, as well as the broader market performance. To this end, we examine the relationship between the market return and the individual stock returns in the context of herding, and highlight the degree, if any, of herding that has taken place over the past twenty-year period of stock returns.

The phenomena of social herding in the markets has been extensively studied in the literature from different perspectives. In Finance, particularly, herding has been viewed as a concern to market participants, as it contributes to the market inefficiency (Fama, 1970; Christie & Huang, 1995), and to the financial market volatility and instability (Bikhchandani & Sharma, 2001). Qawi

(2010) has studied herding in finance and argues that everybody comes with this sort of 'bagage'. That implies that we all have our own "inherent biases and heuristics", and consequently "attach emotion to our judgment and actions".

There are two main avenues of thought in finance: (1) The Neo-classical theory of the rational investor who only makes decisions based on available data and proven mathematical theories. (2) However, Qawi (2010) states that this method consists of incomplete information and abbreviated assumptions of reality that do not consider human behavior element. This leads to the newer theory of psychological finance. It involves understanding the market anomalies and accounting for these inherent biases. Qawi (2010) refers to a study by Pretcher (2001) on human behavior and its' reaction to market performance, that argues that herding behavior is rooted in the limbic system and it is impulsive, uncontrollable and immutable, and thus it is a response to the actions of others that stems from impulsive mental activity.

Qawi (2010) highlights another theoretical framework in regards to herding, called the 'Affect Pricing Model'. This model works with the concept that individuals have perceptions of objects being valued as 'good' or 'bad', and that this mindset can be applied to individual stocks. He refers to a study by Kahneman (2002) that highlights another heuristic called the 'affect heuristic'. Gebka and Wohar (2013) argue that on an international level, there is not much herding to be found in the broader sense of the market. However, there are some herding tendencies found when you dig deeper into the returns of individual sectors and get rid of the broad index returns. They conclude that Fama's Efficient Market Hypothesis (EMH) holds true and is one main reason behind social herding tendencies within the market. The reason, they argue, is that the EMH states that the market is immediately receptive to the development of new information. So, the new information of the market is being accounted for immediately at the same time. As humans, it is in our nature to have the tendency to follow the majority, and that is what is occurring through the EMH.

Chang et al. (2000) have studied herding tendencies across multiple international markets. They conducted the study in the U.S., Japanese, Hong Kong, South Korean, and Taiwanese markets. They have used a variant of the empirical model from Christie and Huang (1995) and examined the investment behavior of market participants within different international markets (i.e., US, Hong Kong, Japan, South Korea, and Taiwan), with regard to their tendency to exhibit herd behavior. Their results for the US were consistent with those results reported by Christie and Huang (1995). They found no evidence of herding on the part of market participants in the US and Hong Kong and partial evidence of herding in Japan. However, they found significant evidence of herding for South Korea and Taiwan, the two emerging markets.

Maquieira, C. and C. Espinosa-Méndez (2022), have analyzed the herding behavior in the Chinese stock markets in the context of the COVID-19 pandemic, using the cross-sectional absolute deviation (CSAD) model proposed by Chang et al. (2000), to detect herding behavior in the time period between January 30, 2001, and June 12, 2020. They split the sample according to the market return level (to identify bull and bear markets) and showed that there is asymmetric behavior, revealing stronger herding behavior in an up market. Their results showed more pronounced herding behavior occurs in bull markets and in low volatility regimes (before and after the COVID-19 event date). They argue that more pronounced herding activity in a low volatility market might be associated with a higher level of agreement in the market regarding the quality of stocks; and thus, in this scenario, it is more likely that investors will coincide in their appraisals of investment decisions. They maintain that in situations with extreme perception of systemic gravity, it is likely that investors may have a greater degree of trust in their own decisions, as opposed to the collective beliefs of market participants.

In their empirical analysis, Christie and Huang (1995) have focused on the price implications of herding by using cross-sectional standard deviation of returns. Therefore, in their study, herding behavior will be measured by decreasing dispersion of returns when individual returns changes are in harmony with market return. Because, there is herd behavior when individual returns follow the lead of the portfolio returns. They have also examined the herding behavior during the periods of abnormally large average price movements, or so-called market stress and conclude that, in contrast, the herding of individual returns around the market translates into a reduced level of dispersion. Therefore, during the market stress, their conclusion supports the predictions of rational asset pricing models and suggests that herding is not an important factor in determining equity returns during periods of market stress. Thus, they had found that it was more common for prices to deviate from the market price in these times of crisis rather than follow it.

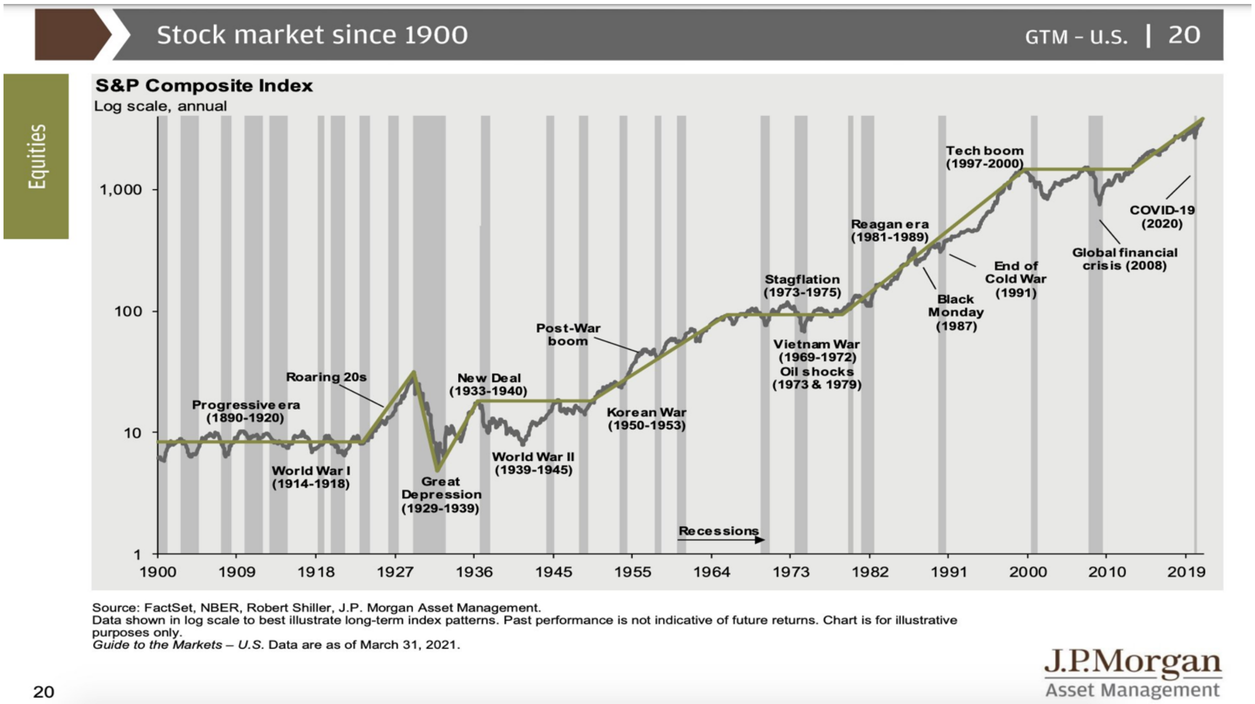
In order to analyze the herding phenomenon in security market, in this study, we will follow the model from Dang and Lin (2016) which had been recreated from another empirical study of herding from Christie and Huang (1995), as well as Cheng et al. (2000). However, in this study, we will focus on the Dow Jones Industrial Average over a twenty-year period from 2000 until 2020. First, we will review the theoretical approaches of herding in the literature, as well as, the empirical studies involving the cross-sectional return dispersion of assets. Next, we will define our analytical framework and the data to develop our model. Finally, we will summarize the empirical findings, and conclusions about herding in the market.

III Modeling Framework

In this section, we formulate herding behavior to capture the magnitude of the dispersion and apply it to long-term portfolio investing, and answer the question of whether or not herding will affect the long-term investment decisions. The model will be used to describe the market volatility for the long-term investor. We use data from early 2000 when the financial tech bubble collapsed, and this gave the market a fresh valuation of asset pricing. The new age of technology has also given investors more access to information and more insight to investment decisions made by the institutional investors. The data set would include the data from the Global Financial Crisis struck and scorned investors' returns and their market behavior.

We have used the daily price activity of the securities comprising the Dow Jones Industrial average from Yahoo!Finance, over a twenty year period spanning from 2000 until 2020. The daily price returns have been calculated by dividing the current stock price of the day by the lagged-one day price. The DJIA also captures the 30 largest stocks on the New York Stock Exchange (NYSE). This study considers price as being the determinant of return dispersion, and the DJIA's criteria for inclusion in the index is the 30 largest stocks, measured by price. There are skeptics on the rationale behind this, for the S&P 500 is comprised of the 500 largest stocks based on market capitalization and weighted on this criterion. However, the measurement of price will be sufficient for this study due to the main focus of this study revolving around price itself. There is one caveat in this data set, and that is that two companies from the DJIA had to be excluded from the individual securities list in order to maintain the consistency and continuity within the data set. The securities that have been removed from the data set are Visa (V) and Salesforce (CRM).

Our purpose in this study is to examine the magnitude of the effect between the daily returns of the overall market index and the dispersion of returns of the individual securities that comprise the index in comparison to the markets' daily returns. Furthermore, we aim to look into the effect herding will have on portfolio returns based off the calculation of securities dispersions on a daily level. The question to be answered in this context is whether or not an individual investor with a buy and hold, long-term investment strategy will need to calculate the risk of current market volatility inherited from herding to better allocate their portfolio.



We assume that herding is viewed as a behavioral aspect of finance, will occurs when security return data mirrors the overall market or index returns. Investors will begin to ignore the information they have and stay away from their beliefs in making the investment decisions they think are best for them, and instead mimicking the investment decisions of other institutional investors. In this modeling, we follow Christie & Huang (1995), Cheng et al. (2000), and Dang & Lin (2016) to measure the herding index of the DJIA. More specifically, we use the Cross-sectional absolute deviation (CSAD) to measure the absolute return dispersion of each individual market security that makes up the DJIA and the Cross-Sectional Standard Deviation (CSSD). The formulas are as follows:

$$CSAD = \frac{1}{N}\sum_{1}^{N}|R_{it} - R_{mt}| \qquad (1)$$

$$CSSD = \sqrt{\frac{1}{N-1}\sum_{1}^{N}(R_{it} - R_{mt})^2} \qquad (2)$$

Where $R_{i,t}$ is the stock return of a specific firm (i) at time t, and $R_{m,t}$ is the cross-sectional average of all N stock returns that comprise the market portfolio at time t. Each of these calculations measure the average deviation of the individual stock returns from the market return ($R_{i,t}$ - $R_{m,t}$). In order to prevent any positive and negative values from canceling each other out, CSAD in (1) takes the absolute value of the deviation values while in equation (2), the CSSD squares the deviation values (Dang & Lin 2016). When looking at the values of deviation, any increasing values of CSAD or CSSD would imply that individual stock returns deviate from the market return, and this would imply that there is no evidence of herding between the individual returns and the market return. On the other hand, smaller values of deviation would imply the potential for herding, however, that may be spurious or intentional, yet to be known.

Furthermore, as Dang and Lin (2016) stated, different stocks may react differently to the market changes with different degrees of sensitivity, and would cause the dispersion to increase as the market return increases in absolute term. However, the presence of herd mentality during the extreme market movements will draw individual stock returns closer to the market return, and reducing dispersion.

In order to capture the herd mentality during extreme market movements, following Christie and Huang (1995), we have used dummy variable regression to test for herd behavior:

$$CSSD = \alpha + \beta_L {D_t}^L + \beta_U {D_t}^U + \varepsilon_t \quad (3)$$

Where the two dummy variables $D^L{}_t$ and $D^U{}_t$, assume binary values: 0 when the market return on day t is outside of the upper or lower tails of the distribution, and a value of 1 if it does fall within the extreme upper and lower tails of the distribution. The criteria for the two dummy variables are the lower 5%, and the upper 5%, of the distribution. Any negative values of β_L or β_U that are statistically significant will indicate that there is a potential for herd behavior in the market (Dang & Lin 2016). We can recalculate this equation similarly for CSAD, by replacing CSSD by CSAD in equation (3).

Furthermore, according to Cheng et. Al (2000), in order for herding to exist, during larger market movements, there would need to be a non-linear relationship between $CSAD_t$ and $R_{m,t}$. They propose the following quadratic regression:

$$CSAD_t = y_0 + y_1|R_{mt}| + y_2 {R_{mt}}^2 + \varepsilon_t \quad (4)$$

Where $|R_{m,t}|$ is the absolute value of the market return at time t, and $R^2{}_{m,t}$ is the quadratic function of the market return at time t. The market would be exhibiting herd behavior if and when the dispersions increases at a less-than proportional rate or, decreases with the market return. This would result in a negative value and statistically significant value for the quadratic term (y_2) (Dang & Lin 2016).

Cheng et al. (2000) have proposed a slight change in equation (4): $CSAD_t = y_0 + y_1 R_{mt} + y_2 {R_{mt}}^2 + \varepsilon_t$, in order to capture the herd behavior in an up market. The importance of this regression model is that the market return does not need to be in the upper or lower tail of extreme market movements to pick up on herd behavior within the market.

A third regression model introduced by Chiang and Zheng (2010) has included $R_{m,t}$ as a regressor. This regression specifically will test for asymmetry between the two variables, the market return and dispersion values. Furthermore, by adding these additional regressors we are able to strengthen the explanatory power of the regression model. They propose two separate ways to test or herding behavior, and suggest splitting the data into two categories; the market behavior on up days and the market behavior on down days. The original equation has been formulated as follows:

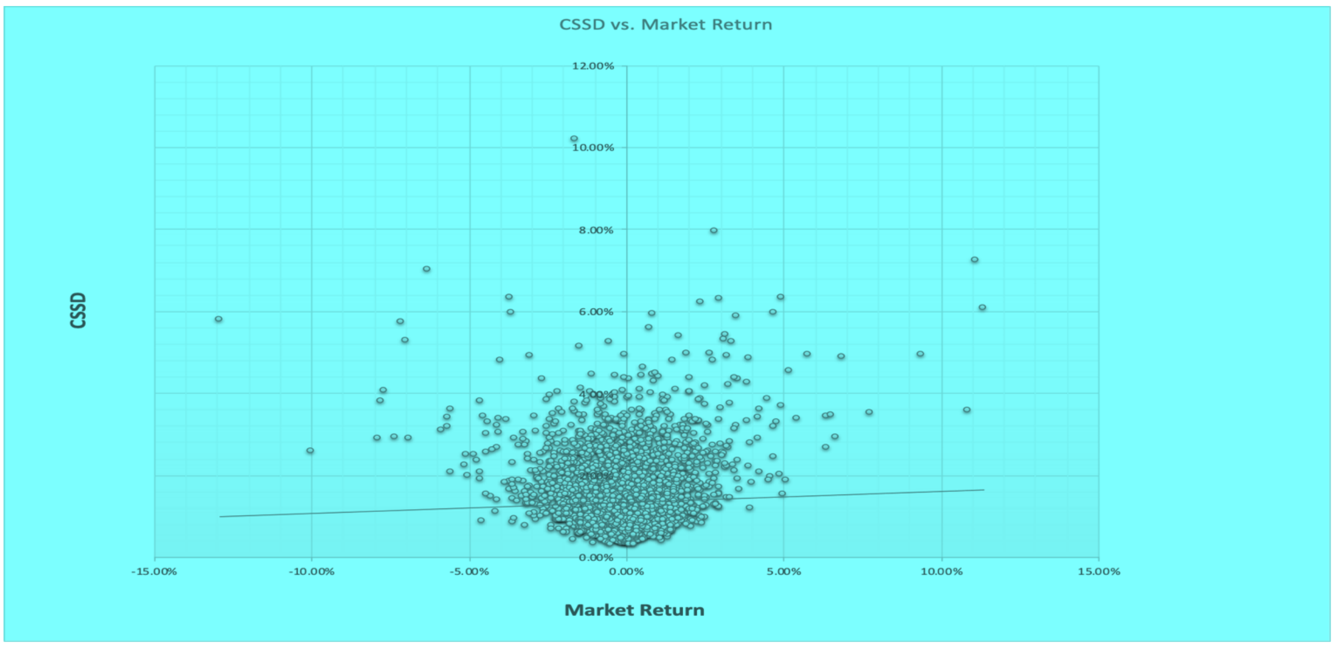
$$CSAD_t = y_0 + y_1 R_{mt} + y_2 |R_{mt}| + y_3 {R_{mt}}^2 + \varepsilon_t \quad (5)$$

They have proposed these changes in order to capture the market on down-days and-up days and thus replace $R_{m,t}$ with (1-D).$R_{m,t}$ and D.$R_{m,t}$ and to replace $R^2_{m,t}$ with (1-D) $R^2_{m,t}$ and D $R^2_{m,t.}$, where the dummy variable, D, has a value of 1 when $R_{m,t} < 0$, and a value of 0 otherwise.

IV Results and Analysis

To begin our analysis, we have chosen to present visual representations of the two return dispersion measures that have been calculated in this study. The first visual graph (figure 1) shows the cross-sectional standard deviation (CSSD as dependent variable plotted on the y-axis. The market return, as independent variable is plotted along the x-axis in this figure 1:

Figure 1. Relationship between (CSSD), and the market return

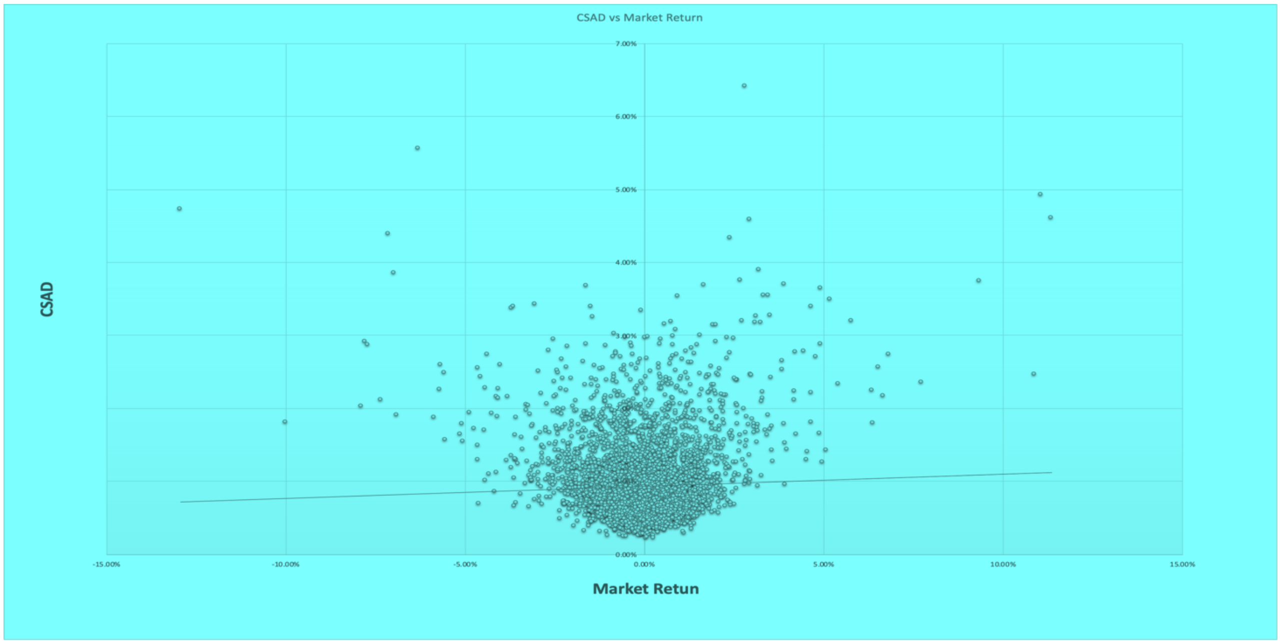


The graph does not show a strong relationship that fits the trend line of the data. Many of the data points exceed 2%, which is a large deviation in terms of financial returns. Another noticeable characteristic of this dataset is the number of outliers. Visually, one can see that there are frequent instances where the individual stock returns deviated upwards of 6% and even deviated as far as 10% away from the market return.

In the second visual representation, the cross-sectional standard deviation (CSSD) has been replaced with the cross-sectional absolute deviation (CSAD), and it is plotted on the same axis as the first graph.

When looking at the graphical representation of the cross-sectional absolute deviation, one can see very similar results. The deviation of individual stock returns continues to show weak signals of herd behavior in the Dow Jones Industrial Average. Each graph does have a cluster of data point around the center of the graph, leading one to believe that there is a slight herding relationship between the two variables — market return and individual stock returns. Later, in the regression analysis sections, it will be shown that the R-squared values do account for some of the data points in this study, but we conclude that they are not statistically significant.

Figure 2. Relationship between (CSAD) , and the market return



Summary Statistics

Table 1 provides summary statistics of the CSSD, CSAD, and the market return over the entire twenty-year time period, with 5282 data points. The mean for the market return over the entire twenty years period is 0.03%. As mentioned earlier, at the start of the dataset period, the market had just come off the tech bubble popping and, shortly later, experienced the Global Financial Crisis. Following the crisis, the market had experienced the longest Bull Run in the history in itself.

One may assume that with having nearly half of the period was in a bull market, the mean would have higher value; however, COVID-19 Pandemic caused a large correction in the DJIA in the final year of the period, which significantly affects the mean over time. Furthermore, by reviewing the basic statistical summary in Table 1, one can see that the mean for both CSSD and CSAD are, 1.34% and 0.93%, respectively. The mean of each of these measurements is significantly larger than the mean of the market return. Each of these values lie within, or extremely close to one standard deviation of the market return mean, however, one standard deviation of the market value is 1.21% which is a significant percentage difference in return value.

Table 1. Summary Statistics of CSSD & CSAD

	Mean	Std. Dev.	Minimum	Maximum
$R_{m,t}$	0.03%	1.21%	-12.93%	11.37%
CSSD	1.34%	0.78%	0.31%	10.21%
CSAD	0.93%	0.53%	0.23%	6.42%

Dummy Variable Regression

We have also used CSSD and CSAD in various regression models to further investigate the herding behavior within the market. In the first regression, we have used two dummy variables describing whether the market return fell within the lower tail or the upper tail of the return distribution. This regression has attempted to capture the herding tendencies of investors during extreme market movements. Earlier in the study we defined the upper tail as any return that is 1.7% and higher, and the lower tail as any return that was -1.83% and lower (Dang and Lin 2016). Table 2 shows the results of the regression analysis.

Table 2: Dummy Variable Regression

	Left	Right	Intercept
Coefficient	0.007751083	0.011381754	0.012437045
Standard Error	0.000460344	0.00045952	0.0001056
R-Square	0.139443911	0.007280243	#N/A
F-Stat.	427.7027475	5279	#N/A
	0.045338154	0.279797261	#N/A
T-Stat.	16.83760502	24.76879225	
P-value	0.00%	0.00%	

The coefficient estimates of the left tail and right tail are positive, thus implying that per change in the market return there is not a drastic or extreme response in the asset prices of the securities that comprise the index; and furthermore, they imply that if there is any change. The value of R-squared, 0.1394, indicates that the regression analysis is accounting for around 14% of all the variations in data points. Furthermore, the p-values are extremely low and near zero, indicating the significance of these values. In the context of study by Christie and Huang (1995), the DJIA behaved rationally and there are no signs of herding over this twenty-year period. The dispersion values continually increased in the left tail and the right tail. This implies that the investors do not herd toward the market signals, and ignore the opinions of key influencers.

CSAD Regression Analysis

We have further expanded the regression analysis by utilizing the cross-sectional absolute deviation (CSAD), and added a third regressor. This time, instead of using dummy variables to determine when the market was within extreme market movements, we were able to capture whether or not there is any non-linearity between the two variables. We shifted our focus towards the return measures and regress the absolute market return and squared market return against the cross-sectional absolute deviation return values.

The regression estimates are shown in Table 3. There is a negative coefficient for the return squared component, with a value of -0.0149. The presence of a negative estimate for the quadratic term (y_2) indicates that there is a potential that herding behavior is present in the market. However, the R-squared value is not that significant, as it is only explaining around 25% of variations in CSAD. The p-value is relatively high which indicates the estimated coefficient is not significant. There is a stronger potential of herding in the market when considering the CSAD model due to the non-linear relationship present in the data set. The model specifically tested for a nonlinear relationship, which would indicate that as the market return increased (decreased) the dispersion measurement would not move in comparison with the market. It instead would move in an opposite direction, increasing the dispersion value. Therefore, the presence of a non-linear relationship is a strong indication of herd behavior.

Table 3: CSAD Regression Table

Components:	$(\text{Return})^2$	ABS Rreturn)	Intercept
Coefficient	-0.01497852	0.293223448	0.007041245
Standard Error	0.20011615	0.012207646	9.72089E-05
R-Square	0.253024616	0.00460304	#N/A
F-Stat.	894.0836443	5279	#N/A
	0.037887656	0.111851355	#N/A
T-Stat.	-0.074849134	24.01965595	72.43417061
P-value	94.03%	0.00%	0.00%

Asymmetry Regression

The third regression that has been conducted is the most powerful of the three in regards to explanatory power. There are two versions of this regression. The first version uses both the market return and absolute market return, as well as the quadratic function from the previous regression model. This model has the potential to capture the market behavior during any conditions, both up and down. More specifically, for every change in the market return, CSAD will change by $Y_2 + Y_1$ for any value that $R_{m,t}$ is positive and change by $Y_2 - Y_1$. Moreover, this means that asymmetry can be quantified as the ratio of $\frac{Y_2+Y_1}{Y_2-Y_1}$ (Dang and Lin 2016). The estimates of this regression are presented in table 4.

Table 4: Asymmetry Regression Table

Equation 5	$(\text{Return})^2$	ABS (Return)	Return	Intercept
Coefficient	-0.031451987	0.295111599	0.02442784	0.007022484
Standard Error	0.199756386	0.012190531	0.005244672	9.71025E-05
R-Square	0.256082274	0.004594045	#N/A	#N/A
F-Stat.	605.6235316	5278	#N/A	#N/A
	0.038345506	0.111393505	#N/A	#N/A
T-Stat	-0.157451725	24.20826442		
P-value	87.49%	0.00%		

The coefficient for the quadratic term is negative, which in turn does present a potential for herding behavior to be present in the market. The R-squared value is still not entirely significant with a value of about 25% of the data points in the study. Although the R-squared value is not significant the p-value does indicate there is some significance to the coefficient estimate for the regression.

The second version of this regression model divides the performance on the market into two separate groups; days when the market is up and days when the market is down. By using dummy variables to create a distinction between the two conditions. The estimates for the regression are presented in table 5. The coefficient estimates for this regression are mainly positive with only one of the regressors having a negative estimate. The dummy term of the regression has the highest p-value levels showing the highest significance, however, the R-squared values range from 2% to 27% of the data points within the dataset. The significance level given by the p-values for the quadratic term and the dummy variable give an indication that there is not a strong significance to these coefficients.

Table 5: Revised Asymmetry Regression (Up & Down)

	D	D.R^2.m,t	(1-D). R^2.m,t	D.Rm,t	(1-D).Rm,t	ABS RET	Intercept
Coefficient	0.2552528	-0.3032706	0	0.1014482	0.24	0.00	0.01
Standard Error	0.2865408	0.2782435	0	0.0243679	0.02	0.00	0.00
R-Square	0.2574049	0.0045908	#N/A	#N/A	#N/A	#N/A	#N/A
F	365.76286	5276	#N/A	#N/A	#N/A	#N/A	#N/A
	0.0385436	0.1111955	#N/A	#N/A	#N/A	#N/A	#N/A
T-Stat	0.8908078	-1.089947		4.1631916	14.139274	3.05915	
P-value	37.31%	27.58%		0.00%	0.00%	#N/A	

V Conclusion

After exploring the scope of the relationship between the market returns and return dispersion, we can conclude that there is not enough evidence to support the statement that herding is prevalent in the Dow Jones Industrial Average during the years of 2000 and 2020. There was not sufficient evidence presented by the Christie and Huang (1995), cross-sectional standard deviation dummy regression calculated in this study, to prove that herding is present in the market during extreme market movements. The only regression that presents a case for herding being present in the market index is the first CSAD regression performed in this study. Although, the R-squared value is not nearly as significant, the coefficient estimate of the quadratic term is still negative and this represents a non-linear relationship between CSAD and the market return. The results of asymmetric regression is quite similar to the non-linear test. The quadratic term does have a negative estimate. However, the R-squared value is not strong enough to indicate that the results present a potential for herd behavior in the market place. The second version of the asymmetric regression does not provide any sufficient evidence that herding occurs on down or up days in any specific pattern.

Based on the findings in this study it is reasonable to conclude that the market behaves in a rationale sense, ignoring the signals of the market and its' largest influencers. In other words, the Efficient Market Hypothesis stands. In opposition to the literature for behavioral finance, based on the empirical evidence, individual investors are able to look past their natural human biases and heuristics. This is not to say that spurious herding does not still occur in today's markets, but there is no evidence that intentional herding is a consistent phenomenon that occurs in the market.

When we examine the meaning of the coefficients throughout each of the regression examples, we noticed that only two of them points towards potential herd behavior in the market. As referenced earlier in this study, the CSAD regression has the strongest indication of herding in the market, due to the negative coefficient. This means that for any move in the market return that is positive, the cross-sectional absolute deviation will move in the opposite direction closing the spread between the market return and the stock returns. The second most indicative regression was the asymmetric regression, which also presents a negative coefficient, leaning towards the presence of potential herd behavior in the market. The p-values do show a strong significance; however, the R-squared values show that the regressions don't represent enough of the dataset to make it significant.

The first regression points to a positive relationship between the market return and the dispersion of stock returns, meaning that as the market return increases, so does the deviation of other stock returns from the market return. For example, during the days of market down, the individual stock returns are likely to move in a positive direction, and on market up days the individual stock returns are likely to move in a negative direction. The CSSD regression has a positive coefficient, which indicates that the market return and the dispersion value move in relation with each other. In other words, as the market price increases so does the dispersion of the individual stock returns. The fact that the R-squared values don't give sufficient backing to the indication of herd behavior in the Dow Jones Industrial Average it leads us to believe the market behaves rationally.

In regards to the earlier questions asked in this study, the return dispersion of individual assets does not present itself as a strong indicator of herding in the market. Instead, it serves as proof that investors do not act on market signals, and instead develop their own investment decision process with the information at hand. As for the second question, there is not sufficient evidence of herding being present in the market; so, it is not reasonable to assume there is or is not an effect on overall asset prices. Instead, the evidence presented in this study lead to the conclusion that the market is overall rational. The investors, individually, use the readily available public knowledge to forge their own investment thesis. The effect of financial information is priced into the market; however, that does not always mean spurious herding cannot occur in this situation. Volatility will always be present in the market, but that does not always mean it is directly correlated to herd behavior.

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Financial Leverage in Renewable Energy and its Future Investment

Asghar Sabbaghi and Drew Ritter*

Abstract

This study will examine the impact of financial leverage on renewable energy sector and the factors that influence leverage, as well as the new financial risks, in today's global environment. We will develop a number of analytical models to analyze the trends and risk factors in renewable energy sector when compared with SPX Index. We will demonstrate that clean energy can be an attractive long-term investment if some financial risks arising from the debt and capital structure can be diversified away, Moreover, we argue that there are high amounts of debt in the capital structure of clean energy, but time will tell how much risk is associated with financial leverage regarding this debt.

Keywords: Financial Leverage, Renewable Energy Investment, Renewable Energy Investment models,

I Introduction

The purpose of this study is to examine the effects of financial leverage on clean sources of energy and the factors that influence leverage, as well as the new risks, in today's financial market and the factors that influence leverage, as well as the new risks, in today's global environment.

The concept of financial leverage, in general, is defined as the ratio of equity and financial debt of a company, and is viewed as an important element of a firm's financial policy. Higher financial leverage implies that there is higher financial debt for a fixed equity. This would allow the company to use more debt to finance assets acquisitions, and to potentially boost the returns on equity capital of a company, especially when the business is unable to increase its operating efficiency and returns on total investment. Due to the assumption that earning on borrowing is higher than interest payable on debt, the company's total earnings will increase, ultimately boosting the earnings of stockholders. Therefore, leverage is often viewed as an essential tool a company's management can use to make the best financing and investment decisions, as it provides a variety of financing sources by which the firm can achieve its target earnings. Leverage is also viewed an important technique in investing as it would help companies to set a threshold for the expansion of business operations. For example, it can be used to recommend restrictions on business expansion once projected return on additional investment is lower than cost of debt.

Leverage is also used by investors to significantly increase the returns that can be provided on an investment. They lever their investments by using various instruments, including options, futures, and margin accounts. Companies also use leverage to finance their assets, and thus, instead of issuing stock to raise capital, companies can use debt to invest in business operations in an attempt to increase shareholder value. However, as financial leverage increases, the cash flow requirements necessary to service additional debt also increases. Therefore, the risk of inadequate cash flow can be a concern in strategic decisions regarding financial structure**.** This suggests that liquidity and leverage are intricately intertwined in these financial decisions.

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Financial risk may also arise from variation in earnings per share (EPS) due to the use of debt capital as well as the risk of insolvency of the common stock shareholders. Moreover, financial risk may be associated with the consequences on uncertainty of firm's financial policy regarding the debt-equity mix and fixed interest charge associated with debt. Introduction of debt capital into a firm's capital structure intensifies the volatility of earnings per share (EPS). Therefore, additional earnings are vital to compensate for the financial cost arising from the debt capital, otherwise, the employed debt capital will increase the firm's financial risk.

According to Ahmed Sheikh and Wang (2011), inappropriate selection of securities such as debts or preferred stock creates a financial distress and ultimately to bankruptcy of the firm. Furthermore, as Luoma and Spiller (2002) state, a particular usage of preferred stock and debt in financing the firm's assets creates financial risk which is directly associated with firm's financial leverage. The impact of financial leverage would depend on economic conditions. Levy and Sarnat (1994) have argued that this impact would likely be positive under good economic condition while it is negative under downturn economic condition. Therefore, capital structure and financial strategy that led to increasing the variability of firm's return may expand the financial risk of the firm.

In this study, we will examine the trends and risk factors to be considered for future investment in clean energy sector, and discuss the following questions: (1) what is the impact of financial leverage on renewable energy? (2) What are the factors that influence leverage? And (3) What are the new risks in today's global environment?

One may argue that a society with previous tendencies to depend upon fossil fuels must eventually switch to cleaner energy sources. Additionally, producers used to borrow without paying close attention to the implications of considerable potential risk due to the pandemic, and consequently deleveraged their finances. According to the International Energy Agency (IEA), renewable energy has shown reasonable resilience, when compared with alternative energy sources throughout 2020. Moreover, for the first time in over 130 years, the United States produced more renewable energy than coal (Francis, 2020). However, many issues associated with the pandemic have stalled progress within renewables, such as tax incentives, supplier issues, and lockdowns disrupting consumer spending. In this study, we will focus on the renewable energy sector and the effects of financial leverage on investment within this sector, and trends that contribute to the risk.

Given the dependency of renewable energy on new technology innovations and the potential for growth, the clean energy sector is becoming an attractive investment. Thus, renewable energy companies have the potential of constant improvement in reducing their cost through applied research and knowledge, similar to technology companies. However, the industry appeal is matched by uncertainty, because investors are repricing the risk in investment in renewable energy due to the current global environment as well as additional focus on clean energy contributors' capital structure. We will examine the leverage in clean energy sector in relation to the implied risk.

II Literature Review

According to the International Energy Agency's annual report (IEA, 2020) the performance of renewable energy has declined, much like the global economy over the same period. However, renewable energy has been more resilient than oil and other energy production subsectors (IEA, 2020). This annual report contains numerous depictions of performance, expectations, sector trends, and what is referred to as the Sustainable Development Scenario (SDS). The SDS is the baseline that has been developed to determine the sustainability measures within energy production compared to sustainable future goals. Hence, the SDS gives a baseline for what future expectations within clean energy sources should be for a healthy environment.

The history of renewable energy sector and its financial performance can help to better understand how financial leverage can determine the industry's value and future expectations. Nissim and Penman (2003) have examined operating, financial, and total leverage to speculate future returns. They also include the equations for calculating each type respectively. They used data from 1963 to 2000, and concluded that the firms with the highest leverage had lower operating income overall. However, they did find that leverage have contributed to future profitability in controllable amounts. They have examined the short-term effect of financial and operating leverage versus the long-term effects of liability and the issues that can arise within those markets due to long-term debt (Nissim and Penman, 2003, pp. 4,).

Baker (2001) has investigated the effect of financial leverage and the greater use of debt capital from a holistic approach. He has used economics and statistical analysis to examine the effect of leverage on profitability and risk (Baker, 2001). This study has used a two-way model for stock market conditions plus leverage and risk variables to explain the leverage's effect (Baker, 2001), and found that leverage is positively correlated to market structure areas, specifically cost stability (Baker, 2001, pp. 4). In this study, we will use the macroeconomic approach and examine if macroeconomic effects such as the leverage for a benchmark of the overall market affect clean energy leverage.

Ozdagli (2012) has developed a model to study the relationship between limited capital irreversibility and risk-free debt contracts to examine the effect of financial leverage on investment, book-to-market ratios, and stock returns. This model shows risk preferences as well as a "benefit from the tax shield of debt, as in the trade-off theory of capital structure" (Ozdagli, 2012, pp. 1034). This study describes how leverage can be irreversible, so that the user cost of capital increases and reduces capital stock, and how leveraging can explain that why expectations do not match reality. However, in his model, Ozdagali isolated external factors by focusing on firms with no operating cost that still had high amounts of financial leverage.

Johnson (2014) has explained the risk analysis methods in developing a diversified portfolio as well as the risk associated with different subsectors within renewable energy. This framework, compares a specific portfolio or individual stock to a diversified index, assuming the S&P 500 as a baseline for acceptable risk, the study shows the variance of risk for any stock, relative to the SPX Index. This framework would help to gauge a comparison between systematic risks of renewables.

Sadorsky (2010) has developed a beta statistical model to determine the drivers for risk within renewable energy, and found that oil price, sales growth, and macroeconomic factors were the three variables that catalyzed growth in returns for clean energy. The model has foundational concepts of a capital asset pricing model with oil and sales growth leading to the most significant contribution in returns. This study found that as the oil price increases, interest in clean energy investment rises, and as sales increase, the company will reduce its risk. Sadorsky (2010) also highlighted the implications of policy decisions, technology, and various factors that influence clean energy returns. In his study for the determinants of higher returns in clean energy. Sadorsky used the Wilderhill Clean Energy ETF as his baseline for clean energy. The analysis considers an assumption that clean energy will be transitioned as a more popular source of power in the future. Moreover, the factors that could facilitate that transition to clean energy could include taxation of fossil fuels and other incentives.

III Modeling Framework

In this section, we develop a model to better describe the financial leverage in renewable energy sector, particularly in relation with other variables such as the new risk factors and renewable energy trends, and to test volatility using beta values. We have selected the securities that would represent different subsectors within clean energy (wind and solar) in the US market and one company with a significant market capitalization in clean energy. In this model, we will focus on determining how returns between the different securities within clean energy compared to the market (SPX Index). We will use daily return data from two periods of high uncertainty: 2007-2009 and 2018-2020, to examine how the securities varied compared to the market and each other (Model I).

This model will show the risk factors associated with leveraged equity in the renewable energy sector compared to the SPX Index in low-demand environments. The beta value can indicate the risk of particular equity without the equilibrium that an investor would otherwise be able to diversify away (Johnson, 2014, Chapter 9). In this current environment, aggregate macroeconomic factors can be critical determinants of equity performance. Moreover, when considering an unprecedented drop in a demand for stock such as renewable energy or oil, new risk factors are considered.

We have selected three major equities from the renewable energy market, as the leading producer of renewable energy in their own areas and based on their market niche within the energy sector in the US market:

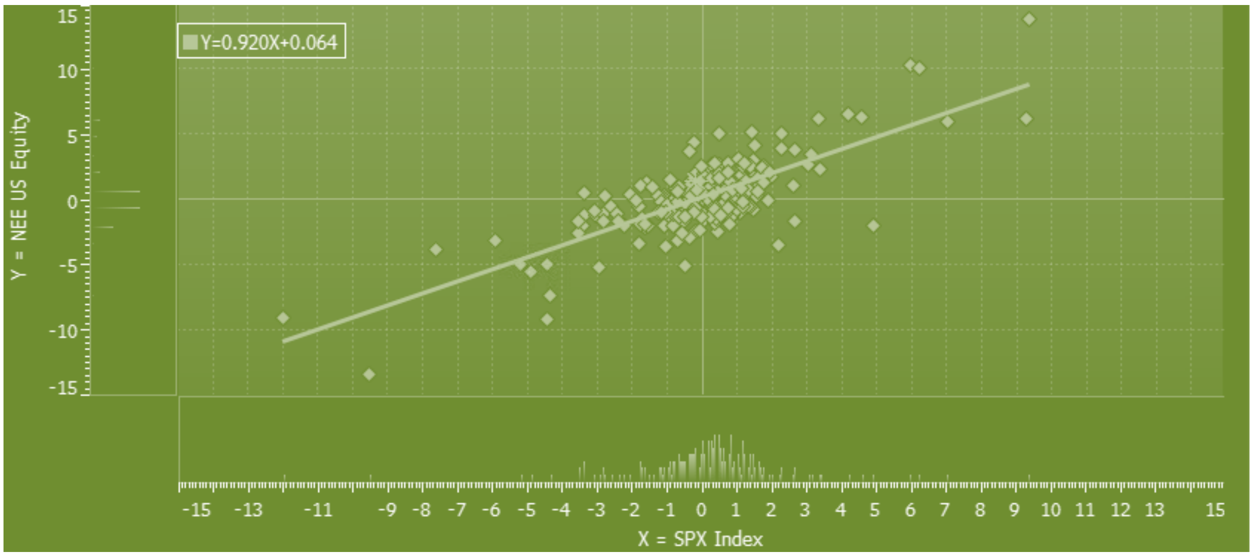
1. Next Era Energy (NEE), an American energy company that is the largest electric utility holding company by market capitalization with subsidiaries that include Florida Power & Light (FPL), NextEra Energy Resources (NEER) LLC. which, together with its affiliated entities, is the world's largest generator of renewable energy from the wind and sun and a world leader in battery storage.
2. Brookfield Renewable Partners, is one of the largest, public pure play renewable businesses globally that owns and operates renewable power assets. As of the end of 2017, Brookfield Renewable owned over 200 hydroelectric plants, 100 wind farms, over 550 solar facilities, and four storage facilities, with approximately 16,400 MW of installed capacity. (Brookfield Renewable Partners L.P. Annual Report" 31 December 2017. Retrieved 27 June 2018.)
3. First Solar Inc. is a leading American solar technology company and global provider of responsibly produced eco-efficient solar modules advancing the fight against climate change.

We have collected data about the equities of these companies, particularly during two low-demand periods from Bloomberg: (1) the periods of 2007-2009 and (2) 2018-2020. We included the time before and after the shock of unexpected risk to mitigate outliers of risk in each desired sample. As Johnson (Ch.9, 2014) argues, by regressing the equity returns against the market returns, one can determine the comparative risk, using the beta value (Johnson, 2014), that is centered around 1.0. When the beta value falls below 1.0, the dependent variable is considered less volatile than the market, and conversely, for beta value above 1.0 would indicate that the dependent variable is considered more volatile than the market (Johnson, 2014).

This model will examine three individual securities that contribute in different ways to clean energy market and their volatility, compares to the SPX Index. Under Bloomberg's default settings, a particular company's historical return data can be compared to the SPX Index over a selected period of time to find the beta. However, as many companies are not public or have not been public long, data is typically short-term. We use Durbin-Watson (DW) statistics to measure the autocorrelation in residuals from the model. In particular, DW would help us to measure the type of autocorrelation in residuals, if any, when each equity regressed on the SPX Index in any sample. While this value will range from 0.0 - 4.0, however, a value around to 2.0 means that there is no autocorrelation detected, a value lower than 2 indicates a positive autocorrelation and greater than 2 signifies a negative autocorrelation. The SPX Index is being used as the baseline for comparison in this analysis to determine the risk associated with leveraged equities in the energy sector.

First, we have compared data for Next Era Energy (NEE) equity from 2007-2009 with the market (SPX Index) in Figure 1. The value for beta=0.920, shows less volatile when compared with SPX during this period. However, according to the Durbin Watson value, NEE has very little autocorrelation but has a slightly negative relationship. The coefficient of determination for the data during 2007-09, is 0.583, indicating that the S&P Index describes 58.3% of variations in NEE.

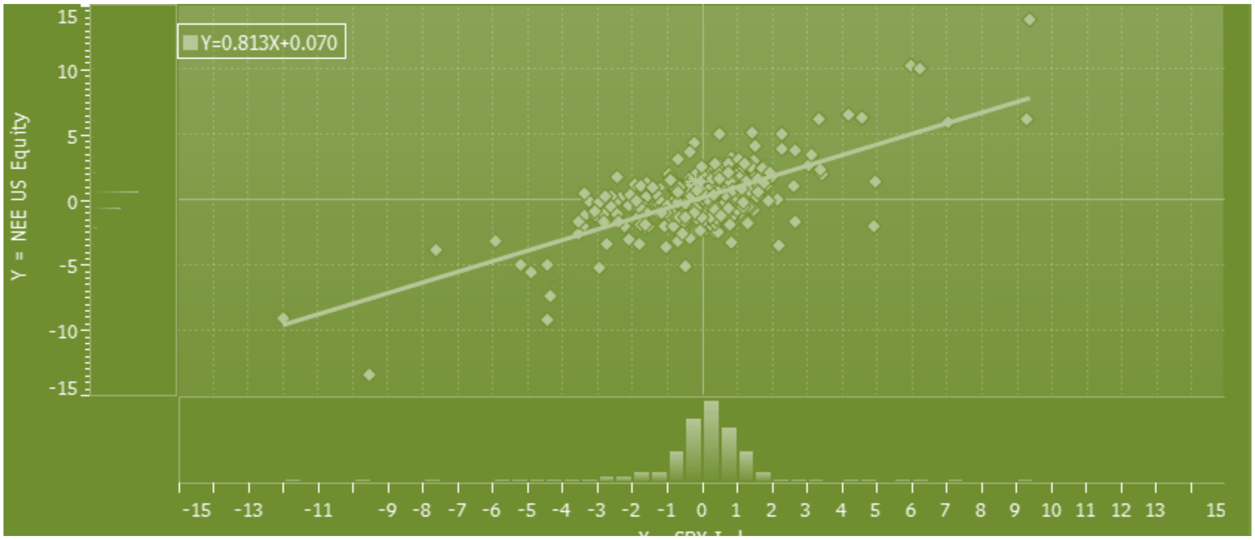
Figure 1: Next Era Energy (NEE 2007-2009)



Statistical Measures	Values
BETA	0.920
ALPHA (Intercept)	0.064
R^2 (Coefficient of Determination)	0.583
Durbin Watson	2.054
Standard Deviation of Error	1.699
Standard Error of ALPHA	0.108
Standard Error of BETA	0.049
Number of Data Points	250

The corresponding relationship for the data of 2018-2020, shown in Figure 2, with correlation coefficient of 0.763, shows a strong positive relationship between the variables. The data shows that, similar to the previous period, Next Era Energy during 2018-20 was less volatile than the SPX Index. The beta value of 0.813 indicates less movement than the more diversified SPX Index. The correlation coefficient in this sample is 0.688, and the coefficient of determination of 0.474 demonstrates that variations in NEE is not described by the variations in S&P Index as much as the previous period.

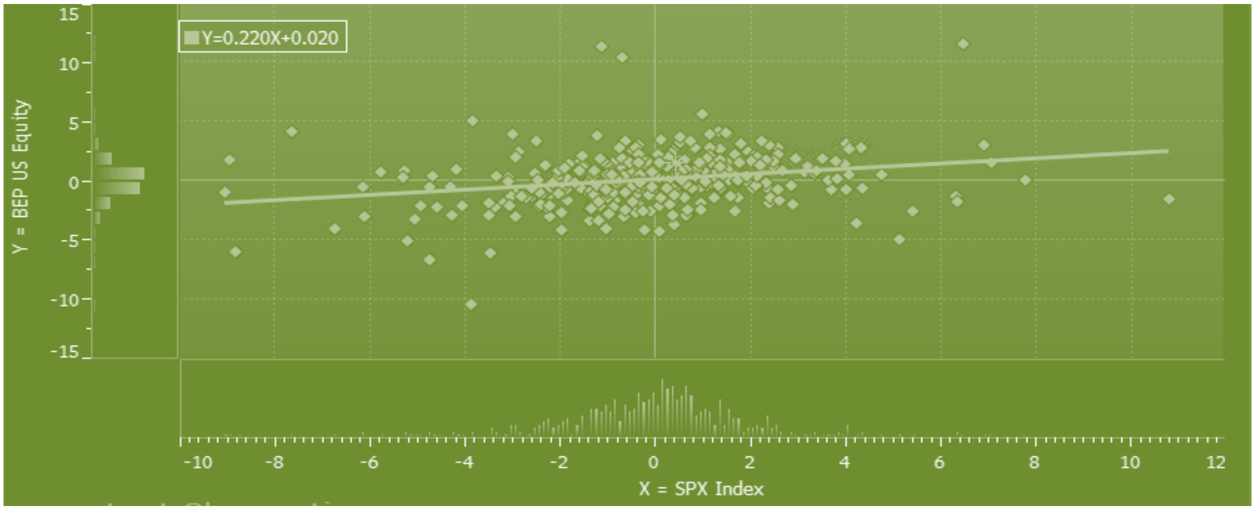
Figure 2: Next Era Energy (NEE 2018-2020)



Statistical Measures	Values
BETA	0.813
ALPHA (Intercept)	0.070
R^2 (Coefficient of Determination)	0.474
Durbin Watson	2.058
Standard Deviation of Error	1.434
Standard Error of ALPHA	0.064
Standard Error of BETA	0.038
Number of Data Points	501

Next, we have examined the data for Brookfield Renewable Partners (BEP) during 2007-2009, displayed in figure 3-1, and it shows that BEP had less market variation when compared with the SPX Index during that period. This sample's correlation coefficient for the data during 2007-2009 is very low (0.249), and the coefficient of determination indicated that the S&P Index variation can describes very little variations in the performance of BEP during this period.

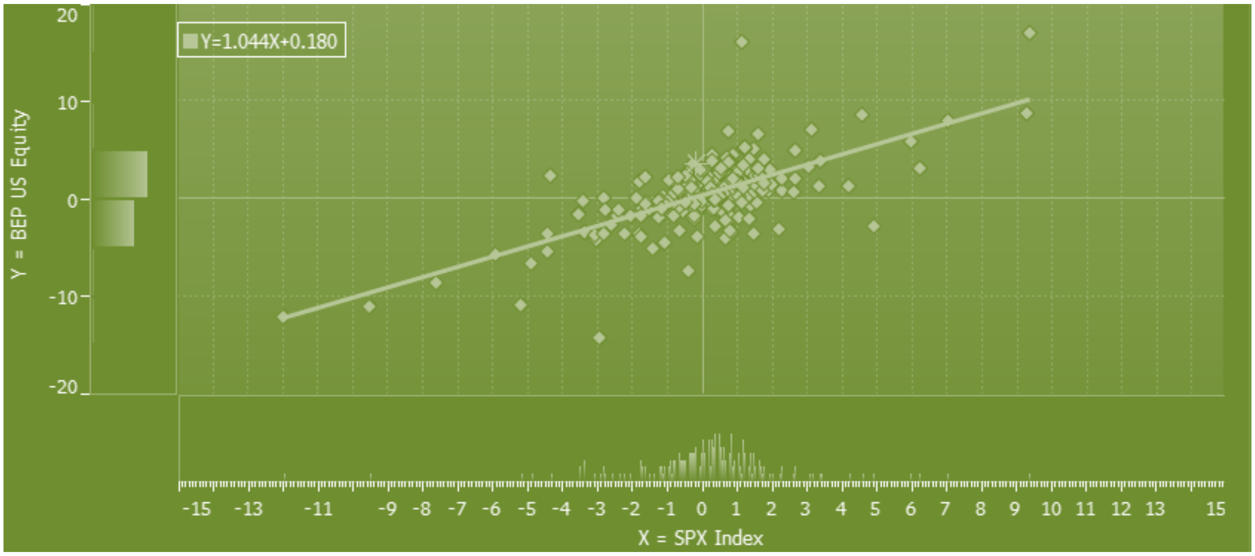
Figure 3: Brookfield Renewable Partners (BEP 2007-2009)



Statistical Measures	Values
BETA	0.220
ALPHA (Intercept)	0.020
R^2 (Coefficient of Determination)	0.062
Durbin Watson	2.195
Standard Deviation of Error	1.884
Standard Error of ALPHA	0.087
Standard Error of BETA	0.039
Number of Data Points	474

The data for the period of 2018-20 in figure 4 shows a significant correlation coefficient (.691) between BEP variations and SPX index, and coefficient of determination (.478). The beta value of 1.044 indicates slightly higher volatility of BEP when compared with SPX index during this period. However, the beta value is very close to 1.0, meaning the volatility associated with BEP during this period is very similar to the SPX Index during the same period. Therefore, these results are similar to the other figures in this model but drastically different from the data sample for BEP from 2007-2009.

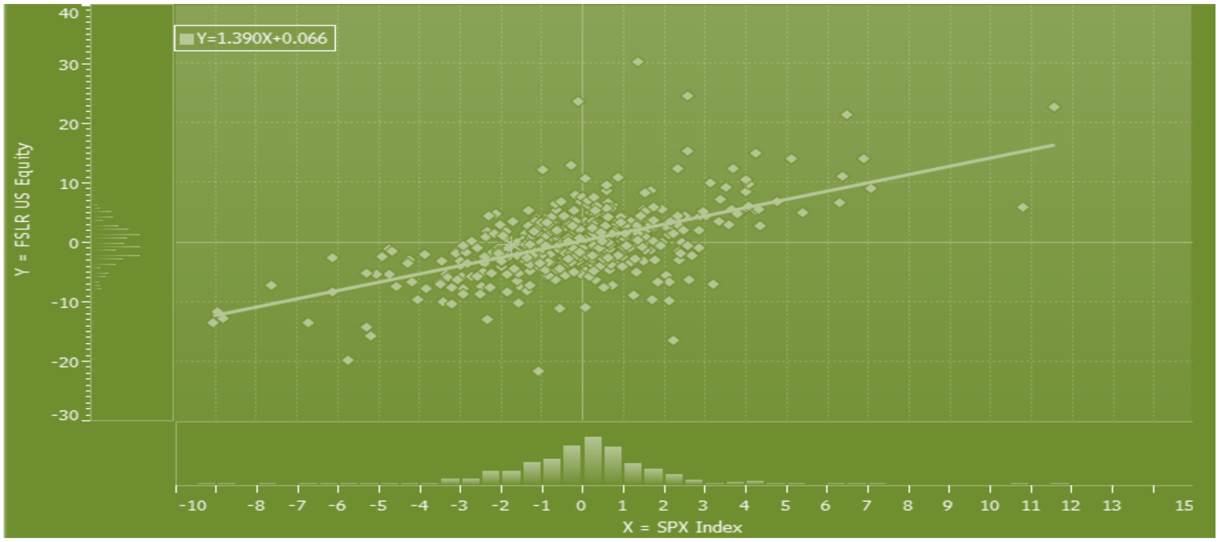
Figure 4: Brookfield Renewable Partners (BEP 2018-2020)



Statistical Measures	Values
BETA	1.044
ALPHA (Intercept)	0.180
R^2 (Coefficient of Determination)	0.478
Durbin Watson	2.163
Standard Deviation of Error	2.385
Standard Error of ALPHA	0.151
Standard Error of BETA	0.069
Number of Data Points	250

The data for First Solar Inc. (FSLR) from 2007-2009, displayed in figure 5 shows the volatility of this security during this period when compared with the SPX Index. This period was a high point of uncertainty for FSLR compared to the SPX Index. The correlation coefficient of 0.567, and the coefficient of determination 0.321 for FSLR shows less predictability of this security by the SPX Index during 2007-09.

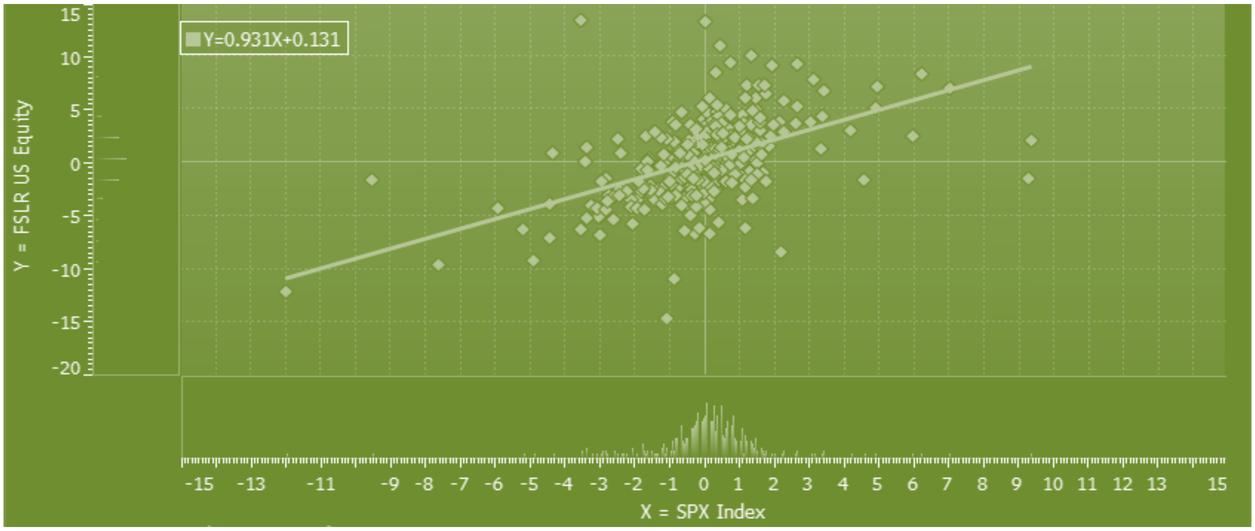
Figure 5: First Solar Inc. (FSLR 2007-2009)



Statistical Measures	Values
BETA	1.390
ALPHA (Intercept)	0.066
R^2 (Coefficient of Determination)	0.321
Durbin Watson	2.217
Standard Deviation of Error	4.478
Standard Error of ALPHA	0.200
Standard Error of BETA	0.091
Number of Points	501

However, the data during 2018-2020 for FSLR in figure 6 shows that the beta value, similar to most of the other samples, was below 1.0, while the coefficient of determination was 0.248, meaning only 24.8% of variations in FSLR could be described by the variations in S&P 500, and the correlation coefficient was 0.498. This relationship implies a moderately positive correlation.

Figure 6: First Solar Inc. (FSLR 2018-2020)



Statistical Measures	Values
BETA	0.931
ALPHA (Intercept)	0.131
R^2 (Coefficient of Determination)	0.248
Durbin Watson	2.352
Standard Deviation of Error	2.717
Standard Error of ALPHA	0.122
Standard Error of BETA	0.073
Number of Points	500

IV WilderHill® Index (ECO) to Measure Clean Energy Industry

In this section, we use the WilderHill® Index (ECO) as the representative index for clean energy industry. This index founded in 2004 by Wilderhill Clean Energy and it is the world's first and best known for climate change solutions to define and track the Clean Energy sector. The producers and publicly traded clean energy peers are the contributors to ECO index and it focuses on businesses that can gain from the transition to alternative energy. The weightings of stocks and sector within the ECO Index are based on their significance for clean energy, technological influence and relevance to preventing pollution.

In order to examine the industry-wide performance, we follow the beta modeling in Figures 1- 6, and use the same type of beta modeling with the WilderHill Clean Energy Index (ECO) as a function of the S&P 500 (SPX), as the industry model. The use of the ECO Index would allow us to effectively describe the industry beta as a whole. We use Bloomberg's data to find each index's quarterly price from 2005-2020, and use price data for ECO Index (y) and the SPX Index (x), to calculate each index's returns between 3-month periods and find the beta for all periods.

Data for debt/equity from 2005-2020 has been used to calculate the unlevered beta for the period. Therefore, we use the following formula for Returns and Beta:

$$Returns = \Delta Q = \frac{Q_2 - Q_1}{Q_1} \quad (1)$$

$$SLOPE = \beta = \frac{\Delta y}{\Delta x} = \frac{\Delta ECO}{\Delta SPX} \qquad (2)$$

Where *Q1*=Old price, and *Q2*=New price*,*

We use the unlevered beta by using the tax rate and the debt/equity ratio of the firm to give a more accurate measure of leverage in clean energy with the beta value ignoring debt's influence. It worth noting that renewable energy companies received different tax incentives based on various metrics. However, it is challenging to compute a flat tax rate on renewable energy. For example, wind tax benefits vary from hydropower, etc. Thus, an average rate from 2005-2020 was determined based on the corporate tax rate during that period. Additionally, using the market beta (β) above, unlevered beta can be calculated according to formula (3), below*:*

$$Unlevered\ Beta = \frac{\beta}{1 + (1 - Tax\ Rate)(\frac{Debt}{Equity})} \qquad (3)$$

A high Debt-to-Equity ($\frac{Debt}{Equity}$) ratio generally indicates that a company has been aggressive in financing its growth with debt. This can result in volatile earnings as a result of the additional interest expense. If the company's interest expense grows too high, it may increase the company's chances of a default or bankruptcy.

Assuming that an industry such as renewables is becoming more reliant on technology, its stocks starting to display a tech stock's characteristics. Moreover, green investors are beginning to re-examine their portfolios to include cleaner sources of returns. Figure 9 shows the performance, based on price, between the market and variables such as oil price during 2003-2020. This figure displays the current uncertainty following the pandemic's height because renewable energy remained resilient despite low oil prices. The figure also compares a technology index, market indices, oil price, and the ECO Index. The analysis is intended to model the following relationships: (1) clean energy performance has dependent on oil price, (2) ECO performs similarly to a tech stock, (3) how ECO performs when compared to market benchmarks.

Lastly, the final regression model sought to find the variables that would influence financial leverage within the ECO Index. The variables affecting the firm's growth and size were highlighted and tested for correlation within the industry. The final regression consists of Research and Development (R&D) expenditure and market capitalization against the financial leverage for ECO and the SPX indices. The same regression will be examined on the SPX Index and to see how the market benchmark compares to the financial leverage clean energy benchmark.

We define the Financial Leverage as the changes in Earning Per Share (EPS) for each unit changes in operating income, also known as Earnings Before Interest and Tax *(EBIT)* as expressed in the following ratio:

$$Financial\ Leverage = \frac{\Delta(EPS)}{\Delta(EBIT)} \qquad (4),$$

Where

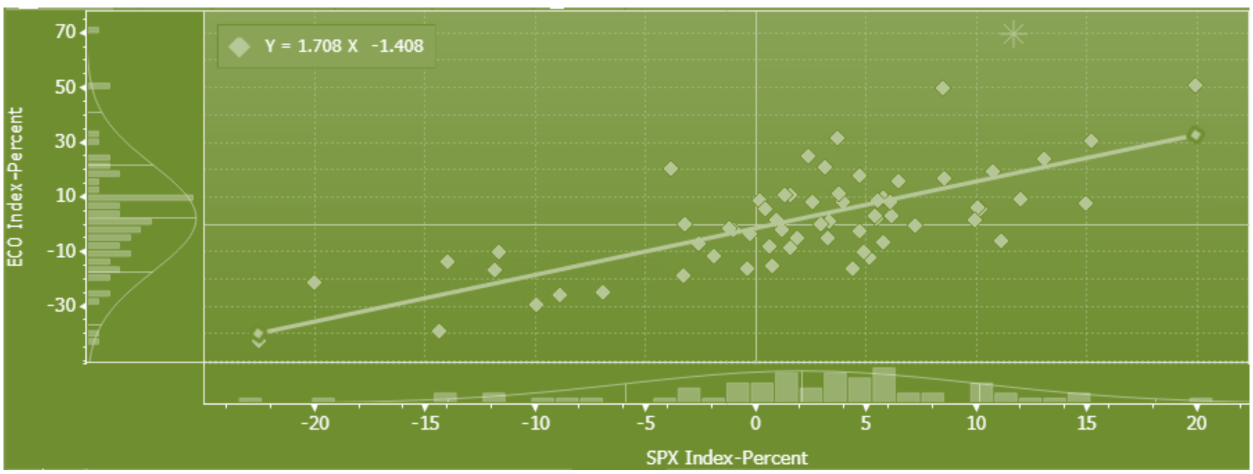
$$EPS = \frac{(EBIT - Interest\ Expense)}{Number\ of\ shares\ Outstanding}$$

The Financial Leverage indicates that the higher the degree of financial leverage, the earnings per share (EPS) will be more volatile. Since interest is a fixed expense, leverage magnifies returns and EPS, which is good when operating income is rising, however can be a problem during downturn economic times when operating income is under pressure

The unlevered beta gives a glimpse of the volatility without the assumption of debt. This modeling would help to better understand the relationship between leverage and implied risk for clean energy. Ambitious financing activities can harshly affect clean energy contributors with a low market cap and small production capacity. The purpose of this regression is to see how much risk is associated with leverage in clean energy. Also, not all variables tested are included in regression output; the final regression represents the highest correlation variables. Specifically, the regression model variables involve the index's size and growth to examine if they increased or decreased financial leverage within the SPX and ECO indices. In the final regression, we will test R&D Expenditure/share, Market capitalization, and financial leverage for ECO and SPX.

Model I Statistical Beta Risk Amongst SPX Index (Bloomberg)

Figure 7: Beta 2005-2020 (Quarterly Data Bloomberg_BETA)



Raw BETA	1.708
Adjusted BETA	1.472
ALPHA (Intercept)	-1.408
R^2 (Coefficient of Determination)	0.496
R (Correlation Coefficient)	0.704
Standard Deviation of Error	14.029
Standard Error of ALPHA	1.814
Standard Error of BETA	0.219
t-Test	7.811
Level of Significance	0.000
Last T-Value	3.581
Last P-Value	1.000
Number of data Points	64
Last Spread	3542.01
Last Ratio	0.057

This model has also used SPX index, to be comparable, and the Beta value for the ECO Index for this period was 1.708, which is higher than the beta values recorded for the three individual companies we examined earlier. The beta test accounted for a more considerable period than the previous samples. Moreover, the previous illustrations were intended to isolate the market during periods of high uncertainty, while this model captured both bullish market conditions and bearish market conditions from 2005-2020.

We have used Bloomberg quarterly return data, the market beta from 2005-2020, to regress the ECO Index on the SPX Index, and the results are shown in Figure 8.

Figure 8: Output for Beta ECO vs. SPX

Regression Statistics	
Multiple R	0.70426
R Square	0.49598
Adjusted R Square	0.48785
Standard Error	0.14029
Observations	64

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1.201	1.201	61.011	0.000
Residual	62	1.220	0.020		
Total	63	2.421			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-0.014	0.018	-0.776	0.441	-0.050	0.022	-0.050	0.022
SPX Index Returns	1.708	0.219	7.811	0.000	1.271	2.145	1.271	2.145

The F value shows the significance of the model while the model is significant and the SPX Index returns explains about 49% of variations in the ECO Index return during this period. The market beta is also significant, as it can help to calculate the unlevered beta for ECO. Using formula (3), can help to calculate the unlevered beta, as it will also assess the risk expected without leveraging on returns. Simultaneously, the tax rate is based on the federal corporate tax rate from the years 2005-2020. We have used the average tax rate from 2005-2020 (0.32375) and the average Debt/Equity for ECO (91.42) to calculate the unlevered beta during this modeling period. Thus, *Unlevered Beta ECO:*

$$\text{Unlevered Beta ECO} = \frac{\beta}{1+(1-Tax\ Rate)\left(\frac{Debt}{Equity}\right)} = \frac{1.708}{1+(1-0.32375)(91.42)} = 0.027188$$

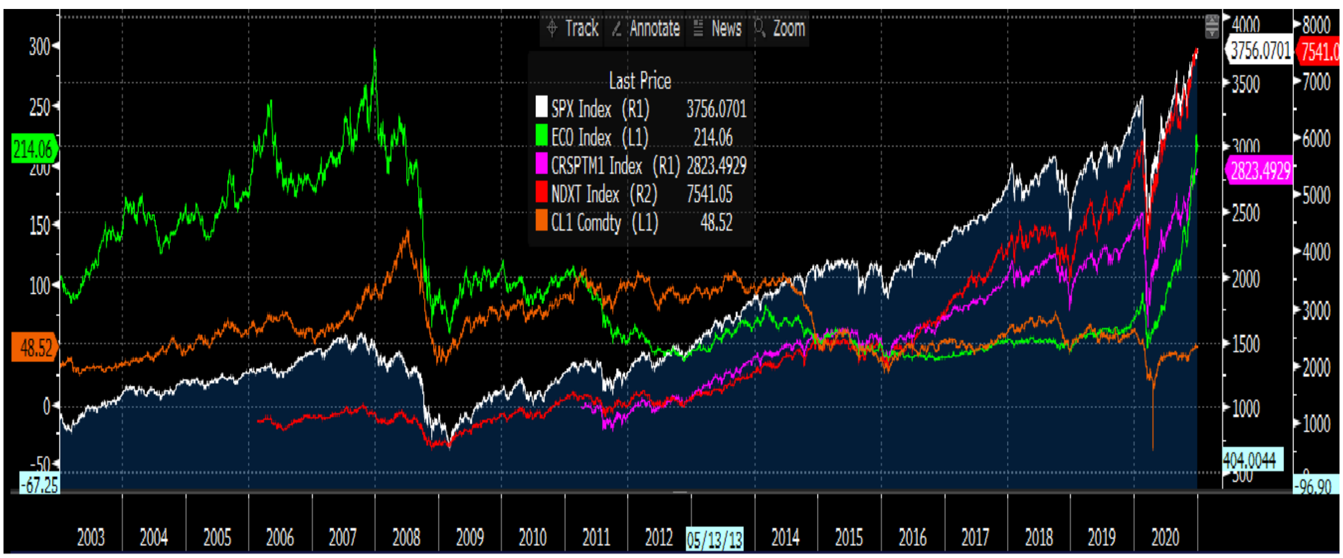
The unlevered beta shows the ECO Index's risk without debt, isolating the ECO Index risk. The significantly lower unlevered beta value demonstrates the riskiness of clean energy in its financing activities. This value is valuable in showing how the removal of leverage can isolate risk from company assets alone. Due to the low unlevered beta, it appears that the risk associated with

ECO is high compared to the SPX Index. According to this value, a high amount of risk can be attributed to the ECO Index's debt. When a stock raises its debt to equity to high levels, a more significant percentage of earnings will finance that debt. Hence, if the debt is high, it will increase investor uncertainty about future earnings.

Clean Energy Index against Market, Technology, and Oil

In order to assess the ECO Index performance when compared to technology, oil, and the general market, Figure 9, shows the price data, compared amongst benchmarks and oil. According to Sadorsky (Sadorsky, 2010, p.42), the relationship between oil price and clean energy sources is typically inverse. When oil prices are higher, there should be more interest in investment for clean and alternative energy sources. However, despite oil price being low renewable energy performed much like the market and technology, based on price. Much of this can be attributed to the low demand for petroleum-based activities from pandemic lockdowns, supplier struggles, and consumer spending. However, it shows the problem that investors have in this current environment, which is repricing clean energy and risks.

Figure 9: Price 2003-2020
(ECO Index, SPX Index, NDXT Index, CL1 Comdty, CRSPTM1 Index)
Graph created in Bloomberg.



Many renewable energy companies perform more like technology companies than energy companies (Sadorsky, p.42, 2010). This shift to more efficient processes through technology could partially explain the stock's behavior when compared to oil. This difference in behavior is due to the importance of technology in reducing their bottom line. As new and more efficient production systems for clean energy are developed , the cost of clean production will decrease. This decrease in cost will increase their profit per sales dollar. According to Sadorsky (2010), sales growth rates are known to be a determinant factor for reducing clean energy risk. With technology actively reducing cost, stakeholders within clean energy will be paying close attention to new production methods. Many investors seek green finance investments, and this concept is slowly gaining traction in the transition to clean energy. However, some investors are still left with uncertainty due to contributors' large debt issuance. The efficiency in new production systems may be counterintuitive if the debt remains high.

V Regression Model and Empirical Results

The focus of the regression model is to capture the variables that would influence financial leverage within the WilderHill Clean Energy Index (ECO) from 2005-2020. We use quarterly data, directly from Bloomberg, for the SPX Index and ECO Index. The model sought to find variables related to leverage in clean energy from the macro-level perspective. However, it is difficult to truly determine the holistic leverage percentage for clean energy producers and other affiliates macro-economically. This difficulty can partially be attributed to some significant contributors to the industry not having public data available to analyze. Hence, the ECO Index's leverage percentage was used as the benchmark to capture a glimpse of financial leverage in the sector.

Several variables were tested against financial leverage of the ECO Index and the SPX Index, but the highest correlation of these variables was R&D expenditure. The final multiple regression used financial leverage for ECO and SPX 2005-2020. The value for the sum of squares (SS) was extremely high as well in the regression. This high SS value indicates a high deviation from the mean value in the multiple regressions. Hence, the mean of the sum of squares (MS) was also heightened because of extreme variation in financial leverage. For example, the earnings before interest and taxes would be consistent in some periods, while the EPS suffered or grew exponentially, causing significant outliers from one quarter to the next. The change on a quarter-to-quarter basis largely contributed to the uncorrelated results. The significance F value indicated a minimal possibility that the model's null hypothesis is correlated with financial leverage. In Figures 10 and 11, the Multiple R output shows very little correlation between the indices' financial leverage and the variables tested. This output is similar to the inconclusive results of other variables tested against the same financial leverage measure within the ECO and SPX indices.

Figure 10: Regression Output ECO

Regression Statistics	
Multiple R	0.1530
R Square	0.0234
Adjusted R Square	-0.0086
Standard Error	19.0618
Observations	64

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	531.491	265.746	0.731	0.485
Residual	61	22164.597	363.354		
Total	63	22696.088			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	2.594	7.168	0.362	0.719	-11.740	16.928	-11.740	16.928
R&D Expense ECO	0.591	0.850	0.696	0.489	-1.109	2.291	-1.109	2.291
Market Capitalization	-0.001	0.001	-0.603	0.549	-0.003	0.001	-0.003	0.001

The average market capitalization for ECO and the SPX indices was used instead of total market capitalization because clean energy comprises small, mid, and large-cap contributors. The average market capitalization gives an average based on the index contributors. Hence, to gain more value from the benchmark, the average market capitalization was appropriate for comparing the SPX and ECO indices.

Figure 11: Regression Output SPX

Regression Statistics	
Multiple R	0.3256
R Square	0.1060
Adjusted R Square	0.0767
Standard Error	149.5192
Observations	64

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	161736.713	80868.356	3.617	0.033
Residual	61	1363715.220	22355.987		
Total	63	1525451.932			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-56.014	93.063	-0.602	0.549	-242.106	130.077	-242.106	130.077
R&D Expense SPX	8.901	4.145	2.147	0.036	0.613	17.189	0.613	17.189
Market Capitalization	-0.007	0.002	-2.682	0.009	-0.011	-0.002	-0.011	-0.002

The variables tested were to emulate prior findings during a financial crisis. In particular, Johnny Jermias and Faith Yigit found that firm size, growth opportunities, the tangibility of assets, and industry mean average to be the factors most influencing leverage during a financial crisis. Their research was based in Turkey and surrounded by data that included harsh economic times similar to the current environment. The tangibility of assets, R&D expenditure, and other variables representing previous literature, specifically growth and tangibility measures, were used. However, we did not find that these growth measures were highly correlated to financial leverage within renewable energy.

The SPX and ECO indices' financial leverage was tested against the R&D expenditure and the average market capitalization from 2005-2020. The regressions had 64 observations quarterly from 2005-2020 to determine if the growth measures or size played a role in ECO's capital structure. However, the ECO and SPX Index outputs had a very low correlation to the variables tested.

VI Renewable's Repricing of Risk

Governmental Risk Factors

Due to Covid-19, horizon risk within the renewable energy sector has increased, but now there are new risks that will affect renewable energy companies and their operations. In the last few years, federal governments have been prone to levy more costs through tariffs. Tariffs will affect the cost of raw materials within the renewable energy sector and their production price. Moreover, Ecuador is the leading producer of the wood needed in turbines for wind power, but Covid-19 production has stalled, causing high demand and cost for the wind power supply chain (Barnett 2020). There is also a rising concern that production tax credit and the investment tax credit will step down in addition to supply chain cost. Currently, any projects constructed after 2019 will have no tax credit benefits for alternative energy production. Guidelines from the US Internal Revenue Service state that residential and commercial solar projects qualify for a 30% ITC through 2019 as long as it is completed by 2024. Beginning in 2020, "the ITC is set to decline to 26%, then to 22% in 2021" (Kang, 2020).

The delay for a tax credit on large-scale wind producers has stalled due to Covid-19 (Barnett 2020). The aid was a catalyst for development in this sector, but now the progress seems to be impeded by the pressures of SARS-COv2. If governmental help does not support renewable energy production, it could significantly affect this sector's growth. The intent of this incentive allowed for renewable energy companies to receive a small percentage of tax breaks for the production of cleaner sources of energy. These were vital drivers in large-scale alternative energy productions, but now these risks create more uncertainty within the sector. Much of power sector investment is based on incentives and regulations for producers. These incentives have been stalled during the global pandemic. Thus, halting the future investment activities of 2021 and thereafter. Although resiliency has been a strong suit of renewables compared to other subsectors in the last year, the next few years have high uncertainty that can partially be credited to stalled incentives on future projects and infrastructure.

Expectations of Uncertainty

Much of the investment activity has been slow for renewable energy due to the lockdowns; this is partly from restrictions but has also affected the supply of goods, machinery, and equipment (IEA, 2020). According to the International Energy Agency, energy producers have pressure to reduce emissions in recent years, but from 2019 – 2020 energy investment dropped by nearly 20%. Despite the drop-in investment activity for the fifth year in a row, power production exceeded the oil and gas supply.

Although the IEA expects renewable energy to drop 10% for the year, it has been more dependable in current market conditions than other energy sectors such as fossil fuels. This resilience can be credited to long-term contracts that stabilized revenues for the period. The duration of this downtrend across the energy sector and renewables is mainly dependent on the return of consumer spending and supply chain normalcy. Hence, the energy sector has high uncertainty leading to 2021. This unprecedented level of low investment activity saw similar drops in the global financial crisis of

2008. However, this crisis is dependent on the recovering global economy and dependent on the effectiveness and speed of a vaccine.

VII Concluding Comments

There is little doubt that an eventual shift towards cleaner energy sources is on the horizon. If not, there could be plenty of repercussions to the long-term effects of climate change on our environment. Along with the environmental risks, there are financial risks associated as well. In examining some of the new risks associated with renewable energy, the focal point in this study was to determine financial leverage's contribution to clean energy's overall risk. In this process, several variables were tested to find the determinants of leverage within the industry, using benchmarking of indexes representing the market and renewable energy. The SPX Index and ECO Index were used for these findings. The findings for the determinants of DCL within ECO were inconclusive because of the high deviation between quarters for leverage. Despite the result, there were some key findings in our study of leverage in this sector. Specifically, the low unlevered beta indicated that ECO has a high amount of debt in their capital structure. This debt appetite could be detrimental in times of high systematic risk.

In pursuit of examining the risk associated with leverage within the sector, the beta was calculated for three individual securities against the SPX Index. These figures gave a snapshot of the volatility between 2007-2009 and 2018-2020, two periods of financial instability, to gain what should be the riskiest time for the market holistically. The securities maintained a beta around 1.0 or typically higher during these six observations. This increased volatility varied for each company, depending on the period. Also, the beta was calculated for ECO to assess the clean energy performance in the market.

Many clean energy contributors were resilient to the pandemic's effect, but the added debt still displays high uncertainty about how future earnings will be used. Using the beta value for ECO, the unlevered beta was calculated (0.02718901). This unlevered beta measure vastly contrasted the market beta for the ECO Index (1.70803735). By stripping away the debt aspect and separating the risk due solely to company assets, the unlevered beta provided some feedback on ECO and its capital structure. In particular, the volatility is more accurately displayed once the debt was removed. The contrast can be misunderstood because the effects of debt can cause significant differences in this volatility measure. As Sadorsky (2010, p.47) argues, high oil prices can lead to more interest in clean energy investment. However, the pandemic questions this relationship. It was shown that during this unprecedented time, oil prices remained very low because of low demand. Yet, renewable energy over this same period rebounded after the initial shock, similar to the behavior of tech and market indices.

Renewable energy investment has increased in the last few years. However, according to IEA (2021), the small-cap size renewable energy securities with a high tolerance for risk leading into the pandemic could see their downfall. This may depend on a number of factors, most notably the vaccine's rollout and effectiveness. Moreover, one of the leading market drivers for wind, solar, and hydropower is tax breaks, and they will decline going forward. These tax breaks, depending on the sector, would give tax breaks to expand activities or tax breaks based on the wattage of power produced. Many of these incentives are getting incrementally downsized for projects following 2020. If the risk and associated risk of leverage can be nullified to safer levels and clean energy proves to be a profitable form of substitute, it would make for a more appealing energy source to investors. Although stifled by restrictions and less consumer spending, this transition could return to normal levels following the vaccine.

Leverage can be used as a shield to disguise the risk associated with clean energy investment. When used appropriately, it can significantly increase returns helping all stakeholders including competitors. However, when leverage is abused, it can result in a significant loss. The empirical evidence suggests that renewable energy has had high uncertainty heading into 2021. That is based on the historical appetite for risk, horizon risk associated with Covid-19, beta value relative to the SPX Index, and reduction in government incentives that help drive clean energy production. Yet, there is little reason to believe renewable energy will become less attractive to investors over time because of environmental concerns and improved efficiency in cost per wattage of production. This will help make clean energy become a more cost-effective form of energy than substitutes. Clean energy can be an attractive long-term investment if some risk is diversified away. Moreover, based on this research, there are high amounts of debt in the capital structure of clean energy, but time will tell how much risk is associated with financial leverage regarding this debt. However, it is only a matter of time before the drastic change in clean energy production is at the forefront of major societal issues.

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