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# Investor Attention, News and the Herd Behavior of Individual Stock Returns

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## Abstract

**Purpose:** This paper examines the herd behavior of individual returns around their industry average in stressful market condition, when industry-wide investor attention is high or low, and when good or bad industry-wide news reach the market.

**Design/Methodology:** Decile portfolios are formed based on proxies of aggregate market condition, industry-wide level of investor attention and industry-wide news signal. Indicator variables identifying the months in the highest and lowest portfolios are then entered in regression tests to capture the degree to which returns herd around their industry. Both cross-sectional and absolute deviations from industry average are used to measure herding.

**Findings:** The analysis reveals that for the majority of industries, herding exist in calm market conditions. Moreover, herding appears to be concentrated in months where the industries record abnormally low returns and in months in which the industries receive good news.

**Practical Implications:** Understanding what drives the herd behavior of individual returns in financial markets portfolio may be of particular value to investment companies, such as hedge funds, who seek to time the market.

**Originality/Value:** The paper offers new insights on the drivers of herding in financial markets. While prior studies focus on examining herding in market turmoil, this paper documents herding around extreme events and following news arrival.

**JEL Classification**: G14, G15, C22
**Keywords**: Herding, Extreme Returns, Investor Attention, Good News, Bad News

## I Introduction

Herding in financial markets is characterized by the tendency of investors to copy each other or replicate the behavior of the aggregate market. This phenomenon has increasingly attracted the attention of researchers, practitioners and regulators over the past decade. In fact, researchers have examined the herding effect in various aspects of financial markets, including in the equity market (Christie and Huang 1995; Chang, Cheng, and Khorana 2000; Hwang and Salmon 2004; Tan et al. 2008; Chiang, Li, and Tan 2010; Economou, Kostakis, and Philippas 2011), the fixed income market (Galariotis et al. 2016), the commodities market (Gleason, Lee, and Mathur 2003; Philippas 2014), the ETFs (Gleason, Mathur, and Peterson 2004) and mutual fund markets (Lakonishok, Shleifer, and Vishny 1992; Wermers 1999; Sias 2004) among others. Spyrou (2013) offers an

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extensive review of theory and empirical results on the effect of herding in financial markets spanning the last two decades.

While there exists some consensus on the existence of herding in emerging economies (Kallinterakis and Kratunova 2007; Economou, Hassapis and Philippas 2018), findings in this context are generally thought to be driven by the endogenous characteristics of those markets, including low trading volume, insufficient regulatory frameworks, information asymmetries and quasi-nonexistence of transparency and information disclosure. In developed economies however, the evidence is mixed. Although theoretical underpinnings of herding in financial markets predict the prevalence of herding during market downturns, empirical evidence is either absent (Christie and Huang 1995; Chang, Cheng, and Khorana 2000), more pronounced in market downturns (Demirer, Kutan, and Chen 2010; Chiang and Zheng 2010; Chen 2013; Philippas et al. 2013; Mobarek, Mollah, and Keasey 2014), or primarily evident in bull markets (Tan et al. 2008; Economou, Kostakis, and Philippas 2011; Economou et al. 2015). Jiang et al. 2022 investigate herding behavior triggered by the COVID-19 outbreak in 2020 by considering six typical Asian stock markets by employing cross-sectional standard deviation (CSSD) and cross-sectional absolute deviation (CSAD) and shows a clear presence of herding in the "Feb 2020-Jan 2021" time window. Hasan et al. 2023 provides new evidence of herding due to non- and fundamental information in 33 global equity markets. Using quantile regressions applied to daily data for 33 countries, Hasan et al. 2023 investigate herding during the Eurozone crisis, China's market crash in 2015–2016, in the aftermath of the Brexit vote and during the Covid-19 Pandemic and find significant evidence of herding driven by non-fundamental information in case of negative tail market conditions for most countries.

In this paper, we revisit the herding behavior of individual stock returns in the US equity market around their industry average. We perform "out-of-sample" tests of the evidence reported by Christie and Huang (1995) using alternative definitions of market conditions. Specifically, we employ the CBOE Volatility Index (VIX) as well as the St. Louis Federal Reserve Financial Stress Index (FSI) as proxies for market condition. For the majority of industries considered (about 75% of the industries on average), we find evidence that herding appears to exist in months where VIX or FSI are at their lowest. In other words, individual stock returns herd around their industry average in calm, not stressful market conditions. In stressful markets, periods of high VIX or high FSI, we find no evidence of individual stock return herding around their industry average for all the industries considered. This finding is consistent with Christie and Huang (1995) and Chang, Cheng, and Khorana (2000), among others.

Barber and Odean (2007) report evidence that individual investors are net buyers of attention-grabbing stocks, defined as those experiencing extreme one-day returns. Also, Bali, Cakici and Whitelaw (2011) find that investors exhibit a preference for stocks with extreme positive returns. These studies raise the possibility that factors other than market condition may induce herding, including the occurrence of extreme returns (e.g., an attention grabbing-event). We therefore explore herd behavior of individual stock returns in months when the industry attracts significant attention based on their recording of unusually high or low returns. We generally find that herding is concentrated in months in which the industries record their worst average daily returns, suggesting that herding is present in industries that attract attention for earning negative returns.

To explore this intuition further, we ask the question of whether individual stock returns herd around their industry average following the arrival of industry-wide good or bad news. Interestingly, we find that the behavioral models of Scharfstein and Stein (1990), Banerjee (1992), Bikhchandani, Hirshleifer, and Welch (1992), Trueman (1994), and Hirshleifer, Subrahmanyam, and Titman (1994) all predict a form of herd behavior of investors based on news arrival, private or otherwise. In this paper, we do not only explore, ex-post, the herd behavior of individual stock returns based on news arrival, but also based on the signal (good or bad) sent to the market by the arrival of news. Using the industry level average stock distance to the fifty-two-week high to capture the arrival of good or bad news as in George and Hwang (2004), we find that herding is concentrated in months in which the industries receive good news and not bad news.

Our study contributes to the literature in a few ways. First, we offer fresh evidence of the herd behavior of individual stock returns around their industry average in calm, not necessarily bull markets, rather than stressful market conditions. Next, we document the herd behavior of individual stock returns in months in which the average firm in the industry records extreme negative rather than positive returns, and in months in which average firm in the industry receives good rather than bad news. To the best of our knowledge, we are the first to document these latter findings. Ultimately, we offer new insight, relevant to academics, practitioners and regulators on the herd behavior of individual stock returns in financial markets.

The remainder of this paper is organized as follows: Section 2 describes the data and method employed, Section 3 presents empirical results and discussions, and Section 4 offers concluding remarks.

## II Data and Method

Our sample builds on every listed security on the Center for Research in Security Prices (CRSP) data files with share codes 10 or 11 from January 1990, to December 2014. We obtain daily prices, returns, SIC codes and market capitalization from the CRSP data files. From Bloomberg, we collect data on the volatility index (VIX) and the St. Louis Federal Reserve Financial Stress Index (FSI). Finally, as is common in the finance literature, we restrict our sample to stocks priced between \$5 and \$1000 U.S dollars.

It is common in the finance literature to build on the Standard Industrial Classification (SIC) scheme to classify firms into industry groups. Established in the United States (U.S.) back in 1937, the SIC scheme groups into an industry companies with comparable production processes or whose products are used or distributed together (see Economic Classification Policy Committee 1994, Chan, Lakonishok and Swaminathan 2007). However, with challenges to the effectiveness of this classification scheme based on the growing importance of services and changes in the technology landscape among others (see Clarke 1989, Fama and French 1997) reorganizes the SIC codes to offer a series of alternative classification systems that are considered the go-to-classification schemes in accounting, finance and economic literatures.

This Fama and French industry classification (FFIC) has been extensively used in accounting (see, Chan, Frankel, and Kothari 2004; Francis, LaFond, Olsson, and Schipper 2005; Richardson 2006), finance (see, Brennan, Wang, and Xia 2004; Daniel and Titman 2006; Ferson and Harvey 1999; Hong, Torous, and Valkanov 2007; Moskowitz and Grinblatt 1999; Pastor and Stambaugh 1999; Purnanandam and Swaminathan 2005, Flannery and Rangan 2006; Graham and Kumar 2006), and economics (see., Bebchuk and Grinstein 2005; Wulf 2002). From the Kenneth French data library, we obtain the Fama and French 12-industry SIC classification that we then use to classify the stocks in our sample.

Next, we follow Christie and Huang (1995) and Hwang and Salmon (2004) among others to compute for every industry portfolio the monthly cross-sectional standard (CSSD) and absolute (CSAD) deviation of return as follows:

$$CSSD_{j,t} = \left[\sum_{i=1}^{i=N} \frac{\left(R_{i,t,j} - \bar{R}_{j,t}\right)^2}{N-1}\right]^{\frac{1}{2}} \tag{1}$$

$$CSAD_{j,t} = \sum_{i=1}^{i=N} \frac{\left|R_{i,t,j} - \bar{R}_{j,t}\right|}{N-1} \tag{2}$$

where $R_{i,t,j}$ is the value-weighted return of stock *i* in month *t* belonging to the industry $j$. $\bar{R}_{j,t}$ is cross-sectional average of the N returns in industry $j$. Christie and Huang (1995) and Hwang and Salmon (2004) argue that these measures (CSSD and CSAD) quantify the degree to which individual returns move in concert with the industry return, and therefore capture the key attribute of herd behavior. Therefore, herding is observed, ex-post, if stressful market condition (VIX or FSI) negatively predicts the dispersion of individual returns around their respective industry returns (CSSD and CSAD).

We also examine the question of whether individual stock returns herd around their industry average following the arrival of good and bad news. George and Hwang (2004) (GH henceforth) argue that stocks whose current prices are near (far) from their fifty-two-week high are those for which good (bad) news recently reached the market. To proxy for the arrival of industry wide good or bad news, we compute each industry's GH ratio as the average of the individual stock distance to their respective fifty-two-week high prices (IGH).

$$GH_{i,t} = \frac{Price_{i,t}}{52WH_{\,i,t}} \tag{3}$$

$$IGH_{j,t} = \sum_{i=1}^{\mathrm{i=N}} \frac{GH_{i,t,j}}{N} \tag{4}$$

George and Hwang (2004) report evidence consistent with the notion that proximity of stock's current price to the 52-week high price generates investor underreaction and subsequent return continuation. We use GH ratio to measure the proximity to the 52-week high price, defined as the ratio of a stock's current price to its 52-week high price. The higher values of GH measure suggest that current price is closer to the 52-week high price. Again, in the extreme, if the formation month end price is the 52-week high price, then the GH measure has the maximum possible value of 1.

Finally, we consider the possibility that individual stock returns herd around their industry average when the industry attracts considerable attention, for positive or negative reasons. To proxy for attention grabbing events, we compute for every month and for each industry an average maximum and minimum daily returns following Barber and Odean (2007) and Bali, Cakici and Whitelaw (2011). Table 1 reports the time series average of our key variables across all industries.

**Table 1. Time Series Averages of Key Variables**

This table reports the time series average of the key variables for each of the twelve industries considered over the period going from January 1990 to December 2014. CSSD is the average firm-level cross-sectional standard deviation of returns, capturing return variability around the industry average. CSAD is the average firm-level cross-sectional absolute deviation of returns around the industry average. MAXRET is the average monthly firm-level maximum daily return for the industry and MINRET is the average monthly firm-level minimum daily return for the industry. IGH is the monthly industry average firm-level price distance to the 52-Week high price.

| Industry | Firms | CSSD | CSAD | MAXRET | MINRET | IGH |
|---|---|---|---|---|---|---|
| 1 | 338 | 2.295 | 2.298 | 0.049 | -0.041 | 0.833 |
| 2 | 158 | 3.333 | 3.335 | 0.061 | -0.052 | 0.789 |
| 3 | 602 | 1.702 | 1.704 | 0.056 | -0.048 | 0.808 |
| 4 | 287 | 3.364 | 3.370 | 0.054 | -0.047 | 0.817 |
| 5 | 125 | 2.098 | 2.107 | 0.055 | -0.047 | 0.816 |
| 6 | 1098 | 2.991 | 2.993 | 0.077 | -0.063 | 0.743 |
| 7 | 212 | 2.398 | 2.404 | 0.064 | -0.053 | 0.792 |
| 8 | 170 | 3.314 | 3.324 | 0.034 | -0.030 | 0.882 |
| 9 | 631 | 2.124 | 2.125 | 0.066 | -0.056 | 0.775 |
| 10 | 602 | 2.669 | 2.671 | 0.080 | -0.064 | 0.741 |
| 11 | 2274 | 2.266 | 2.267 | 0.054 | -0.046 | 0.840 |
| 12 | 1006 | 1.476 | 1.477 | 0.077 | -0.062 | 0.761 |

## III Empirical Results

### Herding and Market Condition

Our empirical exercise follows Christie and Huang (1995) and Hwang and Salmon (2004). Specifically, we estimate the following general models:

$$CSSD_{j,t} = \alpha + \beta^{Stress} D_{j,t}^{Stress} + \beta^{Calm} D_{j,t}^{Calm} + \varepsilon_{j,t} \quad (5)$$

$$CSAD_{j,t} = \alpha + \beta^{Stress} D_{j,t}^{Stress} + \beta^{Calm} D_{j,t}^{Calm} + e_{j,t} \quad (6)$$

where CSSD and CSAD are defined and computed as described earlier. $D_{j,t}^{Stress}$ is an indicator variable that takes the value of one for months in which the variable under consideration (VIX or FSI) is in the top decile of months sorted based on the VIX or FSI respectively; and zero otherwise. $D_{j,t}^{Calm}$ is an indicator variable that takes the value of one for months in which the variable under consideration (VIX or FSI) is in the bottom decile of months sorted based on the VIX or FSI respectively; and zero otherwise. For example, when examining the herding behavior of individual stock returns in stressful market conditions – using the VIX [FSI] to proxy for market condition, $D_{j,t}^{Stress}$ is labeled HVIX [HFSI] and takes the value of one for months in the highest decile of months sorted based on the volatility [financial stress] index and zero otherwise. Similarly, $D_{j,t}^{Calm}$ is labeled LVIX [LFSI] and takes the value of one for months in the lowest decile of months sorted based on the volatility [financial stress] index and zero otherwise. This approach allows us to capture both tails of the distribution of our proxies for market condition.

As pointed by Christie and Huang (1995), rational asset pricing models predict that individual returns dispersion should be higher in stressful market conditions. However, the herding of individual returns is displayed through a reduction of return dispersion under similar market conditions. In the context of this study, unusually stressful market conditions occur when the volatility index (VIX) or the Financial Stress Index (FSI) are at their highest; that is during those months in which the VIX or FSI rank in the highest decile of months sorted based on the VIX or FSI respectively. In contrast, unusually calm market conditions occur when the volatility index (VIX) or the Financial Stress Index (FSI) are at their lowest; that is during those months in which the VIX or FSI rank in the lowest decile of months sorted based on the VIX or FSI respectively. Under these conditions, a finding of positive and significant $\beta^{Stress}$ or $\beta^{Calm}$ will be seen as consistent with rational asset pricing models, whereas negative and significant $\beta^{Stress}$ or $\beta^{Calm}$ will be seen as evidence of herding for the given industry.

*Using the Volatility Index*

Table 2 reports the results of our estimation of equations (5) in Panel A and equation (6) in Panel B. In Panel A, we find that for eight out of the twelve industries considered, the cross-sectional standard deviation of returns around the industry average significantly increases with market stress ($\beta^{Stress}$ are positive and statistically significant). This finding is consistent with Christie and Huang (1995) who find no evidence of herding in stressful market conditions. Our findings are also consistent with traditional asset pricing models that suggests that market stress increase return dispersions. However, we also find that for nine out of the twelve industries considered, the cross-sectional standard deviation of returns around the industry average significantly decreases when market stress is at its lowest ( coefficients for $\beta^{Calm}$ are negative and statistically significant). For example, we find that for the Consumer Non-Durables (1) and Utilities (8) industries, both $\beta^{Calm}$ are -1.08 and -0.97 with t-statistics of -4.31 and -2.70 respectively. This evidence is consistent with the existence of individual stock return herding in nine out of twelve industries, particularly in good or “calm” market conditions.

Using the cross-sectional absolute return dispersion (CSAD), we find in Panel B of Table 2 evidence consistent with those reported in Panel A. While CSAD increases in stressful market conditions, it decreases when the volatility index is at its lowest, exhibiting apparent herding behavior. Similar to our results in Panel A, we find that the herding behavior of individuals is observed in nine out of twelve industries.

*Using the Financial Stress Index*

To add robustness to our earlier findings, we re-estimate equations (5) and (6) using the St. Louis Federal Reserve Financial Stress Index (FSI) to proxy for market conditions. We report the results of this exercise in Table 3. In Panel A of Table 3, we find that for eleven out of the twelve industries considered, the cross-sectional standard deviation of returns around the industry average significantly increases with market stress (coefficients for $\beta^{Stress}$ are positive and statistically significant). However, we also find that for ten out of the twelve industries considered, the cross-sectional standard deviation of returns around the industry average significantly decreases when the financial stress index is at its lowest (coefficients for $\beta^{Calm}$ are negative and statistically

**Table 2. Using VIX as Indicator of Market Condition**

This table reports regression estimates for each industry of equations (3) and (4) over the entire sample period: January 1990 to December 2014. In Panel A. CSSD is defined as earlier and used as dependent variable. In Panel B, CSAD is defined as earlier and used as dependent variable. HVIX is an indicator variable for months in the highest decile of months ranked based on the volatility index (VIX). LVIX is an indicator variable for months in the lowest decile of months ranked based on the volatility index (VIX). We report robust M-Estimation regression estimates using Huber (1964) weight with $c$ = 1.345. T-Statistics are provided in parentheses below the respective coefficients. The symbols ***, **, and * denote statistical significance at the 0.01, 0.05 and 0.10 levels.

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A: CSSD** | | | | | | | | | | | | |
| Industries | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| HVIX | 1.15** | 1.83* | 1.12*** | 0.51 | 0.50 | 1.04 | 1.26** | 2.06*** | 0.72* | 0.82 | 1.08** | 0.71*** |
| $\beta^{Stress}$ | (2.55) | (1.77) | (2.77) | (1.19) | (1.13) | (1.56) | (2.26) | (2.96) | (1.92) | (1.53) | (2.29) | (2.71) |
| LVIX | **-1.08*** ** | **-0.92** ** | **-0.39* ** | **-1.09** ** | **-0.55** ** | **-0.82** ** | **-0.56** ** | **-0.97*** ** | *-0.15* | *-0.53* | *-0.48* | **-0.60*** ** |
| $\beta^{Calm}$ | **(-4.31)** | **(-2.12)** | **(-1.87)** | **(-2.56)** | **(-2.31)** | **(-1.98)** | **(-2.29)** | **(-2.70)** | *(-0.53)* | *(-1.38)* | *(-1.52)* | **(-3.94)** |
| cons | 2.25*** | 3.21*** | 1.61*** | 3.40*** | 2.09*** | 2.94*** | 2.30*** | 3.17*** | 2.06*** | 2.62*** | 2.19*** | 1.45*** |
| | (16.49) | (18.38) | (18.53) | (17.26) | (15.85) | (16.61) | (19.43) | (17.64) | (18.69) | (17.83) | (16.15) | (19.51) |
| $R^2$ | 0.0514 | 0.0403 | 0.0633 | 0.0145 | 0.0124 | 0.0214 | 0.0469 | 0.0604 | 0.0179 | 0.0172 | 0.0306 | 0.0590 |
| adj. $R^2$ | 0.0450 | 0.0339 | 0.0570 | 0.0078 | 0.0057 | 0.0148 | 0.0404 | 0.0541 | 0.0113 | 0.0105 | 0.0241 | 0.0527 |
| **Panel B: CSAD** | | | | | | | | | | | | |
| HVIX | 1.16** | 1.84* | 1.12*** | 0.51 | 0.50 | 1.04 | 1.26** | 2.07*** | 0.72* | 0.82 | 1.08** | 0.71*** |
| $\beta^{Stress}$ | (2.56) | (1.77) | (2.77) | (1.19) | (1.13) | (1.56) | (2.26) | (2.96) | (1.92) | (1.53) | (2.29) | (2.71) |
| LVIX | **-1.08*** ** | **-0.92** ** | **-0.39* ** | **-1.09** ** | **-0.55** ** | **-0.83** ** | **-0.56** ** | **-0.97*** ** | *-0.15* | *-0.53* | *-0.48* | **-0.60*** ** |
| $\beta^{Calm}$ | **(-4.31)** | **(-2.12)** | **(-1.87)** | **(-2.56)** | **(-2.31)** | **(-1.98)** | **(-2.28)** | **(-2.70)** | *(-0.53)* | *(-1.39)* | *(-1.52)* | **(-3.94)** |
| cons | 2.26*** | 3.22*** | 1.61*** | 3.40*** | 2.10*** | 2.94*** | 2.31*** | 3.18*** | 2.06*** | 2.62*** | 2.19*** | 1.45*** |
| | (16.49) | (18.38) | (18.53) | (17.26) | (15.86) | (16.61) | (19.44) | (17.63) | (18.69) | (17.83) | (16.15) | (19.51) |
| $N$ | 300 | 300 | 300 | 300 | 300 | 300 | 300 | 300 | 300 | 300 | 300 | 300 |
| $R^2$ | 0.0514 | 0.0404 | 0.0633 | 0.0145 | 0.0124 | 0.0214 | 0.0468 | 0.0604 | 0.0180 | 0.0172 | 0.0306 | 0.0590 |
| adj. $R^2$ | 0.0450 | 0.0340 | 0.0570 | 0.0078 | 0.0057 | 0.0148 | 0.0404 | 0.0541 | 0.0113 | 0.0105 | 0.0241 | 0.0527 |

**Table 3. Using FSI as Indicator of Market Condition**

This table reports regression estimates for each industry of equations (3) and (4) over the entire sample period: January 1990 to December 2014. In Panel A. CSSD is defined as earlier and used as dependent variable. In Panel B, CSAD is defined as earlier and used as dependent variable. HFSI is an indicator variable for months in the highest decile of months ranked based on the St. Louis Federal Reserve Financial Stress Index (FSI). LFSI is an indicator variable for months in the lowest decile of months ranked based on the St. Louis Federal Reserve Financial Stress Index (FSI). We report robust M-Estimation regression estimates using Huber (1964) weight with *c* = 1.345. T-Statistics are provided in parentheses below the respective coefficients. The symbols ***, **, and * denote statistical significance at the 0.01, 0.05 and 0.10 levels

| Panel A: CSSD | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Industries | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| HFSI | 2.00*** | 2.68** | 1.63*** | 2.39*** | 1.84*** | 1.09* | 0.42 | 2.25*** | 0.91* | 2.29*** | 2.85*** | 0.89*** |
| $\beta^{Stress}$ | (3.18) | (2.17) | (3.29) | (3.54) | (3.06) | (1.69) | (1.05) | (3.22) | (1.89) | (3.73) | (4.50) | (3.09) |
| LFSI | *-0.33* | **-1.08**** | **-0.72***** | *0.05* | **-0.71***** | **-1.77***** | **-0.99***** | **-0.66*** | **-0.91***** | **-0.93***** | **-1.03***** | **-0.32*** |
| $\beta^{Calm}$ | *(-1.40)* | **(-2.51)** | **(-3.43)** | *(0.06)* | **(-3.51)** | **(-6.67)** | **(-3.49)** | **(-1.71)** | **(-2.81)** | **(-2.90)** | **(-3.75)** | **(-1.69)** |
| cons | 2.12*** | 3.13*** | 1.58*** | 3.13*** | 1.96*** | 2.98*** | 2.41*** | 3.13*** | 2.08*** | 2.49*** | 2.04*** | 1.41*** |
| | (17.46) | (19.84) | (20.57) | (18.31) | (17.13) | (16.92) | (18.72) | (17.68) | (20.64) | (18.52) | (18.31) | (19.72) |
| $R^2$ | 0.0780 | 0.0684 | 0.1199 | 0.0591 | 0.0801 | 0.0338 | 0.0161 | 0.0556 | 0.0401 | 0.0946 | 0.1711 | 0.0538 |
| adj. $R^2$ | 0.0718 | 0.0621 | 0.1140 | 0.0527 | 0.0739 | 0.0273 | 0.0095 | 0.0492 | 0.0336 | 0.0885 | 0.1655 | 0.0475 |
| **Panel B: CSAD** | | | | | | | | | | | | |
| HFSI | 2.00*** | 2.69** | 1.63*** | 2.40*** | 1.84*** | 1.09* | 0.42 | 2.26*** | 0.91* | 2.30*** | 2.85*** | 0.89*** |
| $\beta^{Stress}$ | (3.19) | (2.17) | (3.29) | (3.54) | (3.06) | (1.69) | (1.05) | (3.22) | (1.89) | (3.73) | (4.50) | (3.09) |
| LFSI | *-0.32* | **-1.08**** | **-0.72***** | *0.05* | **-0.71***** | **-1.77***** | **-0.99***** | **-0.66*** | **-0.91***** | **-0.93***** | **-1.03***** | **-0.32*** |
| $\beta^{Calm}$ | *(-1.40)* | **(-2.49)** | **(-3.42)** | *(0.06)* | **(-3.50)** | **(-6.67)** | **(-3.48)** | **(-1.71)** | **(-2.81)** | **(-2.90)** | **(-3.75)** | **(-1.69)** |
| cons | 2.12*** | 3.15*** | 1.58*** | 3.14*** | 1.96*** | 2.98*** | 2.41*** | 3.14*** | 2.08*** | 2.50*** | 2.04*** | 1.41*** |
| | (17.46) | (19.84) | (20.57) | (18.31) | (17.14) | (16.92) | (18.73) | (17.68) | (20.64) | (18.52) | (18.31) | (19.72) |
| *N* | 300 | 300 | 300 | 300 | 300 | 300 | 300 | 300 | 300 | 300 | 300 | 300 |
| $R^2$ | 0.0780 | 0.0684 | 0.1199 | 0.0591 | 0.0802 | 0.0338 | 0.0160 | 0.0556 | 0.0401 | 0.0946 | 0.1711 | 0.0538 |
| adj. $R^2$ | 0.0718 | 0.0621 | 0.1140 | 0.0528 | 0.0740 | 0.0272 | 0.0094 | 0.0492 | 0.0336 | 0.0885 | 0.1655 | 0.0475 |

significant). For example, we find that for the Consumer Durables (2) and Utilities (8) industries, both $\beta^{Calm}$ are -1.08 and -0.66 with t-statistics of -2.51 and -1.71 respectively. This evidence is consistent with the existence of individual stock return herding in nine out twelve industries, particularly in good or "calm" market conditions.

Overall, our findings are consistent with the evidence reported in Christie and Huang (1995) and suggest that for the industries considered and in our sample period, herding around the industry average is absent in stressful market conditions. Moreover, we document the herd behavior of individual stock returns around their industry average in relatively calm market conditions. Hwang and Salmon (2004) also reports evidence of herding in bear markets.

**Herding and Extreme Returns**

In the next section, we consider herd behavior of individual stock returns when the industry records unusually high or low returns. This inquiry is motivated by the findings of Barber and Odean (2007) who report evidence that individual investors are net buyers of attention-grabbing stocks, defined as those experiencing extreme one-day returns or abnormally high trading volume. Moreover, Bali, Cakici and Whitelaw (2011) find that investors exhibit a preference for stocks with extreme positive returns. Put together, these studies suggest that investors are attracted by extreme events, which we define, following prior research, as extreme one-day returns, positive or negative.

To identify those months with extreme events, we follow Bali, Cakici and Whitelaw (2011) and identify for each stock in our sample both maximum and minimum daily returns. We then compute each month and for each industry, an industry's average maximum (minimum) daily return. Next, for each industry, we independently sort our sample based on the maximum (minimum) daily returns and form decile portfolios on this basis. Finally, we assign an indicator variable to months in the top and bottom decile portfolios formed based on the industry's average maximum and minimum daily returns. We emphasize the independent sort between maximum and minimum daily returns because a stock's month daily minimum return will not always rank in the lowest decile formed on the given stock's maximum daily return. Therefore, MAX is an indicator variable for months in the highest decile of months ranked based on the industry's average maximum daily return, and MIN is an indicator variable for months in the lowest decile of months ranked based on the industry's average minimum daily return.

Finally, we estimate the following models:

$$CSSD_{j,t} = \alpha + \beta^{High} MAX_{j,t} + \beta^{Low} MIN_{j,t} + \varepsilon_{j,t} \quad (7)$$

$$CSAD_{j,t} = \alpha + \beta^{High} MAX_{j,t} + \beta^{Low} MIN_{j,t} + e_{j,t} \quad (8)$$

where CSSD and CSAD are defined and computed as described earlier. $MAX_{j,t}$ is an indicator variable that takes the value of one for months in the highest decile of months ranked based on the average industry (j) maximum daily return, and zero otherwise. $MIN_{j,t}$ is an indicator variable that takes the value of one for months in the lowest decile of months ranked based on the average industry minimum daily return, and zero otherwise.

We report the results of this exercise in Table 4. In Panel A of Table 4, we find that for nine out of the twelve industries considered, the cross-sectional standard deviation of returns around the industry average significantly increases in months in which the industry's average

**Table 4. Extreme Returns and Herding**

This table reports regression estimates for each industry of equations (3) and (4) over the entire sample period: January 1990 to December 2014. In Panel A. CSSD is defined as earlier and used as dependent variable. In Panel B, CSAD is defined as earlier and used as dependent variable. MAX is an indicator variable for months in the highest decile of months ranked based on the industry's average maximum daily return (MAXRET). MIN is an indicator variable for months in the lowest decile of months ranked based on the industry's average minimum daily return (MINRET). We report robust M-Estimation regression estimates using Huber (1964) weight with $c$ = 1.345. T-Statistics are provided in parentheses below the respective coefficients. The symbols ***, **, and * denote statistical significance at the 0.01, 0.05 and 0.10 levels

| Industries | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A: CSSD** | | | | | | | | | | | | |
| MAX | 1.11** | 1.47** | 2.10*** | 0.13 | 2.74*** | 2.82*** | 0.73 | 2.27*** | 0.57 | 1.79*** | 1.94*** | 0.56** |
| | (2.03) | (2.11) | (4.87) | (0.21) | (4.38) | (3.33) | (1.38) | (3.09) | (1.42) | (2.94) | (3.35) | (2.01) |
| MIN | **-0.67*** ** | **-0.73*** | *-0.23* | *0.14* | **-0.45*** | **-1.42*** ** | **-0.82*** ** | **-0.83** ** | **-0.56** ** | **-0.90*** ** | **-0.54** ** | **-0.38** ** |
| | **(-2.99)** | **(-1.80)** | *(-1.06)* | *(0.30)* | **(-1.65)** | **(-5.08)** | **(-3.45)** | **(-1.98)** | **(-2.39)** | **(-3.77)** | **(-2.42)** | **(-2.31)** |
| cons | 2.25*** | 3.27*** | 1.52*** | 3.34*** | 1.87*** | 2.85*** | 2.41*** | 3.17*** | 2.12*** | 2.58*** | 2.13*** | 1.46*** |
| | (16.52) | (15.47) | (19.30) | (17.66) | (17.75) | (17.82) | (18.94) | (17.69) | (18.99) | (17.86) | (16.46) | (19.21) |
| $R^2$ | 0.0360 | 0.0254 | 0.1840 | 0.0004 | 0.1732 | 0.1210 | 0.0294 | 0.0655 | 0.0213 | 0.0716 | 0.0837 | 0.0318 |
| adj. $R^2$ | 0.0295 | 0.0188 | 0.1785 | -0.0064 | 0.1676 | 0.1151 | 0.0229 | 0.0592 | 0.0147 | 0.0653 | 0.0776 | 0.0253 |
| **Panel B: CSAD** | | | | | | | | | | | | |
| MAX | 1.11** | 1.48** | 2.10*** | 0.13 | 2.75*** | 2.82*** | 0.73 | 2.28*** | 0.57 | 1.79*** | 1.94*** | 0.56** |
| | (2.03) | (2.11) | (4.87) | (0.21) | (4.38) | (3.33) | (1.38) | (3.09) | (1.42) | (2.94) | (3.35) | (2.01) |
| MIN | **-0.67*** ** | **-0.73*** | *-0.23* | *0.14* | *-0.45* | **-1.42*** ** | **-0.82*** ** | **-0.84** ** | **-0.56** ** | **-0.90*** ** | **-0.54** ** | **-0.38** ** |
| | **(-2.98)** | **(-1.79)** | *(-1.06)* | *(0.30)* | *(-1.65)* | **(-5.08)** | **(-3.45)** | **(-1.97)** | **(-2.38)** | **(-3.76)** | **(-2.42)** | **(-2.31)** |
| cons | 2.25*** | 3.28*** | 1.52*** | 3.34*** | 1.88*** | 2.85*** | 2.41*** | 3.18*** | 2.13*** | 2.58*** | 2.13*** | 1.46*** |
| | (16.52) | (15.47) | (19.30) | (17.66) | (17.76) | (17.82) | (18.95) | (17.69) | (19.00) | (17.86) | (16.46) | (19.21) |
| $N$ | 300 | 300 | 300 | 300 | 300 | 300 | 300 | 300 | 300 | 300 | 300 | 300 |
| $R^2$ | 0.0359 | 0.0253 | 0.1840 | 0.0004 | 0.1732 | 0.1210 | 0.0294 | 0.0655 | 0.0212 | 0.0716 | 0.0837 | 0.0318 |
| adj. $R^2$ | 0.0294 | 0.0188 | 0.1785 | -0.0064 | 0.1676 | 0.1151 | 0.0228 | 0.0592 | 0.0146 | 0.0653 | 0.0776 | 0.0253 |

**Table 5. Good News, Bad News and Herding**

This table reports regression estimates for each industry of equations (3) and (4) over the entire sample period: January 1990 to December 2014. In Panel A. CSSD is defined as earlier and used as dependent variable. In Panel B, CSAD is defined as earlier and used as dependent variable. HGH is an indicator variable for months in the highest decile of months ranked based on the industry's average GH ratio (IGH). LGH is an indicator variable for months in the lowest decile of months ranked based on the industry's average GH ratio (IGH). We report robust M-Estimation regression estimates using Huber (1964) weight with $c$ = 1.345. T-Statistics are provided in parentheses below the respective coefficients. The symbols ***, **, and * denote statistical significance at the 0.01, 0.05 and 0.10 levels

| Industries | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A: CSSD** | | | | | | | | | | | | |
| HGH | *-0.26* | *-0.60* | **-0.47**** | *0.47* | **-0.70***** | **-1.40***** | *-0.39* | **-1.27***** | **-0.64***** | **-0.58**** | *-0.36* | **-0.46***** |
| | *(-0.87)* | *(-1.30)* | **(-2.17)** | *(0.72)* | **(-2.91)** | **(-5.26)** | *(-1.37)* | **(-3.30)** | **(-2.86)** | **(-2.05)** | *(-1.51)* | **(-3.03)** |
| LGH | 0.67 | 2.65** | 0.88** | 1.64*** | 1.34*** | 3.50*** | 1.63*** | 0.49 | 1.04** | 1.88*** | 2.44*** | 0.98*** |
| | (1.30) | (2.42) | (2.20) | (2.81) | (2.72) | (4.36) | (2.71) | (0.89) | (2.34) | (2.75) | (3.94) | (3.88) |
| cons | 2.25*** | 3.13*** | 1.66*** | 3.15*** | 2.03*** | 2.78*** | 2.27*** | 3.39*** | 2.08*** | 2.54*** | 2.06*** | 1.43*** |
| | (16.30) | (18.18) | (18.22) | (17.58) | (15.89) | (17.71) | (19.47) | (17.27) | (19.43) | (18.38) | (16.88) | (18.93) |
| $R^2$ | 0.0108 | 0.0671 | 0.0436 | 0.0293 | 0.0543 | 0.1713 | 0.0649 | 0.0207 | 0.0493 | 0.0672 | 0.1224 | 0.0806 |
| adj. $R^2$ | 0.0041 | 0.0608 | 0.0372 | 0.0228 | 0.0479 | 0.1657 | 0.0586 | 0.0141 | 0.0429 | 0.0609 | 0.1165 | 0.0745 |
| **Panel B: CSAD** | | | | | | | | | | | | |
| HGH | *-0.26* | *-0.60* | **-0.47**** | *0.47* | **-0.70***** | **-1.40***** | *-0.39* | **-1.27***** | **-0.64***** | **-0.58**** | *-0.36* | **-0.46***** |
| | *(-0.86)* | *(-1.29)* | **(-2.17)** | *(0.72)* | **(-2.92)** | **(-5.25)** | *(-1.37)* | **(-3.30)** | **(-2.86)** | **(-2.05)** | *(-1.51)* | **(-3.02)** |
| LGH | 0.67 | 2.66** | 0.88** | 1.65*** | 1.35*** | 3.50*** | 1.63*** | 0.49 | 1.04** | 1.88*** | 2.44*** | 0.98*** |
| | (1.30) | (2.42) | (2.20) | (2.81) | (2.72) | (4.36) | (2.71) | (0.89) | (2.34) | (2.75) | (3.94) | (3.88) |
| cons | 2.26*** | 3.15*** | 1.66*** | 3.16*** | 2.04*** | 2.78*** | 2.28*** | 3.40*** | 2.09*** | 2.54*** | 2.06*** | 1.43*** |
| | (16.31) | (18.18) | (18.22) | (17.58) | (15.89) | (17.71) | (19.48) | (17.27) | (19.43) | (18.38) | (16.88) | (18.93) |
| $N$ | 300 | 300 | 300 | 300 | 300 | 300 | 300 | 300 | 300 | 300 | 300 | 300 |
| $R^2$ | 0.0108 | 0.0671 | 0.0436 | 0.0293 | 0.0543 | 0.1712 | 0.0649 | 0.0207 | 0.0493 | 0.0672 | 0.1224 | 0.0806 |
| adj. $R^2$ | 0.0041 | 0.0609 | 0.0372 | 0.0228 | 0.0479 | 0.1657 | 0.0586 | 0.0141 | 0.0429 | 0.0609 | 0.1165 | 0.0744 |

maximum daily return is at its highest (coefficients for $\beta^{High}$ are positive and statistically significant). This finding suggests that there is no evidence of individual stock return herding in months in which the average firm in the industry attracts attention based on extreme positive returns. However, we also find that for ten out of the twelve industries considered, the cross-sectional standard deviation of returns around the industry average significantly decreases in months in which the industry's average minimum daily return is at its highest (coefficients for $\beta^{Low}$ are negative and statistically significant). For example, we find that for the Consumer Non-Durables (1) and Health Care (10) industries, both $\beta^{Low}$ are -0.67 and -0.90 with t-statistics of -2.99 and -3.77 respectively. This evidence is consistent with the existence of individual stock return herding in ten out of twelve industries, in months where the average firm in the industry attracts attention based on extreme negative returns. Finally, using CSAD as the dependent variable (as reported in Panel B of Table 4), we find results quantitatively and qualitatively similar to those reported in Panel A.

## Good News, Bad News and Herding

The evidence reported in Table 4 suggests that individual stock return herding around the industry average is concentrated in months in which firms in the various industries attract attention for earning extreme negative returns. Motivated by this finding, we investigate the herd behavior of individual stock returns around their industry average in months in which the industry received good or bad news. George and Hwang (2004) argue that stocks whose current prices are near (far) from their fifty-two-week high are those for which good (bad) news recently reached the market. To proxy for the arrival of industry wide good or bad news, we compute each industry's GH ratio (IGH) as the average of the individual stock distance to their respective fifty-two-week high prices. See equation (4).

Next, for each industry, we sort our sample based on the industry's average GH ratio and assign indicator variables to months in the top (HGH) and bottom (LGH). Therefore, HGH is an indicator variable for months in the highest decile of months ranked based on the industry's average GH ratio, identifying the months for which the given industry received good news. Similarly, LGH is an indicator variable for months in the lowest decile of months ranked based on the industry's average GH ratio, identifying the months for which the given industry received bad news. Finally, we estimate the following models:

$$CSSD_{j,t} = \alpha + \beta^{High} HGH_{j,t} + \beta^{Low} LGH_{j,t} + \varepsilon_{j,t} \quad (9)$$

$$CSAD_{j,t} = \alpha + \beta^{High} HGH_{j,t} + \beta^{Low} LGH_{j,t} + e_{j,t} \quad (10)$$

where CSSD and CSAD are defined and computed as described earlier. We report the results of this exercise in Table 5. Interestingly, we find in Panel A of Table 5 that for seven out of the twelve industries considered, the cross-sectional standard deviation of returns around the industry average significantly decreases in months in which the industry's average GH ratio is at its highest (coefficients for $\beta^{High}$ are negative and statistically significant). For example, we find that for the Manufacturing (3) and Retail (9) industries, both $\beta^{Low}$ are -0.47 and -0.64 with t-statistics of -2.17 and -2.86 respectively. This finding suggests that for a majority of industries in our sample, there exists evidence of individual stock returns around the industry average when the industry receives good news. We also find that for ten out of the twelve industries considered, the cross-sectional standard deviation of returns around the industry average significantly increases in months in which the industries receive bad news or when the industry average GH ratio is at its lowest ($\beta^{Low}$ are positive and statistically significant). These findings are qualitatively and quantitatively similar to those reported in Panel B of Table 5 where we employ the cross-sectional absolute deviation of returns as the dependent variable.

## IV Conclusion

Recent evidence on the behavior of individual stock returns highlights the importance of herding in financial markets, particularly in stressful market conditions. In this paper, we revisit the notion that individual stock returns herd around their industry averages in stressful market conditions. Using the Volatility index (VIX) and the St. Louis Federal Reserve Financial Stress index (FSI) as measures market condition, we find evidence that herding appears to exist in months where VIX or FSI are at their lowest. In other words, individual stock returns herd around their industry average in calm, not stressful market conditions. In stressful markets, we find no evidence of individual stock return herding around their industry average. This finding is consistent with Christie and Huang (1995) and Chang, Cheng, and Khorana (2000) among others.

Building on the evidence of Barber and Odean (2007) who report that individual investors are net buyers of attention-grabbing stocks, defined as those experiencing extreme one-day returns and on Bali, Cakici and Whitelaw (2011) who find that investors exhibit a preference for stocks with extreme positive returns, we examine the herd behavior of individual stock returns in months when the industry attracts significant attention based on their recording of unusually high or low returns. We generally find that herding is concentrated in months in which the industries record the worst average daily returns (minimum daily returns), suggesting that herding is present in industries that attract attention for earning negative returns. Motivated by this latter finding, we build on the behavioral models of Hirshleifer, Subrahmanyam, and Titman (1994) and Banerjee (1992) among others to examine the herd behavior of individual stock returns in months where the industries receive good or bad news. Using the industry level average stock distance to the fifty-two-week high to capture the arrival of good or bad news as in George and Hwang (2004), we find that herding is concentrated in months where the industries receive good news and not bad news.

Overall, our study contributes to the literature in a few ways. First, we offer fresh evidence of the herd behavior of individual stock returns around their industry average in calm rather than stressful market conditions. Next, we document the herd behavior of individual stock returns in months in which the average firm in the industry records extreme negative rather than positive returns, and in months in which the average firm in the industry receives good rather than bad news. To the best of our knowledge, we are the first to document these latter findings. Ultimately, we offer new insight on the herd behavior of individual stock returns in financial markets. While we do not attempt to explain the apparent asymmetries documented in this study, we leave that for future research.

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# Effect of C-Suite Members' Social Network Capital on Tail Risk

Amy Fairfield*

**Abstract**

The purpose of this research is to analyze the impact of the CEO's and CFO's social network capital on tail risk. The CEO and CFO are the most dominant members of the top management team. Relationships between the CEO, CFO, and a firm's stakeholder groups (shareholders, employees, customers and suppliers, society, the environment, and government) form to create a social network that can evolve into social capital. I tested whether the CEO and CFO, with high social capital, can reduce the probability of their company stock persistently landing in the bottom 10% of yearly returns. Various stakeholders in the hierarchy of a social capital network can contribute to this prevention. I found the CFO total connections variable significant in the base model, the full model, and several subsample models. The interesting result was that CFO and CEO total connections were significant with market risk but not idiosyncratic risk.

**Keywords:** tail risk, CEO, CFO, top management team, C-suite, social capital, social network

## I Introduction

The chief executive officer (CEO) and chief financial officer (CFO), as members of the top management team, are responsible for key corporate strategic initiatives, including financial responsibilities that could impact the company's stock price (Amoozegar, Pukthuanthong, & Walker, 2017). If the market perceives bad news, it reacts accordingly, potentially resulting in extreme negative returns known as tail risk. The stock return of any publicly traded company has the potential to land in the bottom 10% of returns on any given day; it is the persistence of the stock returns landing in the bottom 10% that brings an unfortunate circumstance against which greater social capital may guard. Uncertainty in the market will always exist; strategic managers will be key resources and in times of trouble, social capital may be essential as well.

The purpose of this research is to analyze the relationship between social network capital of both the CEO and CFO and tail risk (defined here as market risk—the average return below the 10th percentile of the yearly distribution of the predicted returns from the market model—and idiosyncratic risk—the average return below the 10th percentile of the yearly distribution of the residuals from the market model; Srivastav, Keasey, Mollah, & Vallascas, 2017), as shown in Figure 1.

The CEO and CFO are members of the top management team and hold the top two positions in the C-suite. These two members of the C-suite have connections with many individuals, throughout their organization, their industry, and the business world at large as well as in their social circles (Bhandari, Mammadov, Shelton, & Thevenot, 2018). Cao, Simsek, and Jansen (2015) referred to the internal relationships as intrafirm and external relationships as interfirm. All these connections make up a member's social network and offer the potential for creation of social capital (Fracassi, 2017; Kanihan, Hansen, Blair, Shore, & Myers, 2013; Pappas, Ongena, Izzeldin, & Fuertes, 2017). The value of social capital is rising, taking its place right next to financial capital (Agarwal, Bersin, Lahiri, Schwartz, & Volini, 2018).

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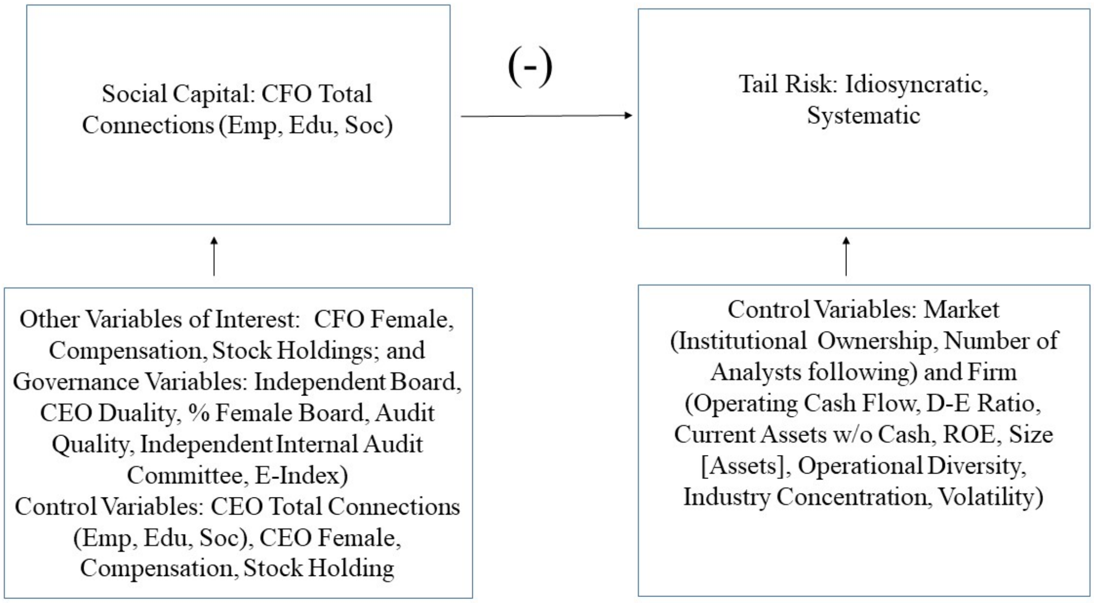
**Figure 1: Conceptual framework of the model.**




This model delineates the conceptual framework of the model I used in the study. Tail risk is the dependent variable, operationalized by idiosyncratic and systematic risk. Social capital is the independent variable operationalized by CFO and CEO total connections. Several variables of interest and control variables are used interchangeably to test various models. The companies' yearly stock return is multiplied by -1 such that higher values indicate a higher exposure to extreme negative returns. Control variables (that affect financial measurements) were added as were market and governance variables. See Appendix A for variable definitions.

In this study, I tested the relationship between tail risk and social network capital. I also included myriad financial variables as control variables and to explore as variables of interest. I used profitability, leverage, and market value ratios; included variables for volatility; and incorporated governance variables. In addition, I controlled for industry and year fixed effects.

The valuation process is becoming more sophisticated. It is not easy for the price of a security to be determined by the intersection of the demand and supply curves or for the market to value a company based on its earnings (Miller, 1977). Ex post investment results cannot be used to measure ex ante investor expectations (Miller, 1977). The type of distribution with the best indication of stock returns has been a debate since the early 1960s, when *fat tails* were first analyzed (Fama, 1963). Tail risk often occurs in systematic macro crises when liquidity is an issue, and not until the global financial crisis of 2007 did tail risk emerge as a serious concern for practitioners and as a topic of interest to academics as well (Andersen, Fusari, & Todorov, 2019; Bollerslev, Todorov, & Xu, 2015; Kaya, Lee, & Pornrojnangkool, 2011). Hedging, as a form of insurance against tail risk, has also gained in popularity as a financial tool (Kaya et al., 2011). The need for further research into variables that impact tail risk is the motivation for this study.

According to upper echelons theory, the firm is a representation of its leaders (Hambrick & Mason, 1984). Similar background characteristics provide a backdrop for leaders on the top management team to have crossed paths with many individuals who ultimately make up their social network (Hambrick & Mason, 1984; Bowen & Bowen, 2016; Liu, 2014; Nahapiet &

Ghoshal, 1998). I relied on upper echelons theory to support the positions of CEO and CFO having the power to use their social capital for the benefit of their company (Khanna, Kim, & Lu, 2015). Social capital theory supports the connectedness of the CEO, CFO, and their social network. Fisher-Tippett extreme value theory addresses the area of the distribution wherein tail risk occurs (Basrak, 2011). Bringing these theories together forms the foundation for my analysis.

I utilized ordinary least squares regression with panel data and tested the impact of CEO and CFO social capital on tail risk. I analyzed the results to determine a reliable conclusion about the impact of CEO and CFO connectedness on tail risk.

Previous literature has explored the relationship between the C-suite and social capital. There is a small body of literature that has shown a relationship between the C-suite and tail risk and an even smaller body of literature that has shown a relationship between social capital and tail risk. However, there is a gap in the literature void of these three variables being examined together. Analyzing the relationship between CEO and CFO social networks and tail risk is important because extreme negative returns have a negative effect on market capitalization and valuations. The market often overreacts to various noisy signals that may be somewhat misguided. Having a social network to assist in the prevention (or management) of situations causing extreme negative events represents strategic effectiveness on the part of the CEO and CFO (Khanna et al., 2015). Analyzing the relationship between the CEO and CFO social network and tail risk provides an indication of the network's persuasive ability, for example, to obtain additional financing (Fracassi, 2017; Javakhadze, Ferris, & French, 2016).

This topic is also important from a regulatory perspective (Van Bekkum, 2016) as well as for finance professionals. Although the concept of tail risk has been studied for several decades, after the global financial crisis of 2007, practitioners began to show an increase in the level of interest for managing tail risk and academics began to show an increase in the level of examination of how tail risk might explain a particular phenomenon (Andersen et al., 2019; Bollerslev et al., 2015; Kaya et al., 2011). As an example, research on securitization agents (vice presidents who work at major investment houses) having prior knowledge of the housing bubble (and the impending crisis) did not produce any systematic evidence; however, Cheng, Raina, and Xiong (2014) suggested future research is needed. They suggest the entire financial system would benefit from greater transparency of tail risk (Cheng et al., 2014). Providing greater understanding of increased tail risk disclosures could assist regulatory bodies in enacting appropriate laws to prevent such a crisis from happening again. Providing an avenue for more transparency will enable better financial decision-making (Hutton, Marcus, & Tehranian, 2009). It is likely that many CFOs work at banks or deal with bankers; CFOs may have a trader working for them or have an investment firm that manages their company's trades. All of these connections are part of the network in which the CEO and CFO might belong that can help them effectively manage their tail risk.

## II Literature Review and Hypothesis Development

Upper echelons theory states that the firm is a representation of those who lead it, that is, the top management team (Hambrick & Mason, 1984). Social capital theory describes the process by which capital is captured and reproduced for returns (Lin, Burt, & Cook, 2001). Using upper echelons theory, Ullah, Ur Rehman, Hameed, and Kayani (2017) found social capital to be a mediator between ethical leadership and corporate social responsibility. LeCounte, Prieto, and Phipps (2017) drew on social capital with regards to CEO succession planning; oftentimes the heir apparent is the CFO. For the purpose of this research, I specifically refer to the CEO and CFO.

The CEO and CFO are the top two positions in the C-suite—a circle of power consisting of seven members whose titles begin with chief—executive officer, financial officer, operations officer, human resources officer, general counsel, marketing officer, and information officer (Groysberg, Kelly, & MacDonald, 2011; LeCounte et al., 2017). Collectively, this group makes up the top management team. The top management team is a dominant coalition of the organization (Hambrick & Mason, 1984), driving organization outcomes by way of its strategic initiatives. Hambrick and Mason (1984) relied on background characteristics, such as functional background, education, and socioeconomic roots, to develop their (upper echelons) theory; these characteristics provide a backdrop for members of the top management team to have crossed paths with many individuals who ultimately make up their social networks. For this analysis, the focus is on the top two positions in the C-suite: CEO and CFO. Relationships are formed between the CEO and CFO and their firm's stakeholder groups (shareholders, employees, customers and suppliers, society, the environment, and government; Cao et al., 2015; Fracassi, 2017; Rezaee, 2016). As these relationships develop, trust is built, and the social network evolves into social capital (Bowen & Bowen, 2016; Liu, 2014; Nahapiet & Ghoshal, 1998). CEOs and CFOs are responsible to these stakeholder groups for the strategic direction of their organization, and they must work effectively and efficiently to manage their firm's status as an ongoing entity. As leaders, CEOs and CFOs need to develop interpersonal relationships to build social capital. The connections will be necessary to enable leaders to influence, work well with others, and make a difference in their organizations (Elkington, Pearse, Moss, Van, & Martin, 2017).

Social capital is "the sum of the actual and potential resources embedded within, available through, and derived from the network of relationships possessed by an individual or social unit" (Nahapiet & Ghoshal, 1998, p. 243). In a business sense, social capital is an investment in social relations with expected returns (Lin, 1999).

Social connections do not, however, come without a cost; developing social ties takes an investment of time and energy on the part of executives (Cao et al., 2015). Cao et al. (2015) describe a CEO's bonding social capital as the social connections with organizational members from various functional units within the firm. The other type of connection Cao et al. (2015) describe is a CEO's bridging social capital; this refers to social connections with individuals from a diverse set of external organizational stakeholder groups, such as customers, suppliers, competitors, partners, financial agencies, industrial authorities, and government agencies. Bridging social capital provides an executive with an avenue to access new, valuable, and strategic information for their firm.

Market noise, agency concerns, and especially information asymmetry can impede seamless decision-making processes. Javakhadze et al. (2016) argued that social capital is a mechanism that potentially alleviates the forces that keep a CFO from becoming successful in today's modern corporate financial environment. Frazzini, Malloy, and Cohen (2008) also studied the impact of social networks on executives' ability to gather superior information about firms. They tested whether analysts gain comparative information advantages through their social networks by way of educational ties with executives and board members of firms they cover (Frazzini et al., 2008). Their findings suggested that the most likely mechanism driving the superior performance of analysts on their school-tied recommendations is direct information transfer (Frazzini et al., 2008).

Cai and Sevilir (2012) examined merger and acquisition transactions between firms with current board connections. They studied two types of board connections: the first type is where the two firms share a common director before the deal announcement; this is referred to as a first-degree connection (Cai & Sevilir, 2012). The second type is where one director from the acquiring firm and one director from the target firm have been serving on the board of a third firm before the deal announcement; this is referred to as a second-degree connection (Cai & Sevilir, 2012). Their results provided new evidence that board connectedness enhances knowledge and improves information flow (Cai & Sevilir, 2012).

With a constantly changing business environment and a noticeable increase in the power of millennials, the importance of social capital is on the rise (Agarwal et al., 2018). The rise in social capital will bode well for members of the C-suite as they strategically lead their company to be an ongoing entity while avoiding tail risk (i.e., avoiding a perpetuating spot in the bottom 10% of the yearly stock return distribution). Social capital can play an integral part in the financial space by maintaining stock price (Engelberg, Gao, & Parsons, 2012) and market capitalization.

The CEOs and CFOs play an instrumental role in controlling risk for their companies. Research has shown that when the person responsible for risk management participates in the corporate governance process and has sufficient power to maintain Securities and Exchange Commission (SEC) regulations, the firm's potential for litigation is reduced and stock price performance improves (Amoozegar et al., 2017). Since the enactment of the Sarbanes-Oxley Act (SOX), CEOs and CFOs have increased accountability and thus are in a position to manage their organizations' risk by properly controlling tail risk (Alkhafaji, 2007; Schminke, Arnaud, & Keunzi, 2007).

Tail risk is extreme negative equity returns defined in this research as the average return below the 10th percentile of the yearly distribution of returns. A key assumption of the capital asset pricing model is that all investors are expected to have the same distribution of returns. Fama (1963) suggested that Mandelbrot's stable Paretian hypothesis will challenge the Gaussian hypothesis (which states the distribution of price changes in a speculative series are approximately normal). The extreme tails of distributions are higher (containing more of the probability), indicating higher yields but also greater losses (Fama, 1963). An investigation into the shape of tails, that is, fat tail behavior, ensued (Akgiray & Booth, 1988; Blattberg & Gonedes, 1974; Hill, 1975; Hols & de Vries, 1991; Jansen & de Vries, 1991). The Fisher-Tippett theorem is the foundation for extreme value theory, an identification of all extreme value distributions (Basrak, 2011). Bali (2003); Gencay and Selcuk (2004); Marimoutou, Raggad, and Trabelsi (2009) have used extreme value theory to investigate share price distributions and the behavior of tails.

Subsequently, value-at-risk (VAR) became a popular risk management tool (Beder, 1995; Duffie & Pan, 1997; Simons, 1996), but there was not a consistent approach for calculating VAR and researchers continued to look for a better way to measure risk. Later, Rockafellar and Uryasev (2000) introduced conditional value-at-risk (CVAR), also known as mean (expected) shortfall (ES; Acerbi, 2002; Acerbi, Nordio, & Sirtori, 2001). The CVAR, or ES, has much better properties than VAR and is considered a more consistent measure of risk (Rockafellar & Uryasev, 2000).

Ellul and Yerramilli (2013) analyzed tail risk as the main risk measure of interest for banks. They acknowledged that banks are in the risk-taking business, and they developed a risk management index to measure the strength of the bank risk management function (Ellul & Yerramilli, 2013). In this context, tail risk is based on the ES measure that is used within financial firms to capture the anticipated loss depending on returns; Ellul & Yerramilli (2013) used tail risk as the dependent variable in their research.

Van Bekkum (2016) used a sample of CEOs and CFOs from small and large U.S. banks, describing stockholder and debtholder risk using tail risk. The study used ES rather than VAR as it provides a better indication of the worst $100\alpha\%$ of cases by indicating average loss suffered in the lower tail of the return distribution; ES was used as a DV in a cross-sectional regression model (Van Bekkum, 2016).

Srivastav et al. (2017), the research on which I based my definition of tail risk, used ES. Srivastav et al. (2017) showed that there is a relationship between tail risk and the CEO; they indicated in their findings that the possibility of a forced CEO turnover in large banks is positively associated with idiosyncratic tail risk. Interestingly, member(s) of the board of directors (one of the characters in the social capital network) were not supportive of the CEO in this bank research; the board was not supportive because the CEO takes undue risk, putting their organization in jeopardy by not managing the downside of bank risk (i.e., extreme negative stock returns; Srivastav et al., 2017). Srivastav et al. (2017) used ES to measure the bank's tail risk exposure. For this analysis, I used ES to measure the market component of tail risk, looking at firms' stock returns landing in the bottom 10% of the yearly return distribution, and the residuals from a market model to measure idiosyncratic risk.

For this study, I examined whether social capital could help ensure that stock returns avoid persistently landing in the bottom 10% of the yearly stock return distribution. I combined upper echelons theory, social capital theory, and extreme value theory to predict that the CEO and CFO, with high social capital, will work diligently with members of their social network to prevent extreme negative returns. Formally stated, my hypothesis is:

> $H_1$: The CEO and CFO will use their social network capital to keep their firm's stock price return from persistently landing in the bottom 10% of the yearly stock return distribution.

Led by the CEO and CFO, the top management team will work strategically to maintain the company stock price and stock returns. They are motivated to do this for various reasons: for the financial health of the company, especially in the eyes of creditors, if the need would arise for additional financing; for their own financial gain; to decrease the likelihood of a takeover; and to be viewed positively in the media, with the perception that they are acting in the best interest of all stakeholders. Both the media and stakeholders keep a watchful eye on stock prices, as stock prices serve as an indicator of how well companies are performing. Collecting stock price returns is the first step toward discovering the relationship between the CEO and CFO social network capital and tail risk. In the next section, the development of that relationship is discussed.

## III Methodology

In this section, I will present my research design. First, I discuss how I captured the key construct in my study, that is, tail risk. Second, I discuss how I proxied for CEO and CFO social capital. Then I present the model used to test my hypothesis on tail risk.

### Measures

*Tail risk*

The concept of tail risk has been evolving for many decades as a risk management tool. The CVAR, also known as ES, is considered a consistent measure of risk (Acerbi, 2002; Acerbi et al., 2001). After the global financial crisis in 2007, tail risk became a more prominent financial metric to help companies in their risk management function (Andersen et al., 2019; Bollerslev et al., 2015;

Kaya et al., 2011). Research into banks' mismanagement of risk, and their ultimate failure, led to the use of ES to measure tail risk (Cheng et al., 2014; Srivastav et al. 2017).

Tail risk has two components: market and idiosyncratic risk. Following Srivastav et al. (2017), I captured the market component using ES to determine the average yearly return below the 10th percentile of the yearly return distribution:

$$ES_i^{\alpha} = -E[R_{i,t} \mid R_{i,t} < R_{i,t}^{\alpha}] \quad (1)$$

where $R_{i,t}$ is the yearly stock return for company *i* at day *t*, and $R_{i,t}^{\alpha}$ is a company's yearly stock return equal to α percentile of the year *t* distribution (multiplied by -1 such that higher values indicate a higher exposure to extreme negative returns).

The idiosyncratic component of a company's yearly stock returns, computed by way of the residuals from a market model (regressed on market returns and industry returns), is shown as:

$$R_{i,t} = \beta_1 + \beta_2 R_{m,t} + \beta_3 R_{b,t} + \varepsilon_{j,t} \quad (2)$$

where $R_{i,t}$ is the return for stock *i* at time t, $R_{m,t}$ is the yearly return of the market index, $R_{b,t}$ is the yearly return of the industry index. The error term captures the residuals, which is the idiosyncratic component of tail risk. The directions for calculating tail risk, along with the Stata code, can be provided upon request.

Since tail risk is influenced by many other factors, I included several additional variables in my model. For operating cash flow, current assets without cash, and acquisitions, I used the natural log to eliminate outliers. Several company characteristics may affect tail risk; thus, it was necessary to include two groups of control variables. The first group controlled for financial and market-based variables, for example, firm size and return on assets (Ayers, Ramalingegowda, & Yeung, 2011; Zhao & Chen, 2008). The second group included market controls: institutional holdings and the number of analysts following a company. All control variables were lagged one year. Another group of variables were added as variables of interest; this group consisted of corporate governance characteristics, for example Big 4 auditors (Chang, Dasgupta, & Hilary, 2009); CEO age and CEO duality (as Chair) on the board (Ayers et al., 2011; Fairfield, 2021); and entrenchment (Morck, Shleifer, & Vishny, 1988). All models were checked with winsorized data, with supporting results. To minimize the impact of time-invariant year and industry characteristics, year- and industry-fixed effects were also included. See Appendix A for variable definitions.

*Social capital*

Social capital emerges when someone you know well can be trusted when seeking advice or who you may be assured will accomplish things efficiently and effectively (Smith, 2009). Social capital is measured by the number of interactions and relationships between executives and other executives (Nahapiet & Ghoshal, 1998). I followed Bhandari et al. (2018) to proxy social network. The variables used to determine social network were CEO and CFO connections with other CEOs and CFOs and board of director members, CEO and CFO prior year employment connections, CEO and CFO education connections, and CEO and CFO social connections. See Appendix A for variable definitions.

## Data analysis

### *Empirical model*

Ordinary least squares regression with panel data was used to examine the impact of CEO and CFO social network on tail risk, (both market and idiosyncratic components). I included profitability, leverage, and market value ratios. I also included variables for volatility and incorporated governance variables as well. In addition, I controlled for industry and year fixed effects. The following variables were utilized: industry Concentration (Herfindahl-Hirschman index), operational diversity (segments), total assets, acquisitions, operating cash flows, debt-to-equity ratio, current assets without cash, ROE, volatility (standard deviation of ROE), institutional ownership (percentage), analysts following, independent board (percentage), CEO duality (as Chair of the Board), female board (percentage), independent internal audit committee, audit quality, entrenchment index, female CFO, female CEO, CFO compensation, CEO compensation, CFO stock holdings, and CEO stock holdings (Morck et al., 1988). These variables of interest were used interchangeably as control variables to test various models. The following regression equation was tested to determine if there was any statistical significance to explain the relationship between social network (and other variables of interest) and tail risk.

$$\text{Tail Risk} = \text{Intercept} + \text{Beta} * \text{Total Connections} + \text{Beta} * \text{Other Variables of Interest} + \text{Beta} * \text{Governance Variables} + \text{Beta} * \text{Firm Control Variables} + \text{Beta} * \text{Market Control Variables} + \text{error} \quad (3)$$

Based on my hypothesis, I expected a negative sign for the beta coefficient on Total Connections.

$$\text{Tail Risk} = \beta_0 + \beta_1 * \text{CFOtotcon} + \beta_2 * \text{CEOtotcon} + \beta_3 * \text{fCFO} + \beta_4 * \text{CFOtotcomp} + \beta_5 * \text{CFOstock} + \beta_6 * \text{fCEO} + \beta_7 * \text{CEOtotcomp} + \beta_8 * \text{CEOstock} + \beta_9 * \text{indbrd} + \beta_{10} * \text{CEOchair} + \beta_{11} * \text{femdirs} + \beta_{12} * \text{auditq} + \beta_{13} * \text{indaudcom} + \beta_{14} * \text{eindex} + \beta_{15} * \text{ocf} + \beta_{16} * \text{deratio} + \beta_{17} * \text{cawocash} + \beta_{18} * \text{roe} + \beta_{19} * \text{lnat} + \beta_{20} * \text{segments} + \beta_{21} * \text{indusconc} + \beta_{22} * \text{volatil} + \beta_{23} * \text{acq} + \beta_{24} * \text{insthold} + \beta_{25} * \text{numanalst} + \varepsilon_{j,t} \quad (4)$$

where Tail Risk is measured by idiosyncratic risk and market risk. CFO total connections and CEO total connections are the variables of interest; other variables of interest are whether the CFO and CEO are female, CFO and CEO total compensation, and stock holdings of both CFO and CEO. Additional variables of interest include several governance variables: the percentage of independent board members, whether the CEO is also the Board Chair, the percentage of female board members, audit quality, if there is an independent internal audit committee, and the entrenchment index. Firm controls are as follows: operating cash flow, debt-to-equity ratio, current assets without cash, ROE, the natural log of total assets, the number of company segments, industry concentration, a volatility measure, and acquisitions. Market control variables include institutional holding percentage and the number of analysts following a company.

*Sample*

The sample began post-SOX, covering thirteen years from 2003 through 2016, and consisted of all U.S. firms with available data. I obtained firms' financial data from the annual Compustat database, return data from CRSP database, governance data from BoardEx database, and salaries data from the Execucomp database. The final sample size for the primary analysis was 88,694 observations. Firm-year observations with missing information were deleted. I ran the models with raw data; I also winsorized all continuous variables at the top and bottom one percentile of their distributions to normalize the data and confirm the results. The following section discusses the results.

## IV Results

### Descriptive statistics

Table 1 presents the descriptive statistics for all the variables I used in this analysis. There are two dependent variables used to measure tail risk: market risk and idiosyncratic risk, representing the lowest 10% decile.

As a robustness test, I also ran models for 5% and 20%. The results for 5% were inconsistent, leaving a very small number of firms to merge with the CFO and CEO social network and other variables of interest. In addition, to keep more data, I scaled up the database since it is in percentage format. The results held for both raw and winsorized data.

**Table 1: Descriptive Statistics**

| Variable | Observations | M | SD | Q1 | Median | Q3 |
|---|---|---|---|---|---|---|
| *idiorisk* | 54,894 | -0.603 | 1.617 | -1.648 | -0.855 | 0.129 |
| *mktrisk* | 54,894 | 5.059 | 0.863 | 4.526 | 4.866 | 5.385 |
| *CFOtotcon* | 3,539 | 103.412 | 321.858 | 0.000 | 0.000 | 22.000 |
| *CEOtotcon* | 4,332 | 293.608 | 506.994 | 0.000 | 81.000 | 342.000 |
| *CFOgender* | 3,506 | 0.095 | 0.293 | 0.000 | 0.000 | 0.000 |
| *CEOgender* | 4,313 | 0.034 | 0.181 | 0.000 | 0.000 | 0.000 |
| *CFOtotcomp* | 3,539 | 7.120 | 1.082 | 6.573 | 7.195 | 7.772 |
| *CEOtotcomp* | 2,563 | 8.261 | 0.964 | 7.636 | 8.344 | 8.922 |
| *CFOstock* | 3,539 | 4.178 | 1.792 | 3.387 | 4.473 | 5.348 |
| *CEOstock* | 2,563 | 1.665 | 4.257 | 0.000 | 0.247 | 1.400 |
| **Governance** | | | | | | |
| *indbrd* | 3,365 | 0.776 | 0.121 | 0.714 | 0.800 | 0.875 |
| *CEOchair* | 3,365 | 0.203 | 0.402 | 0.000 | 0.000 | 0.000 |
| *femdirs* | 3,365 | 0.121 | 0.106 | 0.000 | 0.111 | 0.182 |
| *auditq* | 41,570 | 0.611 | 0.487 | 0.000 | 1.000 | 1.000 |
| *indaudcom* | 20,111 | 0.977 | 0.149 | 1.000 | 1.000 | 1.000 |
| *eindex* | 31,818 | 2.468 | 1.562 | 1.000 | 3.000 | 4.000 |
| **Market Controls** | | | | | | |
| *insthold* | 38,546 | 0.238 | 0.295 | 0.012 | 0.120 | 0.190 |
| *numanalst* | 38,256 | 15.973 | 16.715 | 2.000 | 5.000 | 41.000 |
| **Firm Controls** | | | | | | |
| *ocf* | 58,789 | 4.270 | 2.528 | 2.567 | 4.459 | 6.062 |

| Variable | Observations | M | SD | Q1 | Median | Q3 |
|---|---|---|---|---|---|---|
| *deratio* | 63,272 | 3.613 | 391.114 | 0.000 | 0.125 | 0.659 |
| *cawocash* | 82,274 | 4.091 | 2.541 | 2.070 | 4.190 | 5.924 |
| *roe* | 64,205 | -0.229 | 56.255 | -0.100 | 0.075 | 0.184 |
| *lnat* | 88,694 | 5.542 | 2.784 | 3.539 | 5.635 | 7.552 |
| *segments* | 88,694 | 12.061 | 10.256 | 5.000 | 9.000 | 17.000 |
| *indusconc* | 88,694 | 1.37E+27 | 4.07E+29 | 0.108 | 0.156 | 0.224 |
| *volatil* | 49,182 | 2.120 | 36.932 | 0.032 | 0.093 | 0.354 |
| *acq* | 83,090 | 0.982 | 1.897 | 0.000 | 0.000 | 0.974 |

Table 1 provides descriptive statistics for the variables of interest. *mktrisk* represents market risk, the average return below the 10th percentile of the yearly distribution of the predicted returns from the market model; *idiorisk* represents idiosyncratic risk, the average return below the 10th percentile of the yearly distribution of the residuals from the market model; *CFOtotcon* is the number of total CFO connections; *CEOtotcon* is the number of total CEO connections; *fCFO* indicates whether the CFO is female (1) or not (0); *fCEO* indicates whether the CEO is female (1) or not (0); *CFOtotcomp* represents the CFO total compensation; *CEOtotcomp* represents the CEO total compensation; *CFOstock* represents the total value of restricted stock granted to the CFO plus the total value of stock options granted to the CFO; *CEOstock* represents the total value of restricted stock granted to the CEO plus the total value of stock options granted to the CEO; *indbrd* represents the percentage of independent board members; *CEOchair* indicates whether the CEO is also Chair of the Board (1) or not (0); *femdirs* stands for female directors, the percentage of female board members; *auditq* represents audit quality, 1 if a Big Four, 0 otherwise; *indaudcom* represents independent audit committee, 1 if audit committee is independent, 0 otherwise; *eindex* represents entrenchment index, as developed by Bebchuk, Cohen, and Ferrell (2009); *ocf* represents the natural log of operating cash flows, the net change in cash from all items classified in the operating activities section on a Statement of Cash Flows; *deratio* represent the debt-to-equity ratio; *cawocash* represents the natural log of current assets without cash; *roe* represents return on equity; *volatil* represents volatility, measured by the standard deviation of ROE; *lnat* is the natural log of total assets, used to measure firm size; *segments* represents the product or service segments of a company; *indusconc* represents industry concentration, measured by the Herfindahl-Hirschman index ; *acq* represents the natural log of acquisitions; *insthold* represents the percentage of holdings by institutional investors; *numanalst* represents the number of analysts following a company; Q1 represents the first quarter; Q3 represents the third quarter.

Since the global financial crisis of 2007, tail risk has been a topic of greater interest to researchers and a growing concern for financial executives (Andersen et al., 2019; Bollerslev et al., 2015; Kaya et al., 2011). Social capital and the network of connections play an important role for executives to gain helpful information.

In addition to the social network variables, I included three more variables of interest for both the CFO and CEO: gender, total compensation, and holdings (restricted stock and stock options granted). I also included nine firm performance control variables, two market control variables, and six governance variables. The firm performance variables are as follows: operating cash flows, debt-to-equity ratio, current assets without cash, ROE, natural log of total assets, operational diversity (segments), industry concentration (HHI), volatility (standard deviation of ROE), and acquisitions. The market control variables are percentage of institutional ownership and number of analysts following a company. The governance variables are as follows: percentage of independent board, CEO duality (as Chair of the Board), percentage of female board members, audit quality, independent audit committee, and entrenchment index.

Table 2 presents the correlation among all the variables included in this analysis. The natural log of current assets without cash was highly correlated with the natural log of operating cash flow and the natural log of total assets. Likewise, the natural log of total assets was highly correlated with the natural log of operating cash flow.

## Table 2: Correlation Matrix

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) | (17) | (18) | (19) | (20) | (21) | (22) | (23) | (24) | (25) | (26) | (27) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) *idiorisk* | 1 | | | | | | | | | | | | | | | | | | | | | | | | | | |
| (2) *mktrisk* | -0.22[a] | 1 | | | | | | | | | | | | | | | | | | | | | | | | | |
| (3) *CFOtotcon* | 0.04[b] | -0.05[a] | 1 | | | | | | | | | | | | | | | | | | | | | | | | |
| (4) *CEOtotcon* | 0.00 | -0.03[c] | 0.2[a] | 1 | | | | | | | | | | | | | | | | | | | | | | | |
| (5) *fCFO* | 0.03 | 0.00 | 0.03[c] | 0.05 | 1 | | | | | | | | | | | | | | | | | | | | | | |
| (6) *fCEO* | -0.01 | -0.01 | 0.03 | 0.05[a] | 0.01 | 1 | | | | | | | | | | | | | | | | | | | | | |
| (7) *CFOtotcomp* | -0.17[a] | -0.02 | 0.21[a] | 0.21[a] | -0.01 | 0.05 | 1 | | | | | | | | | | | | | | | | | | | | |
| (8) *CEOtotcomp* | -0.19[a] | -0.02 | 0.23[a] | 0.28[a] | 0.08 | 0.02 | 0.72[a] | 1 | | | | | | | | | | | | | | | | | | | |
| (9) *CFOstock* | 0.02 | 0.01 | 0.09[a] | 0.03 | -0.03 | -0.06[c] | 0.25[a] | 0.30[a] | 1 | | | | | | | | | | | | | | | | | | |
| (10) *CEOstock* | 0.05[a] | 0.03 | -0.05 | -0.09[a] | 0.13[a] | -0.02 | -0.11[b] | -0.18[a] | -0.02 | 1 | | | | | | | | | | | | | | | | | |
| (11) *indbrd* | -0.09[a] | -0.06[a] | 0.01 | 0.21[a] | -0.02 | -0.00 | 0.19[a] | 0.25[a] | 0.06 | -0.13[a] | 1 | | | | | | | | | | | | | | | | |
| (12) *CEOchair* | 0.08[a] | 0.08[a] | 0.02 | -0.08[b] | -0.01 | -0.07[c] | -0.13[a] | -0.05 | 0.04 | -0.08[b] | -0.08[a] | 1 | | | | | | | | | | | | | | | |
| (13) *femdirs* | -0.11[a] | -0.05[a] | 0.16[a] | 0.18[a] | -0.04 | 0.22[a] | 0.22[a] | 0.22[a] | 0.05 | -0.15[a] | 0.29[a] | -0.03[c] | 1 | | | | | | | | | | | | | | |
| (14) *auditq* | -0.19[a] | 0.06[a] | 0.09[a] | 0.11[a] | -0.01 | 0.06[b] | 0.30[a] | 0.21[a] | 0.01 | -0.10[b] | 0.13[a] | 0.03[b] | 0.14[a] | 1 | | | | | | | | | | | | | |
| (15) *indaudcom* | 0.01 | 0.03[a] | -0.16[a] | -0.01 | -0.02 | 0.02 | 0.01 | 0.01 | 0.01 | -0.31[a] | 0.03 | 0.01 | 0.02 | 0.03[a] | 1 | | | | | | | | | | | | |
| (16) *eindex* | 0.28[a] | 0.13[a] | 0.04 | -0.02 | 0.02 | -0.05[c] | -0.08[a] | -0.07 | 0.09[a] | 0.03 | 0.04[c] | 0.22[a] | -0.00 | -0.02[a] | 0.01 | 1 | | | | | | | | | | | |
| (17) *insthold* | 0.10[a] | 0.08[a] | 0.01 | -0.02 | -0.01 | -0.02 | -0.02 | -0.01 | -0.06[c] | -0.00 | 0.02 | 0.09[a] | -0.03[c] | -0.01 | 0.02[a] | -0.03[a] | 1 | | | | | | | | | | |
| (18) *numanalst* | 0.14[a] | 0.03[a] | -0.01 | 0.03 | 0.03 | -0.01 | 0.01 | 0.07[c] | -0.00 | 0.05 | 0.09[a] | -0.24[a] | 0.06[a] | -0.00 | -0.00 | 0.16[a] | 0.11[a] | 1 | | | | | | | | | |
| (19) *ocf* | -0.30[a] | 0.10[a] | 0.23[a] | 0.26[a] | -0.00 | -0.01 | 0.62[a] | 0.67[a] | 0.15[a] | -0.18[a] | 0.22[a] | 0.01 | 0.31[a] | 0.62[a] | 0.00 | 0.00 | 0.00 | 0.04[a] | 1 | | | | | | | | |
| (20) *deratio* | -0.00 | 0.01 | 0.01 | 0.01 | -0.01 | -0.01 | -0.02 | 0.04[c] | 0.04[b] | -0.01 | 0.03 | -0.01 | 0.02 | 0.01[c] | 0.00 | -0.00 | -0.00 | 0.00 | 0.01[c] | 1 | | | | | | | |
| (21) *cawocash* | -0.36[a] | 0.15[a] | 0.24[a] | 0.27[a] | 0.00 | -0.00 | 0.61[a] | 0.64[a] | 0.13[a] | -0.19[a] | 0.20[a] | 0.01 | 0.31[a] | 0.61[a] | 0.03[a] | 0.02[a] | 0.00 | 0.01[c] | 0.90[a] | -0.00 | 1 | | | | | | |
| (22) *roe* | -0.01 | -0.01 | 0.00 | 0.02 | -0.01 | -0.02 | 0.02 | 0.05[b] | -0.05[a] | -0.01 | 0.02 | 0.01 | 0.00 | 0.00 | -0.00 | 0.00 | 0.00 | 0.00 | 0.01[b] | -0.01[b] | 0.01[c] | 1 | | | | | |
| (23) *lnat* | -0.36[a] | 0.14[a] | 0.23[a] | 0.26[a] | -0.00 | 0.00 | 0.60[a] | 0.66[a] | 0.13[a] | -0.19[a] | 0.22[a] | 0.01 | 0.32[a] | 0.64[a] | 0.03[a] | 0.02[a] | -0.00 | 0.02[a] | 0.95[a] | -0.00 | 0.94[a] | 0.01[c] | 1 | | | | |
| (24) *segments* | -0.18[a] | 0.11[a] | 0.06[a] | 0.14[a] | -0.01 | -0.05[a] | 0.25[a] | 0.25[a] | 0.08[a] | -0.09[a] | 0.13[a] | -0.02 | 0.07[a] | 0.31[a] | 0.02[a] | 0.00 | 0.00 | 0.02[a] | 0.42[a] | -0.01[c] | 0.55[a] | 0.00 | 0.50[a] | 1 | | | |
| (25) *indusconc* | 0.00 | -0.00 | -0.05[a] | -0.09[a] | 0.03[b] | 0.03[b] | -0.14[a] | -0.12[a] | -0.04[b] | 0.04[c] | -0.03[b] | 0.01 | -0.04[b] | 0.00 | 0.00 | 0.00 | -0.00 | 0.01[c] | -0.00 | 0.00 | -0.00 | 0.00 | -0.00 | -0.00 | 1 | | |
| (26) *volatil* | 0.02[a] | -0.01[c] | -0.00 | -0.01 | 0.01 | -0.00 | -0.10[a] | -0.01 | -0.02 | -0.02 | -0.02 | -0.02 | 0.01 | -0.02[a] | 0.00 | -0.00 | -0.01 | 0.00 | -0.06[a] | -0.00 | -0.05[a] | -0.40[a] | -0.06[a] | -0.03[a] | -0.00 | 1 | |
| (27) *acq* | -0.18[a] | 0.04[a] | 0.15[a] | 0.17[a] | -0.02 | -0.02 | 0.30[a] | 0.29[a] | 0.10[a] | -0.08[a] | 0.07[a] | -0.01 | 0.09[a] | 0.28[a] | 0.00 | 0.03[a] | -0.00 | -0.01[a] | 0.42[a] | -0.00 | 0.48[a] | 0.00 | 0.47[a] | 0.34[a] | -0.00 | -0.03[a] | 1 |

*Note.* Table 2 presents Pearson correlation coefficients for variables which have been defined in Appendix A.
a=***significance at the 1% level. b=**significance at the 5% level. c=*significance at the 10% level.

After checking the variance inflation factor (VIF) for each model, and running collinearity diagnostics, there was no evidence of multicollinearity in the base model. In the full model, the variables with high VIFs were control variables and they were not collinear with variables of interest; these VIFs can be safely ignored.

**Regression analysis**

Table 3 reports the base model regression results for CFO and CEO total connections and tail risk, including both idiosyncratic risk and market risk. Table 4 reports the full model regression results for the CFO and CEO total connections and tail risk, including both idiosyncratic risk and market risk. In this section, I report the regression results and in the next section, I discuss the results of the relationship between CFO and CEO total connections and tail risk, including both idiosyncratic risk and market risk.

**Table 3: Tail Risk Base Model (Idiosyncratic and Market)**

| | Tail Risk | |
|---|---|---|
| Variables | Idiosyncratic | Market |
| *CFOtotcon* | -0.00013 | -0.00020* |
| | (0.000) | (0.000) |
| *CEOtotcon* | 0.00004 | -0.00008 |
| | (0.000) | (0.000) |
| Constant | -1.42519*** | 5.26353*** |
| | (0.120) | (0.080) |
| Industry Fixed Effects | Yes | Yes |
| Year Fixed Effects | Yes | Yes |
| Observations | 582 | 582 |
| Adjusted $R^2$ | 0.259 | 0.149 |

This table reports estimation from ordinary least squares regression of the relationship between CFO and CEO total connections and market risk. I used both industry and year fixed effects. Also, I clustered standard errors by firm identification number (Gvkey). Robust standard errors were computed using the Huber-White sandwich estimator of variance by clustering on the firm level (Wolter, 2007). Variables are defined in Appendix A.
*$p < .1$. **$p < .05$. ***$p < .01$.

*Tail risk: market risk and idiosyncratic risk*

My hypothesis is that the CEO and CFO will use their social network capital to keep their firm's stock price return from persistently landing in the bottom 10% of the yearly stock return distribution. In the base model (Table 3), only the CFO total connections variable was significant at the 10% level for market risk. In the full model, (Table 4), audit quality was negative and significant at the 10% level for idiosyncratic risk. For market risk, both CFO total connections and CEO total connections were significant, at the 1% and 5% level, respectively. These results were surprising because it is unusual for CEOs and CFOs to have influence over long-term market effects (French, 2003). There is a much greater possibility for them to have control over something micro (firm-level) within their power, which would be measured by idiosyncratic risk. In addition, e-index, operating cash flows, and acquisitions were all negative and significant at the 5% level.

**Table 4*: Tail Risk Full Model (Idiosyncratic and Market)***

| | Tail Risk | |
|---|---|---|
| Variables | Idiosyncratic | Market |
| *CFOtotcon* | 0.002* | -0.002*** |
| | (0.001) | (0.001) |
| *CEOtotcon* | 0.001 | -0.001** |
| | (0.000) | (0.000) |
| *auditq* | -2.757* | 2.346** |
| | (1.616) | (1.128) |
| *eindex* | 0.823 | -1.077** |
| | (0.645) | (0.437) |
| *ocf* | 1.552* | -1.135** |
| | (0.774) | (0.517) |
| *acq* | 0.182 | -0.176** |
| | (0.122) | (0.072) |
| Constant | 4.904 | 1.717 |
| | (6.116) | (4.371) |
| Observations | 40 | 40 |
| Adjusted $R^2$ | 0.602 | 0.619 |

This table reports estimation from ordinary least squares regression of the relationship between CFO / CEO total connections and market risk. I used both industry and year fixed effects. Also, I clustered standard errors by firm identification number (Gvkey). Robust standard errors were computed using the Huber-White sandwich estimator of variance by clustering on the firm level (Wolter, 2007). Variables are defined in Appendix A.
$*p < .1$. $**p < .05$. $***p < .01$.

Next, I discuss the results of the findings between the relationship of CFO and CEO total connections and tail risk, including both market risk and idiosyncratic risk.

## V Robustness Checks

The purpose of this study was to investigate the relationship between CFO and CEO social network and tail risk (both market risk and idiosyncratic risk) to determine whether the CFO's and CEO's connectedness could keep the company's stock return from persistently landing in the bottom 10% of the yearly stock return distribution.

I used the model from Srivastav et al. (2017) to measure tail risk. I captured both components of tail risk: market risk and idiosyncratic risk. I included the same social network variables (and other variables of interest) for the CEO, as control variables, to test whether the CFO or CEO contribute more to the power of social networking. My research showed that both CFO and CEO total connections were associated with tail risk. The results produced were not what I expected. In fact, the results were the complete opposite of what I expected. Next, I discuss potential explanations.

Market risk, or systematic risk, such as inflation risk, interest rate risk, exchange rate risk, and political risk can be monitored and acted on, by savvy CFOs who pay attention to, not only the business of their own firm, but macro issues as well, for example, government regulations and the global economy (Corporate Finance Institute, 2021). Mishra, Talukdar, and Upadhyay (2019) analyzed CFO appointments and firm's debt-equity choice. They found that internal CFOs markedly reduce information asymmetry, which may decrease market risk and the cost of financing through equity issues (Mishra et al., 2019). Cai, Dhaliwal, Kim, and Pan (2014) found evidence that interlocked board of director members wield power to discontinue quarterly earnings guidance. In addition, Cai et al. (2014) pointed out that closely tied to social networks is the overlapping of auditors, (institutional) investors, or analysts. Further, Jung (2013) found that a firm's decision to follow the industry first mover in providing more market-risk disclosures is positively associated with an increase in the institutional investor overlap between the two firms.

Hasan and Habib (2019) found that firm-specific variables do not explain all of a firm's idiosyncratic return volatility; regional social capital also plays a role. There is a great deal of impact a large company can make in a region. Also, social capital is on the rise, and it just may be blurring the line as to whether its presence explains idiosyncratic risk or market risk.

In other untabulated results, I ran myriad models to determine the explanatory power of several variables of interest and control variables. In addition to the network variables (connections made through education, employment, and social organizations and the total of these connections), there are three additional categories: firm performance control variables, market control variables, and governance variables, all described previously.

**Table 5: Tail Risk**

| | Tail Risk | |
|---|---|---|
| Variables | Idiosyncratic | Market |
| *CFOtotcon* | -0.001 | -0.001*** |
| | (0.001) | (0.000) |
| *insthold* | -0.081 | -0.943* |
| | (0.991) | (0.502) |
| *deratio* | 0.004 | 0.023** |
| | (0.012) | (0.011) |
| *Roe* | -0.126 | -0.275*** |
| | (0.242) | (0.060) |
| *Segments* | -0.014 | 0.029*** |
| | (0.023) | (0.009) |
| *Volatile* | -0.075 | -0.055** |
| | (0.057) | (0.025) |
| Constant | -4.221 | 4.990*** |
| | (3.383) | (0.662) |
| Observations | 103 | 103 |
| Adjusted $R^2$ | 0.181 | 0.236 |

*Note.* This table reports estimation from ordinary least squares regression of the relationship between the CFO and CEO total connections and market risk. The model excludes other CFO and CEO variables of interest and governance variables. I used both industry and year fixed effects. Also, I clustered standard errors by firm identification number (Gvkey). Robust standard errors were computed using the Huber-White sandwich estimator of variance by clustering on the firm level (Wolter, 2007). Variables are defined in Appendix A.
$*p < .1$. $**p < .05$. $***p < .01$.

The regression results for Table 5 are from a model including CFO and CEO total connections, firm performance control variables, and market control variables, but excluding other variables of interest for CFO and CEO and governance variables. The CFO total connections remained negative and significant at the 1% level for market risk. The variable for ROE was negative and significant at the 1% level for market risk; volatility, the standard deviation of ROE, was negative and significant at the 5% level. The variable for institutional holdings, the percentage of market capitalization owned by institutional investors, was significant at the 10% level. The debt-to-equity ratio and operational diversity (segments) were significant, but the coefficients had an unexpected sign. There were no significant results for idiosyncratic risk.

Next, I ran models with all CFO and CEO variables of interest (including network variables) and some combination of control variables. These were all small data sets as well. The untabulated results indicated the CFO total connections variable continued to be significant but the same was not true for CEO total connections; it was not consistent. Gender, compensation, and holdings appeared in three separate models, but the coefficients had an unexpected sign. Operational diversity and current assets without cash were both significant but with an unexpected sign.

**Table 6: Tail Risk**

| | Tail Risk | |
|---|---|---|
| Variables | Idiosyncratic | Market |
| *CFOtotcon* | 0.002** | -0.002*** |
| | (0.001) | (0.001) |
| *CEOtotcon* | 0.001** | -0.001* |
| | (0.000) | (0.000) |
| *CEOgender* | 2.931* | -0.425 |
| | (1.509) | (1.578) |
| *CFOtotcomp* | 1.087* | -0.784 |
| | (0.575) | (0.532) |
| *CEOtotcomp* | -0.971** | 0.815** |
| | (0.427) | (0.332) |
| *auditq* | -1.753* | 0.978 |
| | (0.873) | (0.971) |
| *indaudcom* | -3.440 | 3.773** |
| | (2.913) | (1.860) |
| *ocf* | 1.362** | -0.936** |
| | (0.623) | (0.442) |
| *roe* | -2.276** | -0.565 |
| | (0.999) | (0.921) |
| *acq* | 0.165** | -0.117** |
| | (0.075) | (0.057) |
| Constant | 5.304 | -2.351 |
| | (5.464) | (4.405) |
| Observations | 45 | 45 |
| Adjusted $R^2$ | 0.746 | 0.405 |

*Note.* This table reports estimation from ordinary least squares regression of the relationship between the CFO and CEO total connection and market risk, including all CFO and CEO variables, governance, and firm controls, but excluding market variables. I used both industry and year fixed effects. Also, I clustered standard errors by firm identification number (Gvkey). Robust standard errors were computed using the Huber-White sandwich estimator of variance by clustering on the firm level (Wolter, 2007). Variables are defined in Appendix A.
$^{*}p < .1$. $^{**}p < .05$. $^{***}p < .01$.

The small data set with the combination of all CFO and CEO variables of interest, governance variables, and firm control variables, with market controls excluded, produced significant results for idiosyncratic risk; CEO total compensation, audit quality, and ROE were negative and significant. Both CFO and CEO connections were significant, as was CEO gender, CFO total compensation, operating cash flows, and acquisitions, but with an unexpected sign. Both CFO and CEO total connections continued to be negative and significant for market risk, as were operating cash flows and acquisitions. CEO total compensation and independent internal audit committee were also significant but with an unexpected sign. These regression results can be found in Table 6.

In Table 7, I report the regression results from CFO and CEO total connections and market variables, wherein institutional ownership was significant. I was interested in this result because of the literature cited in the Discussion section, that is, Cai et al. (2014) referring to institutional investors. Also, Jung (2013) referred to market-risk disclosure and institutional investor overlap between firms.

**Table 7: Tail Risk**

| | Tail Risk | |
|---|---|---|
| Variables | Idiosyncratic | Market |
| *CFOtotcon* | -0.00031 | -0.00034* |
| | (0.000) | (0.000) |
| *insthold* | -0.76124 | -0.47969* |
| | (0.484) | (0.274) |
| Observations | 167 | 167 |
| Adjusted $R^2$ | 0.269 | 0.150 |

This table reports estimation from ordinary least squares regression of the relationship between the CFO and CEO total connections and market risk, including only CFO and CEO network variables and market variables. I used both industry and year fixed effects. Also, I clustered standard errors by firm identification number (Gvkey). Robust standard errors were computed using the Huber-White sandwich estimator of variance by clustering on the firm level (Wolter, 2007). Variables are defined in Appendix A.
$^*p < .1$. $^{**}p < .05$. $^{***}p < .01$.

**Limitations of this study**.

The full model for tail risk had a very small number of observations. In addition, I only had 13 years of data; a larger sample size was not readily available but could be created using another method to connect C-suite executives, board members, and other constituents in a network. Although we do research in the area of finance, the CEO (not the CFO) continues to be the primary position for study. The literature on CFOs is still growing; hence, there does not seem to be an ample supply of prior work. SOX has changed this phenomenon, but it will be important to continue to build the stream of literature on CFOs.

**Suggestions for future research**.

The results for this study were somewhat surprising. I anticipated there would be more significant results for idiosyncratic risk. Given the results, additional research is needed to determine the impetus for the influence CFOs and CEOs have in the marketplace.

In addition, as mentioned previously, gathering a larger data set to create a new model using a different method would be an avenue for future research. One such idea is to use an Eulerian path (in graph theory). Hochberg, Ljungqvist, and Lu (2007) utilized graph theory in their network analysis of centrality, to measure the degree and quality of relationships. It is interesting to see this as cross-sectional data, but it would also be interesting to see CFOs' careers in a longitudinal research project.

## V Conclusion

In this study, I sought to discover if the CFO and CEO have enough social capital in their social networks to keep their company's stock return from consistently falling into the bottom 10% of the yearly stock return distribution. Interestingly, the component of risk over which I assume CFOs and CEOs have more control did not support that. In the base model, only the CFO total connections variable was significant, at the 10% level, for market risk. In the full model, audit quality was negative and significant at the 10% level for idiosyncratic risk. For market risk, both CFO total connections and CEO total connections were significant, at the 1% and 5% level, respectively. This result was surprising because it is unusual for CEOs and CFOs to have influence over long-term market effects (French, 2003). There is a much greater possibility for them to have control over something micro (firm-level) within their power, which would be measured by idiosyncratic risk. In addition, under market risk, e-index, operating cash flows, and acquisitions were all negative and significant at the 5% level. For robustness checks, I ran several models with various combinations of CFO and CEO total connections, other CFO and CEO variables of interest, governance variables, firm control variables, and market control variables. Fairly consistent results indicated there was not very much explanatory power for idiosyncratic risk. The CFO total connections variable consistently provided explanatory power for market risk. When the market controls were included in the model, the institutional investors variable was consistently negative and significant. Although the results did not turn out as expected, the results provide an interesting avenue for future research.

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## Appendix A

### Variable Definitions

| Variable | Definition |
|---|---|
| **Tail Risk** | |
| *idiorisk* | Idiosyncratic Risk, the average return below the 10th percentile of the yearly distribution of the residuals from the market model (scaled up, multiplied by a factor of 100, i.e., 10x100, because it is in percentage form); |
| *mktrisk* | Market Risk, the average return below the 10th percentile of the yearly distribution of the predicted returns from the market model (scaled up, multiplied by a factor of 100, i.e., 10x100, because it is in percentage form); |
| **Social Network** | |
| *CEOtotcon* | CEO Total Connections, the number of total CEO connections from the summation of employment, education, and social connections in this study; |
| *CEOemp* | CEO Employment Connections, current or past coworkers who are executives or directors; |
| *CEOedu* | CEO Education Connections, education connections exist when two executives or directors went to the same school and graduated with similar degrees; |
| *CEOsoc* | CEO Social Connections, social connections formed when two executives or directors have an advanced role in the same non-profit organizations; |
| *CFOtotcon* | CFO Total Connections, the number of total CEO connections from the summation of employment, education, and social connections in this study; |
| *CFOemp* | CFO Employment Connections, current or past coworkers who are executives or directors; |
| *CFOedu* | CFO Education Connections, education connections exist when two executives or directors went to the same school and graduated with similar degrees; |
| *CFOsoc* | CFO Social Connections, social connections formed when two executives or directors have an advanced role in the same non-profit organizations; |
| **Other Variables of Interest** | |
| *fCEO* | Female CEO, 1 if the CEO is female, 0 otherwise; |
| *fCFO* | Female CFO, 1 if the CFO is female, 0 otherwise; |
| *CEOtotcomp* | CEO Total Compensation, comprised of salary and bonus; |
| *CEOstock* | CEO Stock, total value of restricted stock granted to CEO plus total value of stock options granted (using Black-Scholes); |
| *CFOstock* | CFO Stock, total value of restricted stock granted to CFO plus total value of stock options granted (using Black-Scholes); |

| Variable | Definition |
|---|---|
| **Governance Variables** | |
| *indbrd* | Independent Board, the percentage of independent board members; |
| *CEOchair* | CEO Chair, 1 if CEO is also the Chair, 0 otherwise; |
| *femdirs* | Female Directors, the percentage of female board members; |
| *auditq* | Audit Quality, number associated with auditing firm that audited the financial statements of a company; 1 if a Big Four, 0 otherwise; |
| *indaudcom* | Independent Audit Committee, 1 if audit committee is independent, 0 otherwise; |
| *eindex* | Entrenchment Index, as developed by Bebchuk, Cohen, and Ferrell (2009); |
| **Firm Control Variables** | |
| *ocf* | Operating Cash Flows, the net change in cash from all items classified in the operating activities section on a Statement of Cash Flows; |
| *deratio* | Debt-to-Equity Ratio, total debt divided total stockholders' equity; |
| *cawocash* | Current Assets without Cash, total current assets minus cash; |
| *roe* | Return on Equity, net income divided by shareholders' equity; |
| *volatil* | Volatility, measures as the standard deviation of ROE; |
| *lnat* | Natural Log of Total Assets, natural log of assets used to measure firm size; |
| *segments* | Segments, product / service segments of a company; |
| *indusconc* | Industry Concentration, the level of concentration in a company's industry, measured by the Herfindahl-Hirschman index (HHI); |
| *acq* | Acquisition, cash outflow of funds used for and/or the costs relating to acquisition of a company in the current year or effects of an acquisition in a prior year carried over to the current year; |
| **Market Control Variables** | |
| *insthold* | Institutional Holdings, percentage of market capitalization owned by institutional investors; |
| *numanalst* | Number Analysts, number of analysts following a company. |

# An Event Study on the Collapse of Silicon Valley Bank

Sara Kabir and Drew Winters*

**Abstract**

The failure of Silicon Valley Bank was one of the largest bank runs in American history. In this paper, we conducted an event study to discover the impact of SVB's collapse on the returns of large banks in the US. Our results indicate that the collapse of Silicon Valley Bank had a negative impact on the top 20 banks. Pre-event estimation showed insignificant results as investors could not anticipate the collapse. On the contrary, we uncovered that most banks had significant adverse effects due to unfavorable market reactions in the post-event study.

**Keywords:** SVB Failure, Event Study, Large Banks, Too Big to Fail

## I Introduction and motivation

A number of banks in 2023 encountered deposit runs that, by historical standards, were exceptionally speedy and massive (Rose, 2023). One of the most noteworthy deposit runs in the US banking sector was Silicon Valley Bank's (SVB), as the run led to its collapse. At the time of its collapse, SVB was among the largest US banks[1]

At the end of 2022, SVB had substantial assets in "Held-to-Maturity" securities with about half of these securities having maturities of 15 years or more. In March of 2022 the Fed began regularly increasing its target rate from 0% in March 2022 to 4.5% in March of 2023. As rates increased, these securities lost value, but Held-to-Maturity security losses are not recorded in the financial statement because these securities are not marked-to-market. At the same time, 94% of SVB's deposits were uninsured, and these depositors began leaving SVB as rates increased. In response to the exit, SVB announced on March 8th, 2023, that it would liquidate $21 billion of its bond portfolio, which resulted in a $1.8 billion loss. SVB attempted to raise capital to cover the loss, but the effort failed. The bank collapsed on March 10, 2023, and was ultimately taken over by the FDIC.[2] We investigate the market response of large bank stocks to the collapse of SVB.

Our research is guided by Goodhart's (2006) discussion of the need for financial stability in the banking system and the need to assess the virulence and speed of potential shocks. Goodhart is concerned about the banking system not having sufficient liquidity. Our "shock" is the Fed's increase in interest rates at a time when SVB's lacked the liquidity to handle depositor withdrawals and we examine how investors in large banks responded to the closure of SVB.

Our study fits in the literature on large bank failures. O'Hara and Shaw (1990) investigated the effect on bank equity values after the Comptroller of the Currency's announcement that some banks were Too-Big-to-Fail (TBTF). They find a positive reaction to the announcement for the TBTF banks and a negative reaction for other banks. The Dodd-Frank Act includes a provision to

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[1] SVB had $209 bil. in total assets at the time of its collapse. This would rank SVB as about the 20th largest bank in the US based on total assets.

[2] Despite the Federal Deposit Insurance Corporation's (FDIC) protection, certain institutions are nevertheless highly susceptible to a bank run (Diamond and Dybvig, 1983).

eliminate TBTF banks. Allen, Cyree, Whitledge, and Winters, (2018) examined the Dodd-Frank elimination of TBTF and find no reaction for the largest banks but a negative reaction for smaller banks. They conclude that the market does not believe that TBTF has been eliminated.

We use the event study methods of O'Hara and Shaw (1990) and Allen, Cyree, Whitledge, and Winters, (2018) to analyze the impact of the SVB collapse on the stock prices of large banks. Our sample is the 20 largest US financial institutions that take deposits, and for ease of exposition, we refer to these institutions as banks. We select the top 20 banks based on their market value of equity at the end of 2022 and use their daily stock returns from January 24th, 2023, to April 24th, 2023, for our event study. We find that the failure of SVB had an adverse effect on the top 20 banks with 20 significant parameter estimates for the main event, all of which are negative.

Our paper contributes to the recent research on the SVB failure. Yousaf and Goodell (2023) examine the impact of the SVB failure on 11 different sectors of the US economy. All 11 sectors had a negative reaction to the SVB failure with the responses in Financials, Materials and Real Estate being statistically significant. Pandey, Hassan, Kumari, and Hasan (2023) examine global stock market reactions to the failure of SVB. They find that all market indices decline across the March 10, 2023, SVB collapse. We take a more narrow focus and analyze the 20 largest US banks, which include some banks that the market may believe to be TBTF.

## II Background

### Collapse of SVB

Silicon Valley Bank (SVB) was a state-chartered commercial bank headquartered in Santa Clara, California. As a Bay Area regional bank, SVB offered services tailored to the demands of the tech industry, and it swiftly rose to become the largest bank by deposits in Silicon Valley and the preferred bank of almost half of all venture-backed tech startups. In March 2023, after the central bank raised interest rate during the 2021–2023 inflation surge, there was a run on its deposits, which led to its collapse and seizure on March 10, 2023, by the California Department of Financial Protection and Innovation (DFPI), its regulator. State officials at the DFPI named the Federal Deposit Insurance Corporation (FDIC) receiver of the bank, citing insufficient liquidity and declaring bankruptcy. This wound up being the third-largest bank failure in American history.

On March 12, 2023, Treasury Secretary Janet Yellen, Federal Reserve Chairman Jerome Powell, and FDIC Chairman Martin Gruenberg issued a joint statement clarifying that all depositors at SVB would be fully protected and would have access to both insured and uninsured deposits beginning the following Monday, March 13. The FDIC subsequently founded Silicon Valley Bridge Bank, N.A., as a bridge bank successor, which instantaneously acquired ongoing business. First Citizens Bank & Trust Company, a subsidiary of First Citizens BancShares, acquired all customer deposits and loans of Silicon Valley Bridge Bank from the FDIC on March 27, 2023, and resumed running all SVB branches. Table 1 shows the timeline for major announcements related to SVB collapse.

With the collapse of SVB from its depositor run and the coverage of all SVB deposits on March 13, 2023, there were questions about deposit protection for other banks if their depositors ran during the stress on banks from rising interest rates. On March 20, 2023, Treasury Secretary Yellen told Congress that she was not considering blanket insurance on deposits.

**Table 1: Timeline of major events**

| Date | Event |
|---|---|
| **March 8** | SVB reported that it has raised $500 million from General Atlantic and intends to sell $1.25 billion worth of common stock together with an additional $500 million worth of depository shares. |
| **March 9** | As soon as the markets opened, SVB's shares sank 30% (and subsequently 60% that day), and more venture capitalists and startups began to withdraw their funds from the bank. |
| **March 10** | On Friday morning, US authorities took control of the bank and shuttered it. This marked the third-largest bank failure in U.S. history. |
| **March 12** | A joint statement was issued by Secretary of the Treasury Janet Yellen, Federal Reserve Chairman Jerome Powell, and FDIC Chairman Martin Gruenberg, declaring that all depositors at SVB would be fully protected and would have access to both insured and uninsured deposits beginning the following Monday, March 13. |

**Reasons for collapse**

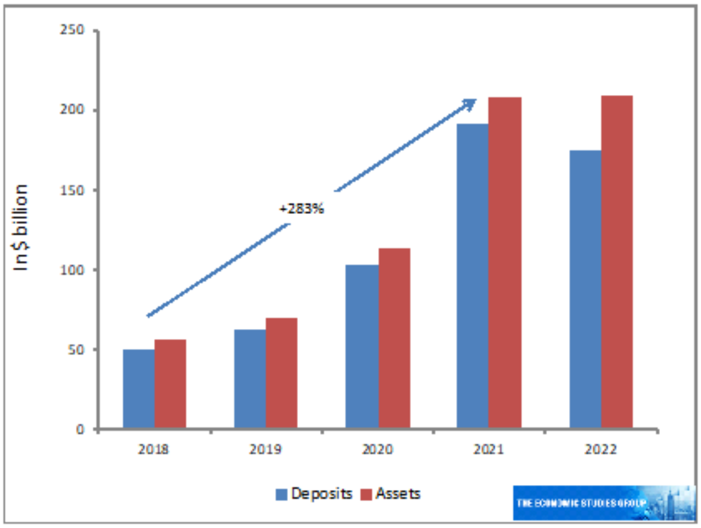
Numerous factors contributed to the failure, including a lack of diversification and a classic bank run, in which a large number of customers withdrew funds immediately out of uncertainty about the bank's stability. According to Allen, Baig, and Winters (2023), before their collapse, SVB should have been able to identify (internally and externally) and reduce (internally or via regulatory oversight) any balance sheet risks that were present. The quantity of uninsured deposits held by the bank is a major factor that contributed to the run on the bank. Nearly 94% of SVB's deposits were not covered by insurance. Many of its loans and depositors are from Silicon Valley, which is a tech-heavy region. Tech startups had a big chunk of loans and deposits at SVB.

The year 2021 witnessed significant funding raised for start-ups through venture capital firms. Deposits at SVB climbed dramatically over the previous four years, from $50 billion in 2018 to about $191 billion in 2021, before dropping to $176 billion at the end of 2022 (graph 1). Deposits increased by 280%, compared to 30% for all insured banks. SVB was inundated with deposits, predominantly from start-ups and tech businesses, which created in a specific client/deposit base that held large percentages of uninsured deposits. This specific client/deposit base exposed SVB to the risk of a depositor run.

SVB's customer base created a large unstable deposit base and moderate demand for loans. With the moderate loan demand SVB chose to generate additional returns through investing in long-term securities rather than holding shorter-term instruments or cash (Siokis, 2023). Silicon Valley Bank placed a significant amount of its bank deposits in long-term US Treasury bonds and agency mortgage-backed securities.

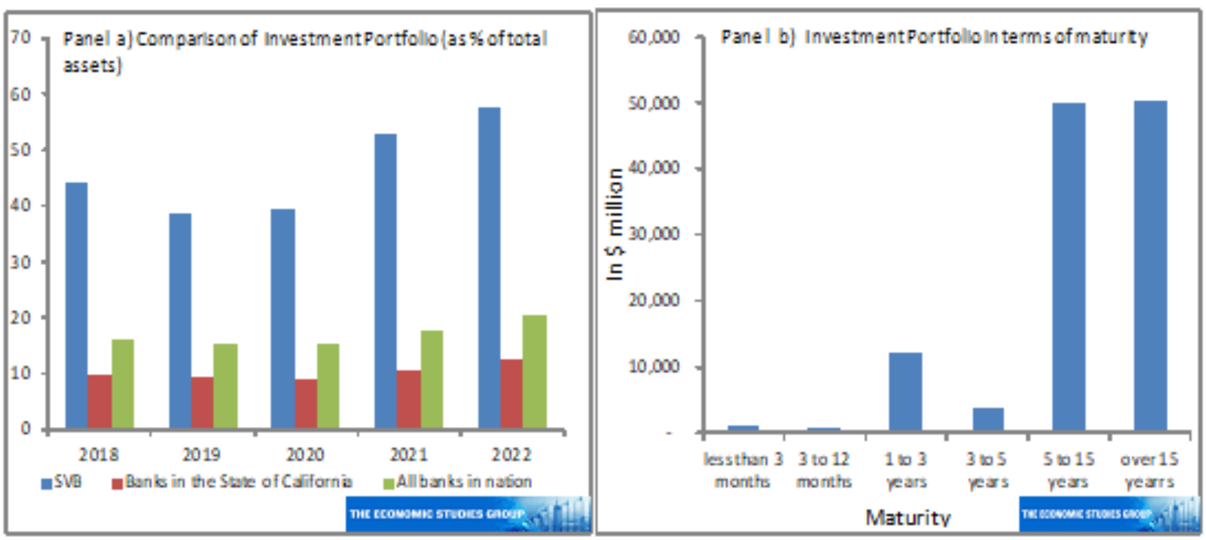
The value of the securities owned was a large percentage total asset. The ratio increased from 39% in 2020 to 57% in 2022, far higher than the average of 13% for banks in California and 20% nationwide (graph 2, left panel). Since more than 85% of the money was invested in securities with an average duration of more than five years, one could argue that SVB failed to hedge risk by diversifying its investment portfolio (right panel).

**Graph 1: Deposit and assets trend of SVB**




Source: Federal Financial Institutions Examination Council, Schedule RC-Balance Sheet

**Graph 2: Comparison of SVB's Investment Portfolio with peer groups and maturity**




Source: Federal Financial Institutions Examination Council, Schedule RC-Balance Sheet and Securities

As SVB customers made withdrawals, SVB lacked the liquidity necessary to cover the withdrawals. They started selling their bonds at a huge loss, distressing buyers and investors. The bank failed 48 hours after revealing the sale of assets (Hetler, 2023).

## III Data and Methodology

### Sample Selection

To analyze the impact of the collapse of Silicon Valley Bank on top banks, we first collect the bank-level data from CRSP of all publicly traded banks for the year 2022. Although there are more than 12,000 financial institutions in the financial sector, the majority are privately held companies with no active stock trading. We gather data for the banks whose daily stock price data were publicly available and actively traded throughout our estimation period. This results in a sample of 124 banks. Then, we rank all publicly traded banks based on their market value of equity at the end of 2022. Based on this ranking, we select the top 20 banks (excluding SVB) as our sample for our research. The top 20 banks (plus SVB) are shown in Table 2, along with their market equity value (MVE) at the end of 2022.

**Table 2: List of the 20 banks in the final sample listed in order of decreasing MVE of 2022**

| Bank Name | MVE |
|---|---|
| JPMORGAN CHASE & CO | 393342.81 |
| BANK OF AMERICA CORP | 265702.94 |
| WELLS FARGO & CO NEW | 157335.18 |
| CITIGROUP INC | 87603.86 |
| U S BANCORP DEL | 64796.74 |
| P N C FINANCIAL SERVICES GRP INC | 63700.20 |
| BANK OF NEW YORK MELLON CORP | 36792.91 |
| CAPITAL ONE FINANCIAL CORP | 35482.74 |
| STATE STREET CORP | 28463.54 |
| DISCOVER FINANCIAL SERVICES | 26729.70 |
| M & T BANK CORP | 25039.24 |
| FIRST REPUBLIC BANK S F NEW | 21543.08 |
| HUNTINGTON BANCSHARES INC | 20342.55 |
| REGIONS FINANCIAL CORP NEW | 20146.66 |
| NORTHERN TRUST CORP | 18442.73 |
| KEYCORP NEW | 16252.34 |
| SYNCHRONY FINANCIAL | 14804.78 |
| ***SVB FINANCIAL*** | ***13602.19*** |
| FIRST HORIZON CORP | 13151.70 |
| FIRST CITIZENS BANCSHARES INC NC | 10237.10 |
| EAST WEST BANCORP INC | 9288.410 |

For our sample of 20 large banks, we collect daily stock price data from Yahoo Finance covering the range of January 24th, 2023, to April 24th, 2023.[3] We use the adjusted close price as it is adjusted for dividends. We collect target interest rates from Federal Reserve Economic Data (FRED) for the same period. FRED reports the upper and lower limits of the target interest rates from which we calculate the mid-point for our analysis.

**Event Window Determination**

Determining the timing of information release to the market is vital for an event study. As mentioned above (see, Table 1), on March 10th, US authorities took control of the bank, proclaiming the bank's collapse and shutting it down. Accordingly, March 10, 2023, is our event day (t = 0).

[3] Note, we collect price data from Yahoo Finance because the CRSP data for 2023 is not available.

## Examination of Stock Price Changes

Examining returns has the drawback that any reported changes might possibly be the result of other ongoing events. However, a review of the *Wall Street Journal* for the days surrounding March 10 did not uncover any indication of confounding pronouncements, so we believe that we have a clean event. We use returns on a broad market index to control overall market movements.

One method for conducting an event study is the event-parameter method, in which the valuation model is estimated for the entire sample period with dummy variables specified for the identified event(s) (Cornett and Tehranian, 1990; Mathur and Sundaram, 1997). We follow the event-parameter method from Allen, Cyree, Whitledge & Winters (2018) and estimate the following event study model. We estimate the model for each of the 20 banks in our sample in a system of seemingly unrelated equations (SUR methods).

$$\begin{gathered} R_{1,t} = \alpha_1 + \beta_1 Rm_t + \sum y_1 D_t + \eta_1 I_t + \varepsilon_{1,t} \\ \dots\dots\dots \\ R_{20,t} = \alpha_{20} + \beta_{20} Rm_t + \sum y_{20} D_t + \eta_{20} I_t + \varepsilon_{20,t} \end{gathered} \quad (1)$$

$R_{i,t}$ is the daily return for bank i on day t (t = daily observations from January 24, 2023, through April 24, 2023, which cover 45 days before and after the event). $Rm_t$ is the daily market return on the S&P 500. $D_t$ is a dummy variable equal to one during the event window and 0 otherwise. We test a variety of event windows below. $I_t$ is a dummy variable equal to one on the day of change in the discount window target rates and the day before. An increase in interest rates typically reduces bank stock values, resulting in negative returns, so we need to control for interest rate changes (Flannery and James (1984)).

## IV Results

### Main estimation

Our research question is whether or not large banks' stock prices responded to the shutting down of SVB. We begin with the estimation of Equation 1 on the 20 large banks in our sample in a system of seemingly unrelated equations. The results from the estimation of Equation 1 are reported in Table 3. Table 3 lists the banks in the same order as Table 2 and provides the market value of equity from Table 2 for ease of reference. Table 3 also reports if a bank was identified in Allen, Cyree, Whitledge and Winters (2018) as Too-Big-to-Fail (TBTF) (specifically stress-tested banks, which includes GSIBs).

We only report the event's parameter estimates to keep the table manageable. Not reported in Table 3 are the market parameter estimates and the target rate parameter estimates. The parameter estimates for current market returns are significant and positive across all banks. The parameter estimates on the target rate change are mostly insignificant across all banks.

Table 3 shows that the event dummy variable (window from t-5 to t+5) has 20 significant parameter estimates, and all 20 are negative. Our results suggest that the collapse of Silicon Valley Bank had a negative impact on the returns of the top 20 banks. Our results are consistent with Yousaf and Goodell (2023). Table 3 contains some banks that Allen, Cyree, Whitledge and Winters (2018) identify as TBTF (Yes) and some banks that they did not label as TBTF (No).

However, being previously identified for special attention from regulators (i.e. TBTF) did not affect the market's reaction to the collapse of SVB.

**Table 3: Regression results**

| Bank Name | MVE | Event | TBTF |
|---|---|---|---|
| JPMORGAN CHASE & CO | 393342.81 | -0.0120** | Yes |
| BANK OF AMERICA CORP | 265702.94 | -0.0160*** | Yes |
| WELLS FARGO & CO NEW | 157335.18 | -0.0175*** | Yes |
| CITIGROUP INC | 87603.86 | -0.0133** | Yes |
| U S BANCORP DEL | 64796.74 | -0.0272*** | Yes |
| P N C FINANCIAL SERVICES GRP INC | 63700.20 | 0.0148*** | Yes |
| BANK OF NEW YORK MELLON CORP | 36792.91 | -0.0142*** | Yes |
| CAPITAL ONE FINANCIAL CORP | 35482.74 | -0.0158*** | Yes |
| STATE STREET CORP | 28463.54 | -0.0180*** | Yes |
| DISCOVER FINANCIAL SERVICES | 26729.70 | -0.0186*** | No |
| M & T BANK CORP | 25039.24 | -0.0179*** | No |
| FIRST REPUBLIC BANK S F NEW | 21543.08 | -0.0923** | No |
| HUNTINGTON BANCSHARES INC | 20342.55 | -0.0301*** | No |
| REGIONS FINANCIAL CORP NEW | 20146.66 | -0.0193*** | Yes |
| NORTHERN TRUST CORP | 18442.73 | -0.0088** | No |
| KEYCORP NEW | 16252.34 | -0.0318** | Yes |
| SYNCHRONY FINANCIAL | 14804.78 | -0.0192*** | No |
| FIRST HORIZON CORP | 13151.70 | -0.0317*** | No |
| FIRST CITIZENS BANCSHARES INC NC | 10237.10 | -0.0387** | No |
| EAST WEST BANCORP INC | 9288.410 | -0.0241** | No |

This table reports the coefficient results from the SUR model from Eq. (1). Control variables are omitted for readability. The estimates for the event are shown for each bank. The first column lists the banks with their associated MVE ($ Billions) listed in the second column. Dummy variables are equal to one for an eleven-day window around the event day (the return on the day of the event and five-day window around the event day). Parameter estimate significance is identified with *** < 1%, ** < 5%, * < 10%.

Note: TBTF (Too-Big-to-Fail) designation comes from the sample of Allen, Cyree, Whitledge and Winters (2018).

To provide more information about the event response we re-estimate equation (1) with different event windows. Specifically, we define dummy variables for a pre-event window (t-5 to t-2) and post-event window (t+1 to t+5). On the event day (t = 0), the operations of SVB were seized by government authorities. For 19 out of 20 banks, the pre-event window coefficients are insignificant. These results are consistent with relevant news prior to the bank run of SVB not influencing other banks' stock prices or the collapse of SVB not being anticipated by the market. For all 20 banks, the post-event window coefficients are negative and significant, indicating the strong negative impact of the SVB collapse on the other banks. Table 4 reports the results of pre-event and post-event analysis.

Our findings diverge from Allen, Cyree, Whitledge, and Winters (2018). Their event study examines the market's reaction to the legal elimination of TBTF through the implementation of Dodd-Frank Act. They find that the returns of the largest banks and those getting special attention (stress-tested banks), generally did not respond to the implementation while smaller banks generally exhibited negative returns following the elimination of TBTF. Their results for the largest banks support the contention that the TBTF policy has not been eliminated for the very largest systemically important banks. Investors had confidence that the TBTF would continue to exist and that authorities would continue to bail out them when they were in crisis; therefore, these banks' stock prices did not decline. We have similar banks to Allen, Cyree, Whitledge, and Winters (2018) in our sample. However, we find the all the largest banks show a negative reaction from the market when SVB failed. Our results suggest that the collapse of SVB signaled a weakening of the fundamentals of large banks and may suggest that investors do not believe that the authorities will continue to bail out TBTF banks.

**Table 4: Estimated results for pre-event and post-event analysis**

| Bank Name | MVE | Pre-event | Post-event |
|---|---|---|---|
| JPMORGAN CHASE & CO | 393342.81 | -0.0079 | -0.0168** |
| BANK OF AMERICA CORP | 265702.94 | -0.0063 | -0.0196*** |
| WELLS FARGO & CO NEW | 157335.18 | -0.0114 | -0.0220*** |
| CITIGROUP INC | 87603.86 | -0.0042 | -0.0215*** |
| U S BANCORP DEL | 64796.74 | -0.0008 | -0.0438*** |
| P N C FINANCIAL SERVICES GRP INC | 63700.20 | -0.0068 | -0.0229*** |
| BANK OF NEW YORK MELLON CORP | 36792.91 | -0.0013 | -0.0243*** |
| CAPITAL ONE FINANCIAL CORP | 35482.74 | -0.0077 | -0.0227*** |
| STATE STREET CORP | 28463.54 | -0.0054 | -0.0248*** |
| DISCOVER FINANCIAL SERVICES | 26729.70 | -0.0048 | -0.0257*** |
| M & T BANK CORP | 25039.24 | -0.0166* | -0.0181** |
| FIRST REPUBLIC BANK S F NEW | 21543.08 | -0.0098 | -0.1650*** |
| HUNTINGTON BANCSHARES INC | 20342.55 | -0.0062 | -0.0499*** |
| REGIONS FINANCIAL CORP NEW | 20146.66 | -0.0113 | -0.0276*** |
| NORTHERN TRUST CORP | 18442.73 | -0.0001 | -0.0114** |
| KEYCORP NEW | 16252.34 | -0.0043 | -0.0563*** |
| SYNCHRONY FINANCIAL | 14804.78 | -0.0083 | -0.0275*** |
| FIRST HORIZON CORP | 13151.70 | -0.0024 | -0.0565*** |
| FIRST CITIZENS BANCSHARES INC NC | 10237.10 | -0.0139 | -0.0514 |
| EAST WEST BANCORP INC | 9288.410 | -0.0047 | -0.0298** |

This table reports the coefficient results from the SUR model from Eq. (1). Each bank's estimates for the event are shown. The first column lists the banks with their associated MVE ($ Billions) listed in the second column. For pre-event analysis, dummy variables are equal to one for a four-day window (-5 -2) before the event day. For post-event analysis, dummy variables are equal to one for a five-day window (+1 +5; the return on a five-day window after the event day). Parameter estimate significance is identified with *** < 1%, ** < 5%, * < 10%.

## Robustness

We conduct another test for robustness. We look at alternate event windows (t+3 t-3) in the model to determine whether the main analysis's findings were consistent. The robustness test results are shown in Table 5. As we can see, the outcomes of these tests did not create materially different results. The robustness test displays that all the parameters have a negative impact, and 18 out of 20 are statistically significant, consistent with the main analysis.

**Table 5: Robustness test with an event window of t+3 t-3**

| Bank Name | MVE | Event |
|---|---|---|
| JPMORGAN CHASE & CO | 393342.81 | -0.0129** |
| BANK OF AMERICA CORP | 265702.94 | -0.0200*** |
| WELLS FARGO & CO NEW | 157335.18 | -0.0204*** |
| CITIGROUP INC | 87603.86 | -0.0160** |
| U S BANCORP DEL | 64796.74 | -0.0287*** |
| P N C FINANCIAL SERVICES GRP INC | 63700.20 | 0.0203*** |
| BANK OF NEW YORK MELLON CORP | 36792.91 | -0.0157*** |
| CAPITAL ONE FINANCIAL CORP | 35482.74 | -0.0132* |
| STATE STREET CORP | 28463.54 | -0.0213*** |
| DISCOVER FINANCIAL SERVICES | 26729.70 | -0.0182*** |
| M & T BANK CORP | 25039.24 | -0.0220*** |
| FIRST REPUBLIC BANK S F NEW | 21543.08 | -0.1000** |
| HUNTINGTON BANCSHARES INC | 20342.55 | -0.0394*** |
| REGIONS FINANCIAL CORP NEW | 20146.66 | -0.0310*** |
| NORTHERN TRUST CORP | 18442.73 | -0.0067 |
| KEYCORP NEW | 16252.34 | -0.0430*** |
| SYNCHRONY FINANCIAL | 14804.78 | -0.0215*** |
| FIRST HORIZON CORP | 13151.70 | -0.0353*** |
| FIRST CITIZENS BANCSHARES INC NC | 10237.10 | -0.0407 |
| EAST WEST BANCORP INC | 9288.410 | -0.0230** |

**Secondary event**

SVB collapsed from a deposit run. Specifically, a run on uninsured deposits. On March 13, regulators stepped in to cover all SVB deposits to stem the run. This move led to questions about whether regulators might provide a blanket endorsement on all deposits to prevent contagion. On March 20, Treasury Secretary Yellen told Congress that regulators had no intention of providing blanket coverage of banking deposits. Accordingly, we add a second event for the March 20 announcement to Equation (1) and re-estimate our regressions to determine how the market responded to this announcement. Our results on the second event appear in Table 6.

Our results show that only one of the 20 banks has a significant (and negative) parameter estimate. In other words, the market did not react to the Treasury Secretary's announcement. Our combination of results suggests that the market fully reacted to the SVB failure when it collapsed, that the market is comfortable with the stability of the largest banks, and that the size of the parameter estimates in Table 3 are not large enough to suggest that the market was concerned about a collapse of all the largest banks.

## V Conclusion

Silicon Valley Bank (SVB) was one of the largest US banks and its failure was significant in the US banking industry. The bank run of SVB was influenced by several factors, including the hikes in interest rates, a high-risk deposit base, poor interest rate risk management, the sale of bonds at a significant loss, and regulatory failures (Gortsos, 2023).

**Table 6: Regression results**

| Bank Name | Event |
|---|---|
| JPMORGAN CHASE & CO | -0.0005 |
| BANK OF AMERICA CORP | -0.0139 |
| WELLS FARGO & CO NEW | -0.0213 |
| CITIGROUP INC | -0.0169 |
| U S BANCORP DEL | 0.0308 |
| P N C FINANCIAL SERVICES GRP INC | 0.0181 |
| BANK OF NEW YORK MELLON CORP | 0.0054 |
| CAPITAL ONE FINANCIAL CORP | -0.0099 |
| STATE STREET CORP | 0.0099 |
| DISCOVER FINANCIAL SERVICES | 0.0021 |
| M & T BANK CORP | -0.0204 |
| FIRST REPUBLIC BANK S F NEW | -0.5246*** |
| HUNTINGTON BANCSHARES INC | 0.0154 |
| REGIONS FINANCIAL CORP NEW | -0.0033 |
| NORTHERN TRUST CORP | 0.0181 |
| KEYCORP NEW | -0.0068 |
| SYNCHRONY FINANCIAL | -0.0165 |
| FIRST HORIZON CORP | 0.0102 |
| FIRST CITIZENS BANCSHARES INC NC | 0.0829 |
| EAST WEST BANCORP INC | -0.0197 |

This table reports the coefficient results from the SUR model from Eq. (1) for the second event dummy variable. Control variables and the first event variables are omitted for readability. The estimates for the second event are shown for each bank. Parameter estimate significance is identified with *** < 1%, ** < 5%, * < 10%.

Using event study methods, we analyze the impact of SVB failure on the stock prices of the top 20 banks. With an event window period of t-5 t+5, we observed negative abnormal returns for all 20 banks. For the pre-event window period (t-5 t-2), most of the parameters have insignificant results, indicating no leakage of information on or anticipation of the collapse of SVB. On the other hand, for the post-event window period (t+1 t+5), most banks had negative abnormal returns, suggesting that the collapse of SVB had a significant impact on the stock prices of the top 20 banks.

Our results suggest that investors see the collapse of SVB as a negative market event. However, the lack of any additional reaction to the Treasury Secretary stating there would be no blanket coverage of deposits suggests that the negative market reaction for large banks at the SVB failure is about the weakening of bank values and not concern over the collapse of the US banking system.

Investors and portfolio managers could utilize our findings to better understand the impact of the SVB collapse on various financial institutions, while regulators can benefit from an enhanced understanding of the SVB disaster's ramifications.

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# The Consequence of COVID-19 on Cryptocurrency Returns

Umesh Kumar and Biqing Huang*

## Abstract

This study scrutinizes the COVID-19 measures and their effect on leading cryptocurrency returns. Our direct measures of COVID-19 show that cryptocurrency returns are significantly influenced by COVID-19 and are most visible throughout pre-vaccination phase. The intraday price movement becomes wider during vaccination period compared to cryptocurrency returns. The findings demonstrate that even negative news of COVID-19 did not deter investors from being optimistic in the pre-vaccination period. Further, COVID-19 impacts on the cryptocurrency market diverge depending on the size of currency once vaccination begins. It reflects a different underlying dynamic process in cryptocurrency trading.

**JEL Classification:** C 30 G11, G14, G15
**Keywords:** Cryptocurrency, Coronavirus, Intraday, Asset Pricing

## I Introduction

Cryptocurrency has been a significant innovation among financial products in recent years. It forms a digital version of a traditional currency and is usually resilient to inflation. The cryptocurrency market has undergone rapid growth and transformed into a global phenomenon. The ongoing pandemic, COVID-19, has brought unprecedented challenges to financial markets and affected the fragility of cryptocurrency markets. Academicians and policymakers have focused on the COVID-19 proliferation and its potential shock on the financial markets and overall economy. The current pandemic has generated excessive volatility, economic anxiety, and weakened economic sentiment in financial markets. It is perceived to be in response to COVID-19 policy measures (Baker et al., 2020; Fetzer et al., 2020).

Several studies have focused on the pandemic and examined the impact of COVID-19 on various asset classes such as stocks, bonds, currencies, commodities, and cryptocurrencies. However, most studies evaluating the effect of COVID-19 have examined volatility or asset returns. James et al. (2021) studied the erratic behavior of cryptocurrency during COVID-19 and concluded that cryptocurrency returns and variance perform differently pre-and post-pandemic. The volatility of central fiat and cryptocurrency markets has been severely stressed during COVID-19 (Umar & Gubareva, 2020). The pandemic has adversely affected the potential role of cryptocurrencies as diversifying investments (Gil-Alana et al., (2020). Mnif et al. (2020) show that COVID-19 positively influences the cryptocurrency market efficiency. Similarly, Montasser et al. (2022) analyze the cryptocurrency price bubbles and price stability during the pre and post-COVID-19 announcement and contend that the pandemic has impacted cryptocurrency market efficiency. However, recent literature (Filippou et al., (2021)) points out that the studies on cryptocurrency return predictability could be more extensive.

The COVID-19 pandemic has prompted substantial attention and research in decentralized finance (DeFi), particularly in cryptocurrencies. There has been significant research and interest in cryptocurrencies such as Bitcoin and Ethereum. However, many leading cryptocurrencies and

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their dynamics still need to be understood. We note that there need to be more studies addressing the pandemic response to the cryptocurrency market, given government measures, particularly vaccination. This study fills this research gap by exploring the linkage between cryptocurrency returns and COVID-19 contagion. It explores the relationship between cryptocurrency price and COVID-19 intensity using the top 10 cryptocurrencies.

Additionally, many recent papers have discussed and analyzed the economic effect of COVID-19 at global, country, and sectoral levels. However, there is a shortage of studies investigating the changes in COVID-19 measures such as vaccination and intensity, i.e., infections, deaths, and hospitalizations. We hypothesize that COVID-19 measures to prevent illnesses and deaths may influence cryptocurrency returns. The hypothesis is centered on the study that documents, using 146 observations (January 01, 2020, to June 15, 2020), how the varying intensity of COVID-19, characterized by infections and deaths, influences the daily returns of the top ten cryptocurrencies (Iqbal et al., 2021). They show that changes in pandemic intensity have a differential impact on cryptocurrencies. Therefore, it is interesting to see how cryptocurrencies perform in an ongoing pandemic, mainly because of vaccine availability and other government initiatives.

This paper extends the emerging literature on the cryptocurrency market and COVID-19. Regan (2021), in his Bloomberg article, reports that "institutional investor portfolios worth $7 trillion are exposed to cryptocurrencies". The role of algorithmic trading, the speed of information, and ever-expanding technological development in the financial markets have essential considerations for cryptocurrencies. Therefore, it is important to revisit and examine the relationship between COVID-19 and cryptocurrency return and intraday price movement. We use direct measures of COVID-19 intensity such as new covid cases, total covid cases, new covid deaths, total covid deaths, icu covid patients, and hospitalized covid patients on a given day. Most importantly, we use a more comprehensive data set to understand whether the returns of cryptocurrencies are related to COVID-19 intensity, given the role of vaccination and its effectiveness combined with other government measures. To the best of our knowledge, we are the first to use several measures of COVID-19 for cryptocurrencies during pre-and vaccination periods of an ongoing pandemic.

The paper uses a sample of the top 10 cryptocurrencies traded globally and COVID-19 variables from the U.S. It is noted that many cryptocurrency exchanges operate independently and nonintegrated. They exist in parallel across geographic regions. However, we restrict the COVID-19 intensity variables to the U.S. since the cryptocurrencies are reported in U.S. dollars, and COVID intensity variables are reliable. Further, the U.S. is a unique laboratory for evaluating and assessing COVID-19 policies. We employ multivariate regressions and generalized autoregressive conditional heteroskedasticity in mean (GARCH-M) to test the hypotheses.

Our study finds that COVID-19 intensity continues to affect the cryptocurrency market. First, we specifically study the effect during the pre-vaccination period. All statistical models suggest that COVID-19 has a positive and significant association with cryptocurrency returns/price movement in particular cryptocurrency or aggregate level. The results are consistent with the findings of prior literature. However, when we conduct a similar analysis during vaccination (immunization availability), the cryptocurrencies behavior varies with the COVID-19 variables. Several measures of COVID-19 intensity, i.e., ICU and Hospitalized COVID Patients, are negatively and significantly related to cryptocurrencies. Some variables have no or lower level of association with cryptocurrencies.

Further, we find that big and small cryptocurrencies differ during vaccination. Our contribution to the literature is from a methodological perspective using several models to confirm our findings. Second, we extend the study period to cover the vaccination period and other government initiatives for COVID-19.

## II Literature Review

The cryptocurrency market, a pivot of decentralized finance and embodiment of blockchain technology, has drawn significant interest from academicians, researchers, policymakers, investors, and government bodies. There has been a growing number of empirical studies on COVID-19 and the cryptocurrency market in a short time. Research shows that the current COVID-19 episode differs from comparable pandemics/epidemics such as SARS and EBOLA in recent history. Albulescu (2020) considers that COVID-19 has generated considerable volatility in financial markets and the real economy. Baldwin and Mauro (2020) note that being a health or non-economic crisis, the pandemic has produced considerable turmoil in largescale economic activity and the financial markets, further impacting other sectors. Baker et al. (2020) suggest that government restriction on business activity and lockdowns during the COVID-19 pandemic has substantially caused stock market volatility in the history of pandemics.

Global financial market stress can cause significant variations in the returns of cryptocurrencies (Bouri, Gupta, Lau, et al., 2018). A recent study suggests that in times of severe financial and economic disruption, crypto-assets do not act as hedges or safe havens but, perhaps, instead, as a broadening of contagion (Conlon & McGee, 2020). Diversification benefits among cryptocurrencies are short-term, while market connectedness and volatility linkages are sensitive to liquidity and volatility (Omane-Adjepong & Alagidede, 2019). Further, the ongoing COVID-19 crisis will have enormous economic costs (Goodell, 2020).

The cryptocurrency market has been studied from several perspectives. Prior literature documents that even popular cryptocurrencies such as Bitcoin and Ethereum are not a safe bet and may need a better diversification strategy. Their addition augments to portfolio's downside risk. Portfolio risk can be reduced by including Bitcoin in a portfolio of gold, oil, and others (Conlon et al., 2020; Guesmi et al., 2019; Smales, 2019). In contrast, earlier Bouri et al. (2017) and Tiwari et al. (2019) report that Bitcoin is a weak hedge and unsuitable for diversification purposes. Liu et al. (2022) document that momentum and size are essential in depicting cryptocurrency returns.

Thus, a growing strand of financial studies investigates the cryptocurrency market from several dimensions and its implications on asset pricing. The consequences of COVID-19 on financial and cryptocurrency markets are studied; however, no direct measure of COVID-19 intensity is identified, such as covid cases, deaths, and hospitalization. Hence, it needs further investigation. This paper aims to extend the study of cryptocurrencies and understand their behavior before and during COVID-19.

## III Data and Variables:

Cryptocurrency data is obtained from https://www.investing.com/crypto/ currencies. It is one of the leading price and trading volume providers for cryptocurrencies. The data comprises an opening, closing, high and low prices, and trading volume in USD terms. We select the daily frequency data of the top 10 cryptocurrencies since other currencies are less liquid and need more daily data. The sample period starts from the first COVID-19 case reported, i.e., January 22, 2020, to August 31, 2022. The COVID-19 variables dataset is collected from GitHub (https://github.com/owid/covid-19-data/tree/master/public/data). It contains comprehensive information on worldwide COVID-19 related to confirmed cases, deaths, hospitalizations, testing, and other variables of potential interest. We gather control variables data, i.e., Crypto Volatility

Index from https://cvi.finance/, the MSCI All-Country World Equity Index from https://www.investing.com/indices/msci-world-stock-historical-data, and one-year U.S. treasury bill from the Federal Reserve Bank of St. Louis.

Cryptocurrency data meets the requirements of the International Organization of Securities Commission (IOSCO) Principles for Financial Benchmarks and the criticism of Alexander and Dakos (2020). We use COVID-19 variables from the U.S. as it provides a representation of the pandemic impact on the cryptocurrency market. The MSCI All-Country World Equity Index is used as a representative of world equity markets, a one-year U.S. treasury bill as a risk-free measure. At the same time, the Crypto Volatility Index is selected to illustrate the volatility in cryptocurrency returns. All indices are priced in U.S. Dollars, and daily logarithmic returns are calculated. $P_t$, $H_t$, and $L_t$ are a cryptocurrency's closing price, daily high and daily low, respectively, at time $_t$. $R_t$ and $HL_t$ are currency log returns and intraday movement, respectively.

$$R_t = \log\left(\frac{Pt}{Pt-1}\right)$$

$$HL_t = \log\left(\frac{logHt-logLt}{logPt}\right)$$

We explore the US COVID-19 data response on cryptocurrency prices. Therefore, the study period starts from the first COVID case reported in the U.S., i.e., January 22, 2020. Cryptocurrency Index is a value-weighted index of the leading ten cryptocurrencies. The biggest cryptocurrency, Bitcoin, has a 48.07% weightage in the index. Since cryptocurrencies are traded daily without holidays, these currencies' prices vary substantially during the day. Therefore, we use the log returns and intraday movement for each cryptocurrency and cryptocurrency index.

Based on prior literature on asset pricing, we use the control variables such as the MSCI All-Country World Equity Index, Crypto Volatility Index, one-year U.S. treasury bill rate, cryptocurrency trading volume based on each cryptocurrency trading volume and corresponding weight, and daily number of COVID-19 cases of the U.S. between January 22, 2020, to August 31, 2022. The COVID-19 cases are confirmed new and total cases, confirmed new and total deaths, and total ICU and hospitalized COVID-19 patients. Appendix 1 lists the top 10 cryptocurrencies globally based on market capitalization.

The COVID-19 data have followed varying protocols to count cases, deaths, and hospitalizations. New cases, total cases, new deaths, and total deaths of COVID-19 are clear cases whenever reported. Therefore, it is possible that these data variables of COVID-19 may not correctly represent the actual cases and deaths triggered by COVID-19. ICU and hospitalized COVID-19 patients are the number of COVID-19 patients in the hospital on a given day. In order to capture the effect of daily changes and the effect of COVID-19, we use COVID-19 proxies standardized per million people.

Figure 1 below displays daily new COVID-19 cases reported from 1st case on January 22, 2020, to August 31, 2022. The graph indicates three strong waves of COVID-19 spreading in the country. However, Figure 2 on total cases suggests steady upward daily total cases of COVID-19. Now, Figure 3 shows the base price series cryptocurrency and equity prices. It is apparent that the crypto and equity markets fell once COVID-19 was considered a pandemic on March 11, 2020. Both markets recovered and started doing well. The equity market is growing steadily with lower volatility, while the crypto market later in 2020 picked up with much volatility. Figure 4 illustrates the volatility in the cryptocurrencies returns and has been volatile during the sample period. Overall, the graphs signal a volatile cryptocurrency market.

## IV Methodology and Results

Multivariate regressions such as Ordinary Least Squares (OLS), Seemingly Unrelated Regression (SUR), Cointegration, and Granger Causality, among others, have been applied in analyzing asset prices. Financial market data often present volatility clustering, where time series data display high and low volatility cycles. Time-varying volatility is more common, particularly with economic and financial data, and therefore, a good model of time-varying volatility is crucial in analyzing data.

Recent studies show that the association of cryptocurrency, such as Bitcoin, with equity markets is not symmetric (Gajardo et al., 2018). Further, Iqbal et al. (2021) find that COVID-19 has asymmetric dynamics with cryptocurrencies. This paper uses the autoregressive error model since COVID data and cryptocurrency variables are asymmetrical. We use the following model that estimates regression models for time series data. The effects of the regressor variables are distributed across time. It can include any number of regressors with distribution lags and any number of covariates.

$$Y_t = \alpha + \sum_{i=0}^{p} \beta_i X_{t=i} + \gamma z_t + \ \dots\dots \ + \varepsilon_t \qquad (1)$$

Here, $x_t$ is the regressor with a distributed lag effect. $z_t$ is a simple covariate, and $\boldsymbol{\varepsilon}_t$ is an error term. Almon lag polynomials model the distribution of the lagged effects. The coefficients $b_i$ of the lagged values of the regressor are assumed to lie on a polynomial curve.

$$b_i = \alpha_0^* + \sum_{j=1}^{d} \alpha_j^* i^j$$

Where $d$ ($\leq p$) is the degree of the polynomial. For efficient estimation, orthogonal polynomials as follow is used.

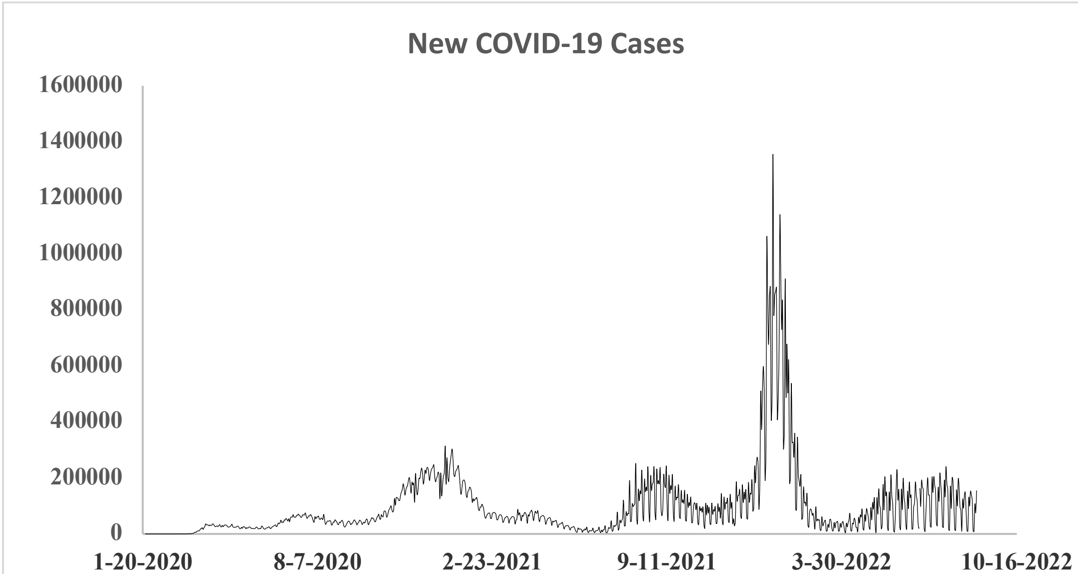
$$b_i = \alpha_0 + \sum_{j=1}^{d} \alpha_j f_j(\dot{i})$$

Where $f_j(\dot{i})$ is a polynomial of degree $j$ in the lag length $i$, and $\alpha_j$ is a coefficient estimated from the data. The model can specify a minimum degree and a maximum degree for the lag distribution polynomial, and the procedure fits polynomials for all degrees in the specified range. Therefore, the equation can be written as follows:

$$CryIndRet_t = \alpha + \sum_{i=0}^{p} \beta_i COVID - 19\ Cases_{t=i} + \sum_{i=0}^{j} \gamma\ Control\ Variables_{t=i} + \ \dots\dots\dots\dots\dots \ + \varepsilon_t$$

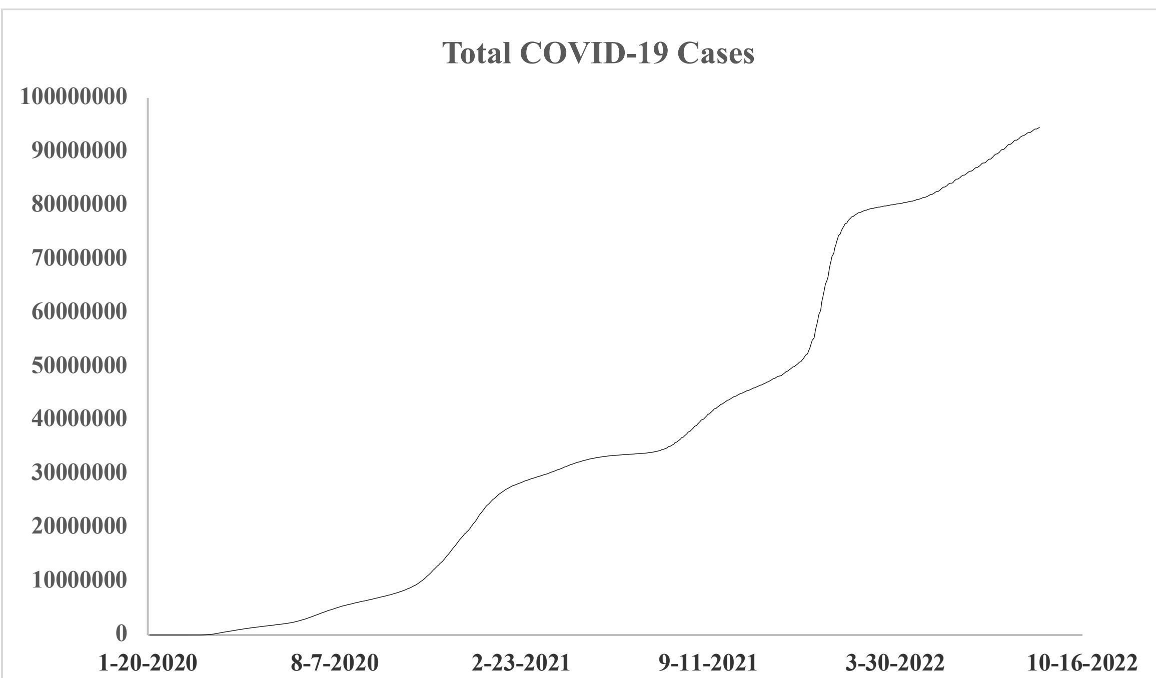
$CryIndRet_t$ is the Cryptocurrencies Index Return, a log value proxy using leading ten cryptocurrencies by market capitalization. COVID-19 cases are the log-transformed cases per million population. Control Variables are the change in Crypto Volatility Index, MSCI World Index Return, One-Year Risk-Free Rate, and Crypto Trading Volume, and $\boldsymbol{\varepsilon}$t is an error term.

**Figure 1: New COVID-19 Confirmed Cases**



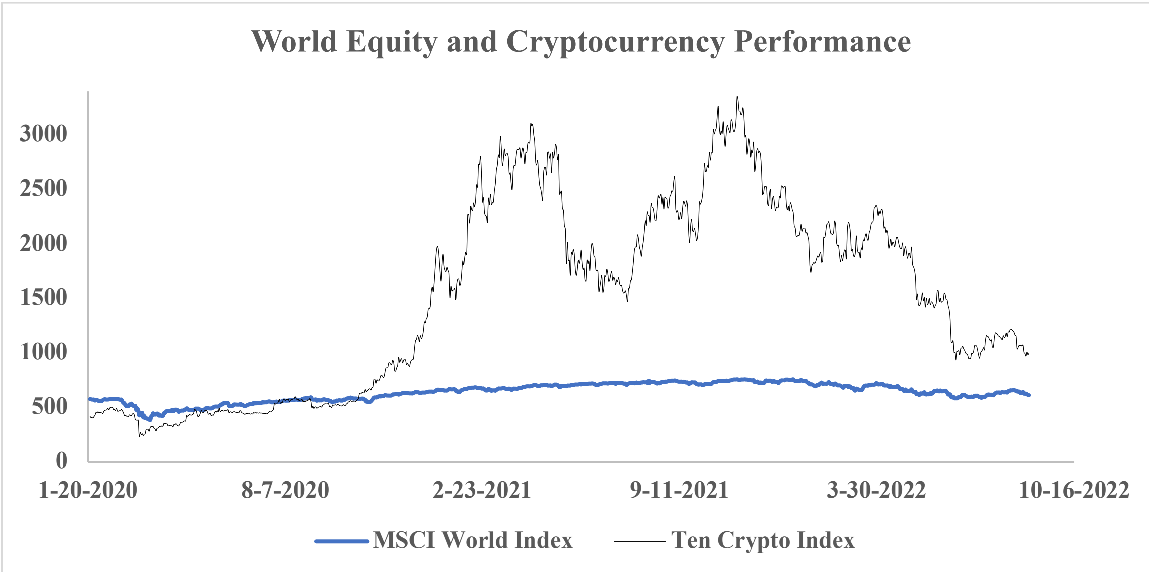

This figure presents new COVID-19 cases reported daily. There are waves of higher new cases during November -December 2020, August-September 2021, and increasing in March 2021.

**Figure 2: Total COVID-19 Confirmed Cases**



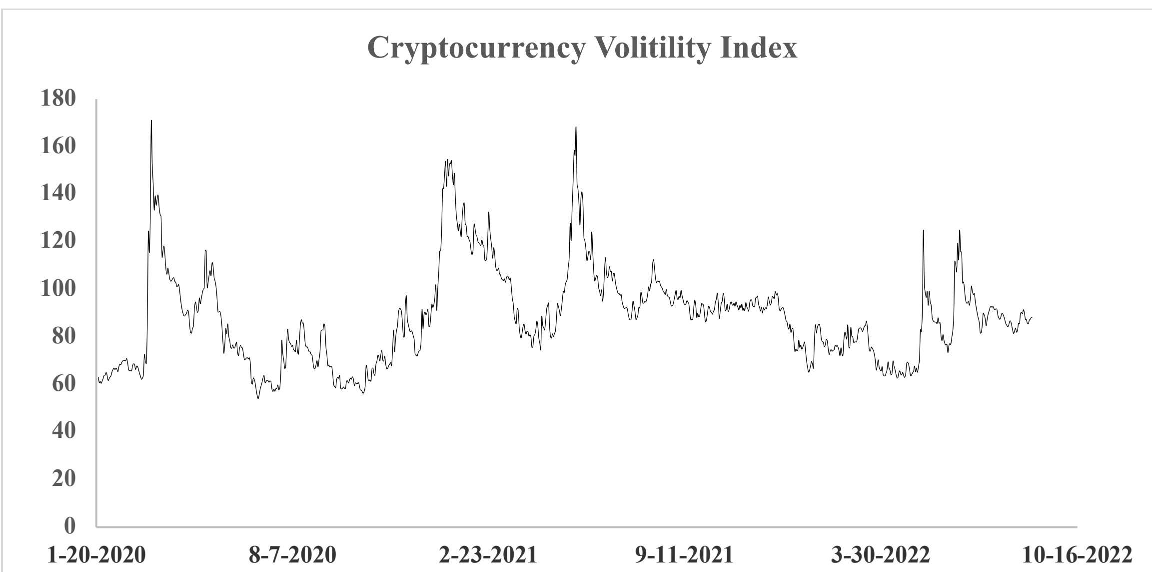

This figure plots total COVID-19 cases reported.

**Figure 3: World Equity and Top 10 Cryptocurrency Index**




This figure illustrates the daily index value of World Equity and the Top 10 Cryptocurrency movement. The Cryptocurrency Index is based on market capitalization as on August 2022. The y-axis is the index value of both indices. The graph indicates that cryptocurrencies are more volatile.

**Figure 4: Cryptocurrency Volatility Index Movement**




This figure illustrates daily volatility of Cryptocurrencies.

Daily asset prices, such as stock returns, can have heavy-tailed probability distributions or outliers. The conditional variance changes and the outliers occur when the variance is significant, as exhibited in cryptocurrency prices. Therefore, we use alternative models to augment the analysis of the results using two generalized autoregressive conditional heteroscedasticities (GARCH) Models. GARCH is used considerably within the economic or return data as asset prices are conditional heteroskedastic. First, we use the GARCH model of Bollerslev (1986), an essential time series model for heteroscedastic data. It unequivocally models a time-varying conditional variance as a linear function of past squared residuals and their past values.

$$Y_t = x_t\beta + \gamma\sqrt{h_t} + \varepsilon_t$$

The residual $\varepsilon_t$ is modeled as

$$\varepsilon_t = \sqrt{h_t} * v_t$$

Where $v_t$ is *i.i.d.* with zero mean and unit variance, and where $h_t$ is expressed as

$$h_t = \kappa + \delta_1 h_{t-1} + \delta_2 h_{t-2} + \ldots + \delta_{p1} h_{t-p} + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \ldots + \alpha_{q1} u_{t-q}^2$$

Alternative GARCH model is the Exponential GARCH (EGARCH) model used in this study has the conditional variance of $u_t$ as follows:

$$\log h_t = \omega + \sum_{i=1}^{q} \alpha_i\, g(z_{t-i}) + \sum_{j=1}^{p} \gamma_j\, ln(h_{t-j})$$

Where

$$g(z_t) = \theta z_t + \gamma[|z_t| - E|z_t|]$$
$$z_t = u_t/\sqrt{h_t}$$

The EGARCH (1, 1) model has additional leverage terms to denote asymmetry in volatility clustering. Further, the GARCH (1,1) model has a minor information criterion according to Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Hannan-Quinn Criterion (HQC) values.

*Descriptive Statistics*

Summary statistics are presented in Table 1. It defines the primary variables of interest. Panel A of Table 1 presents the summary of variables prior to vaccination, while Panel B of Table shows the statistics of the vaccination period. The average cryptocurrency index return is 0.305% daily during the pre-vaccination period. The daily difference between the high and low prices of cryptocurrencies is 4.474%. The volatility Index is 77.98 with a standard deviation of 19.32. Further, the mean value of the World Equity Index Return and One-year Risk-Free Rate is 0.026% and 0.313% per day. The average logarithmic trading volume of cryptocurrencies is 6.127 per day.

Learning about vaccines' availability during the pandemic was essential as they changed investor sentiment from being optimistic, pessimistic, or neutral. There may need to be more than the development and availability of vaccines to be optimistic towards the economy; instead, it needs more assurance in the efficacy of the vaccination. Government initiates policy measures to

## Table 1: Summary Statistics

Panel A: Descriptive Statistics for Pre-Vaccination Period

| Variables | No. of Obs. | Mean | Median | Standard Deviation | Minimum | Maximum |
|---|---|---|---|---|---|---|
| **Cryptocurrencies Index Return (%)** | 324 | 0.305% | 0.333% | 3.373% | -32.515% | 14.537% |
| **Cryptocurrencies Intraday Movement (%)** | 324 | 4.474% | 3.697% | 4.225% | 1.037% | 60.492% |
| **Crypto Volatility Index** | 324 | 77.98 | 72.23 | 19.32 | 54.00 | 170.55 |
| **MSCI World Index Return (%)** | 324 | 0.026% | 0.080% | 1.684% | -9.510% | 8.390% |
| **One-Year Risk-Free Rate** | 324 | 0.313% | 0.150% | 0.416% | 0.100% | 1.510% |
| **Crypto Trading Volume (log)** | 324 | 6.127 | 6.143 | 0.293 | 5.428 | 7.086 |
| **New COVID Cases Per Million** | 323 | 145.09 | 102.69 | 150.76 | 0 | 699.45 |
| **Total COVID Cases Per Million** | 324 | 12348.78 | 8088.51 | 12139.03 | 0.003 | 46863.63 |
| **New COVID Deaths Per Million** | 286 | 3.06 | 2.84 | 1.95 | 0 | 8.757 |
| **Total COVID Deaths Per Million** | 286 | 414.96 | 422.13 | 244.28 | 0.003 | 876.24 |
| **ICU COVID Patients Per Million** | 149 | 37.61 | 33.92 | 13.64 | 0.003 | 73.104 |
| **Hospitalized COVID Patients Per Million** | 149 | 139.08 | 118.64 | 65.12 | 75.61 | 311.72 |

Panel B: Descriptive Statistics for Vaccination Period

| Variables | No. of Obs. | Mean | Median | Standard Deviation | Minimum | Maximum |
|---|---|---|---|---|---|---|
| **Cryptocurrencies Index Return (%)** | 629 | 0.165% | 0.239% | 3.457% | -16.675% | 14.698% |
| **Cryptocurrencies Intraday Movement (%)** | 629 | 5.697% | 4.941% | 3.324% | 1.644% | 38.764% |
| **Crypto Volatility Index** | 629 | 93.40 | 91.55 | 18.18 | 62.79 | 168.18 |
| **MSCI World Index Return (%)** | 629 | -0.001% | 0.500% | 0.952% | -3.650% | 2.760% |
| **One-Year Risk-Free Rate** | 629 | 0.796% | 0.115% | 1.041% | 0.040% | 3.370% |
| **Crypto Trading Volume (log)** | 629 | 6.09 | 5.92 | 0.63 | 4.12 | 8.96 |
| **New COVID Cases Per Million** | 629 | 371.57 | 239.45 | 466.70 | 12.66 | 4021.90 |
| **Total COVID Cases Per Million** | 629 | 158476.72 | 134681.74 | 72172.58 | 47566.88 | 280582.94 |
| **New COVID Deaths Per Million** | 629 | 3.56 | 2.39 | 3.14 | 0.02 | 13.04 |
| **Total COVID Deaths Per Million** | 629 | 2207.36 | 2174.64 | 634.26 | 886.13 | 3105.65 |
| **ICU COVID Patients Per Million** | 629 | 35.03 | 28.29 | 25.13 | 4.25 | 85.73 |
| **Hospitalized COVID Patients Per Million** | 629 | 155.92 | 116.69 | 108.15 | 29.28 | 458.50 |

This table presents summary statistics of variables scrutinized for the top 10 cryptocurrencies and COVID-19. Cryptocurrencies Index Return is the daily percentage return in the top 10 cryptocurrencies prices. Cryptocurrencies Intraday Movement is the percentage difference between daily high and low prices. Crypto Volatility Index is a decentralized VIX for crypto that allows users to hedge against market volatility and impermanent loss. MSCI World Index Return is the percentage change in the MSCI World index value. One-Year Risk Free-Rate is the one-year U.S. treasury bill daily yield. Crypto Trading Volume is the average trading volume of the top 10 cryptocurrencies. New COVID Cases Per Million is new confirmed cases of COVID-19 per million population. Total COVID Cases Per Million is the total number of confirmed cases of COVID-19 per million population. New COVID Deaths Per Million is new deaths attributed to COVID-19 per million population. Total COVID Deaths Per Million is the total number of deaths attributed to COVID-19 per million population. ICU COVID Patients Per Million is the total number of COVID-19 patients in hospitals on a given day per million population. Hospitalized COVID Patients Per Million is the total number of COVID-19 patients in hospitals on a given day per million population.

leverage its effect and positively induce investor sentiment, thus lowering pessimism. Rouatbi et al. (2021) conclude that COVID-19 vaccination stabilizes the financial markets, particularly equity markets, and its impact is much more substantial within advanced economies.

After the vaccine's introduction on December 11, 2020, the government's measures to restrict the pandemic contagion can have very different pricing behavior in cryptocurrencies. The vaccination began with medical professionals and increasingly expanded to a broader population. We anticipate that the expansion and availability of vaccination will subdue the number of covid cases. Panel B of Table shows that the cryptocurrency index return is lower (0.165%) than in the pre-vaccination period. The volatility in their price and the daily high-low price have increased on an aggregate basis. An important question arises whether vaccination availability has affected cryptocurrency prices. The daily return has moderated during the vaccination period, but the volatility has increased, as observed in standard deviations. Analysis of COVID-19 variables reveals that vaccination availability has not improved the situation of COVID-19-related cases.

We check the correlations of variables used in the analysis and find that the correlations are within the range below 0.50. However, the correlations of returns of individual cryptocurrencies are all highly correlated and consistent with prior studies (Hu et al. (2018)). As expected, cryptocurrencies are negatively and highly correlated with the crypto volatility index suggesting the fears associated with the market risk premium. COVID-19 variables have solid associations and correlations, but we use them in the regression analysis individually. Therefore, they do not warrant the problem of multicollinearity. However, we test the multicollinearity issue in our regressions using the variance inflation factor. For brevity, we do not report the correlation statistics in a table.

*Regression Results*

To assess the importance of COVID-19 variables to the cryptocurrencies, we use the baseline model, i.e., ordinary least squares, to examine the structural relationship between cryptocurrencies and COVID-19 variables. The t-statistics in parentheses below the estimates follow heteroskedasticity and autocorrelation-robust standard errors. Tables 2 and 3 contain standard multivariate cross-sectional regressions for cryptocurrencies index returns and covid cases. The relationship between cryptocurrencies and COVID-19 has been assessed during pre-and post-vaccination periods. Based on existing literature in asset pricing, we initially use the control variables such as cryptocurrency volatility, world equity measure, and risk-free rate in the regressions as reported in Table 2. Panel A of Table 2 reports the regressions results. Covid Cases, an independent variable, represents the covid intensity, such as new covid cases, total covid cases, new covid deaths, total covid deaths, icu covid patients, and hospitalized covid patients. They show that all COVID-19 variables positively and statistically significant with cryptocurrencies index return. Panel B of Table 2 shows that icu and hospitalized covid patients are negatively and significantly related to cryptocurrencies. However, total covid cases, new covid deaths, and total covid deaths positively relate to cryptocurrencies index return.

## Table 2: Multivariate Cross-Sectional Regression for Cryptocurrencies Market

Panel A: Pre-Vaccination Period Analysis

| Variables | Cryptocurrencies Index Return as Dependent Variable | | | | | |
|---|---|---|---|---|---|---|
| | **New COVID Cases** | **Total COVID Cases** | **New COVID Deaths** | **Total COVID Deaths** | **ICU COVID Patients** | **Hospitalized COVID Patients** |
| **Δ Crypto Volatility Index** | **-0.003** | **-0.005** | **-0.006** | **-0.005** | **-0.003** | -0.003 |
| | **(-2.51)** | **(-2.23)** | **(-2.62)** | **(-2.27)** | **(-1.75)** | (-1.56) |
| **MSCI World Index Return** | **2.173** | **2.230** | **3.439** | **2.799** | **2.472** | **2.146** |
| | **(9.97)** | **(6.68)** | **(13.02)** | **(8.58)** | **(10.95)** | **(9.63)** |
| **One-Year Risk-Free Rate** | **-2.939** | **-2.051** | **-3.526** | **-2.581** | **-3.202** | **-3.102** |
| | **(-5.31)** | **(-2.71)** | **(-4.59)** | **(-3.25)** | **(-5.39)** | **(-5.55)** |
| **COVID Cases** | **0.180** | **0.251** | **0.076** | **0.333** | **0.276** | **0.255** |
| | **(12.94)** | **(6.62)** | **(4.10)** | **(4.79)** | **(11.15)** | **(12.65)** |
| Intercept | **-5.698** | **-7.724** | **-12.795** | **-10.894** | **-7.590** | **-5.780** |
| | **(-4.14)** | **(-4.10)** | **(-7.41)** | **(-5.94)** | **(-5.32)** | **(-4.15)** |
| *Adj.R* Square | 0.90 | 0.84 | 0.81 | 0.82 | 0.89 | 0.90 |

Panel B: Vaccination Period Analysis

| Variables | Cryptocurrencies Index Return as Dependent Variable | | | | | |
|---|---|---|---|---|---|---|
| | **New COVID Cases** | **Total COVID Cases** | **New COVID Deaths** | **Total COVID Deaths** | **ICU COVID Patients** | **Hospitalized COVID Patients** |
| **Δ Crypto Volatility Index** | 0.007 | 0.001 | 0.005 | 0.090 | 0.055 | 0.054 |
| | (0.38) | (0.61) | (0.31) | (0.54) | (0.31) | (0.30) |
| **MSCI World Index Return** | **2.682** | **1.126** | **2.726** | **0.491** | **2.645** | **2.613** |
| | **(16.31)** | **(4.69)** | **(16.52)** | **(1.98)** | **(16.33)** | **(16.02)** |
| **One-Year Risk-Free Rate** | **-0.100** | **-0.304** | **-0.091** | **-0.336** | **-0.134** | **-0.116** |
| | **(-9.78)** | **(-11.80)** | **(-8.11)** | **(-14.44)** | **(-10.88)** | **(-10.77)** |
| **COVID Cases** | -0.002 | **0.364** | **0.015** | **0.632** | **-0.057** | **-0.051** |
| | (-1.57) | **(8.57)** | **(2.04)** | **(11.10)** | **(-4.86)** | **(-4.44)** |
| Intercept | **-7.518** | **-1.571** | **-7.884** | 2.090 | **-7.122** | **-6.868** |
| | **(-6.95)** | **(-1.26)** | **(-7.27)** | (1.58) | **(-6.67)** | **(-6.36)** |
| *Adj.R* Square | 0.63 | 0.67 | 0.63 | 0.69 | 0.64 | 0.64 |

This table presents the regressions results of the top cryptocurrencies index return and COVID-19 variables. The regression models present the response of COVID-19 variables on cryptocurrencies after controlling for financial market variables. The variables are defined in Table 1 legend. The regression estimates are reported in the upper part, and t-statistics are in parenthesis.

## Table 3: Multivariate Cross-Sectional Regression for Cryptocurrencies Market

Panel A: Pre-Vaccination Period Analysis

| Variables | Cryptocurrencies Index Return as Dependent Variable | | | | | |
|---|---|---|---|---|---|---|
| | New COVID Cases | Total COVID Cases | New COVID Deaths | Total COVID Deaths | ICU COVID Patients | Hospitalized COVID Patients |
| **Δ Crypto Volatility Index** | **-0.003** | -0.003 | **-0.006** | -0.003 | **-0.005** | **-0.004** |
| | **(-2.06)** | (-1.29) | **(-2.60)** | (-1.43) | **(-2.65)** | **(-2.17)** |
| **MSCI World Index Return** | **2.120** | **1.851** | **3.450** | **2.440** | **2.459** | **2.156** |
| | **(9.57)** | **(5.27)** | **(12.94)** | **(6.96)** | **(11.31)** | **(9.85)** |
| **One-Year Risk-Free Rate** | **-2.895** | **-1.666** | **-3.537** | **-2.199** | **-3.257** | **-3.150** |
| | **(-5.23)** | **(-2.22)** | **(-4.59)** | **(-2.77)** | **(-5.68)** | **(-5.73)** |
| **Crypto Trading Volume** | 0.020 | **0.059** | -0.008 | **0.056** | **-0.059** | **-0.039** |
| | (1.27) | **(2.89)** | (-0.35) | **(2.52)** | **(-3.49)** | **(-2.49)** |
| **COVID Cases** | **0.181** | **0.288** | **0.077** | **0.403** | **0.305** | **0.267** |
| | **(13.02)** | **(7.36)** | **(4.08)** | **(5.47)** | **(12.07)** | **(13.10)** |
| Intercept | **-5.717** | **-6.785** | **-12.724** | **-10.119** | **-6.545** | **-5.192** |
| | **(-4.17)** | **(-3.64)** | **(-7.30)** | **(-5.54)** | **(-4.66)** | **(-3.74)** |
| *Adj.R* Square | 0.90 | 0.84 | 0.81 | 0.82 | 0.89 | 0.90 |

Panel B: Vaccination Period Analysis

| Variables | Cryptocurrencies Index Return as Dependent Variable | | | | | |
|---|---|---|---|---|---|---|
| | New COVID Cases | Total COVID Cases | New COVID Deaths | Total COVID Deaths | ICU COVID Patients | Hospitalized COVID Patients |
| **Δ Crypto Volatility Index** | 0.026 | 0.025 | 0.026 | 0.024 | 0.024 | 0.024 |
| | (1.49) | (1.49) | (1.49) | (1.44) | (1.37) | (1.38) |
| **MSCI World Index Return** | **2.864** | **1.619** | **2.874** | **0.939** | **2.833** | **2.823** |
| | **(18.31)** | **(6.71)** | **(18.31)** | **(3.80)** | **(18.08)** | **(17.89)** |
| **One-Year Risk-Free Rate** | **-0.094** | **-0.254** | **-0.093** | **-0.298** | **-0.111** | **-0.102** |
| | **(-9.73)** | **(-9.85)** | **(-8.80)** | **(-13.00)** | **(-9.14)** | **(-9.77)** |
| **Crypto Trading Volume** | **0.093** | **0.075** | **0.093** | **0.072** | **0.085** | **0.087** |
| | **(8.83)** | **(7.10)** | **(8.66)** | **(7.23)** | **(7.72)** | **(7.91)** |
| **COVID Cases** | -0.007 | **0.183** | 0.018 | **0.244** | **-0.027** | **-0.023** |
| | (-1.03) | **(2.67)** | (0.26) | **(3.70)** | **(-2.29)** | **(-2.02)** |
| Intercept | **-10.435** | **-5.234** | **-10.545** | -1.512 | **-7.122** | **-9.972** |
| | **(-9.72)** | **(-4.01)** | **(-9.85)** | (-1.11) | **(-6.67)** | **(-9.05)** |
| *Adj.R* Square | 0.67 | 0.69 | 0.67 | 0.71 | 0.67 | 0.67 |

This table presents the regression results of the top cryptocurrencies index return and COVID-19 variables. The regression models present the response of COVID-19 variables on cryptocurrencies after controlling for financial market variables. The variables are defined in Table 1 legend. The regression estimates are reported in the upper part, and t-statistics are in parenthesis.

Table 3 multivariate regressions include cryptocurrencies trading volume, a measure of liquidity. Panel A of Table 3 results show that the cryptocurrency index return is positively and significantly associated with COVID-19 variables, as reported in Table A of Table 2. The estimates and t-statistics are of similar magnitude. It indicates that during the pre-vaccination period, COVID-19 proxies are significantly associated with cryptocurrencies' return. The results in Panel B of Table 3 show that the inclusion of liquidity factor, i.e., trading volume, has decreased the magnitude of estimates and t-statistics for COVID-19 variables during the vaccination period. As reported in Panel B of Table, total covid cases and deaths are positively related to cryptocurrency return, while icu and hospitalized patients are negatively related to cryptocurrency return. The results show varying responses of COVID-19 variables on returns for cryptocurrencies. Notably, the risk-free rate is significantly and negatively associated with cryptocurrencies. Treasury bill is a predictor of cryptocurrency returns. It only suggests that lower returns on treasury bills induce the investor to bet on cryptocurrencies. It may arise because cryptocurrencies are unregulated and considered fiat currency alternatives.

We consider the vaccination period, i.e., starting on December 11, 2020, and onwards, a significant policy measure to combat the COVID-19 crisis. Muller (2020) contends that governments should minimize uncertainty through precise communication and fast implementation of policy measures. The regression analysis during the vaccination period and other policy measures for COVID-19 may be somewhat not so sensitive to factors influencing cryptocurrency returns. Therefore, using multivariate models to understand better the daily variation in cryptocurrency intraday price (high and low) and whether they are affected similarly to COVID-19 proxies. Panel A of Table 4 provides the results for the pre-vaccination period. The analysis shows that COVID-19 variables are positively and significantly related to the intraday price movement of cryptocurrencies. However, the responses to COVID-19 have become negative to the cryptocurrency intraday movement during the vaccination period. The fact that cryptocurrencies are decentralized financial assets that do not respond to the traditional market fundamentals could be a factor for showing asymmetric response to COVID-19 proxies during the pre-and vaccination period. It suggests that traditional financial asset price factors differ from cryptocurrency price movement.

It is vital to test whether similar results come out for individual cryptocurrency return analysis. Table 5 provides the results where each model represents the regression for individual cryptocurrencies. For brevity, we report each row's estimates of covid proxy variables. The results are obtained similarly to the regression model of Table 3 using control variables and a single covid proxy in the model. Panel A of Table 5 reveals that overall, individual cryptocurrency returns have a significant relationship to contemporaneous new covid cases, new covid deaths, total covid deaths, icu covid patients, and hospitalized covid patients. In a few cases, estimates are negative and significant. It is noted that those cryptocurrencies are smaller in size as model 1 represents the most prominent cryptocurrency and model 10 the smallest cryptocurrency. The top 3 cryptocurrencies behave in tandem and drive the cryptocurrency market. A notable point in Model 1 is that it shows the similar and significant relationship of Bitcoin to COVID-19 variables, as reported in Panel A of Tables 2-4.

Panel B of Table 5 examines the relationship of individual cryptocurrency returns to COVID-19 proxies during the vaccination period. Model 1, representing Bitcoin, shows a negative and significant relationship with COVID-19 variables. Most cryptocurrencies have a negative association with COVID-19 variables. Overall, our results show that significant cryptocurrencies generate lower returns during vaccination and become moderate in price movement. The smaller cryptocurrencies have higher price fluctuation making cryptocurrencies riskier. Consistent with the asset pricing literature, it contends that risk-averse investors demand higher returns to hold riskier assets.

Consistent with evidence on the time-series behavior of daily observations of covid variables and cryptocurrencies, we find that covid variables are autocorrelated. Further, Liu and Serletis (2019) employ the GARCH-M and find significant shock and volatility transmission

## Table 4: Multivariate Cross-Sectional Regression for Cryptocurrencies Market

Panel A: Pre-Vaccination Period Analysis

| **Variables** | **Cryptocurrencies Intraday Movement as Dependent Variable** | | | | | |
|---|---|---|---|---|---|---|
| | **New COVID Cases** | **Total COVID Cases** | **New COVID Deaths** | **Total COVID Deaths** | **ICU COVID Patients** | **Hospitalized COVID Patients** |
| **Δ Crypto Volatility Index** | **-0.044** | **-0.039** | **-0.050** | **-0.040** | **-0.046** | **-0.044** |
| | **(-3.76)** | **(-3.42)** | **(-4.12)** | **(-3.45)** | **(-3.90)** | **(-3.77)** |
| **MSCI World Index Return** | **0.366** | -0.033 | **0.608** | 0.111 | **0.493** | **0.441** |
| | **(2.31)** | (-0.17) | **(4.32)** | (0.60) | **(3.23)** | **(2.75)** |
| **One-Year Risk-Free Rate** | -0.455 | 0.165 | -0.563 | 0.054 | -0.547 | -0.528 |
| | (-1.11) | (0.40) | (-1.38) | (0.13) | (-1.36) | (-1.32) |
| **Crypto Trading Volume** | **0.643** | **0.808** | **0.578** | **0.822** | **0.515** | **0.545** |
| | **(5.85)** | **(7.20)** | **(5.00)** | **(7.07)** | **(4.33)** | **(4.74)** |
| **COVID Cases** | **0.362** | **1.074** | **0.201** | **1.723** | **0.482** | **0.428** |
| | **(3.64)** | **(5.00)** | **(2.02)** | **(4.48)** | **(2.71)** | **(2.88)** |
| Intercept | **-3.085** | **-1.800** | **-4.321** | **-2.754** | **-3.629** | **-3.389** |
| | **(-3.14)** | **(-1.76)** | **(-4.70)** | **(-2.89)** | **(-3.68)** | **(-3.34)** |
| *Adj.R* Square | 0.54 | 0.58 | 0.52 | 0.56 | 0.53 | 0.53 |

Panel B: Vaccination Period Analysis

| **Variables** | **Cryptocurrencies Intraday Movement as Dependent Variable** | | | | | |
|---|---|---|---|---|---|---|
| | **New COVID Cases** | **Total COVID Cases** | **New COVID Deaths** | **Total COVID Deaths** | **ICU COVID Patients** | **Hospitalized COVID Patients** |
| **Δ Crypto Volatility Index** | **-0.022** | **-0.021** | **-0.023** | **-0.022** | **-0.022** | **-0.022** |
| | **(-5.06)** | **(-5.12)** | **(-5.33)** | **(-5.22)** | **(-5.06)** | **(-5.08)** |
| **MSCI World Index Return** | -0.312 | **-1.167** | -0.257 | **-2.304** | -0.332 | -0.347 |
| | (-0.82) | **(-1.92)** | (-0.67) | **(-3.60)** | (-0.86) | (-0.90) |
| **One-Year Risk-Free Rate** | **-0.325** | **-0.432** | **-0.297** | **-0.535** | **-0.321** | **-0.328** |
| | **(-13.73)** | **(-6.65)** | **(-11.61)** | **(-8.99)** | **(-10.81)** | **(-12.83)** |
| **Crypto Trading Volume** | **0.263** | **0.246** | **0.242** | **0.237** | **0.262** | **0.259** |
| | **(10.27)** | **(9.29)** | **(9.29)** | **(9.15)** | **(9.67)** | **(9.62)** |
| **COVID Cases** | **-0.038** | **-0.185** | **-0.052** | **-0.550** | 0.011 | 0.005 |
| | **(-2.19)** | **(-3.73)** | **(-3.04)** | **(-3.79)** | (0.37) | (0.04) |
| Intercept | 0.421 | **0.818** | **0.437** | **1.385** | **0.452** | **0.471** |
| | (1.61) | **(2.49)** | **(1.68)** | **(3.92)** | **(1.69)** | **(1.75)** |
| *Adj.R* Square | 0.43 | 0.43 | 0.42 | 0.44 | 0.42 | 0.41 |

This table presents regression results of top cryptocurrencies' intraday movement and COVID-19 variables. The regression models present the response of COVID-19 variables on cryptocurrency intraday movement after controlling for financial markets variables. The variables are defined in Table 1 legend. The regression estimates are reported in the upper part, and t-statistics are in parenthesis.

## Table 5: Multivariate Cross-Sectional Regression for Cryptocurrencies Market

Panel A: Pre-Vaccination Period Analysis

| Variables | Top 10 Cryptocurrencies Price Return as Dependent Variable | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Model 7 | Model 8 | Model 9 | Model 10 |
| Δ Crypto Volatility Index | | | | | | | | | | |
| MSCI World Index Return | | | | | | | | | | |
| One-Year Risk-Free Rate | | | | | | | | | | |
| Crypto Trading Volume | | | | | | | | | | |
| New COVID Cases | **0.243** | **0.199** | **0.100** | -0.008 | **0.088** | **0.277** | **-0.203** | **-0.066** | **-0.047** | 0.045 |
| | **(17.31)** | **(2.08)** | **(3.92)** | (-0.25) | **(5.40)** | **(1.67)** | **(-2.77)** | **(-5.03)** | **(-4.50)** | (1.17) |
| Total COVID Cases | **0.410** | 0.051 | **0.409** | **-0.189** | **0.083** | 0.100 | **0.426** | **-0.090** | -0.035 | **0.167** |
| | **(9.58)** | (1.03) | **(9.23)** | **(-2.96)** | **(2.14)** | (1.17) | **(2.68)** | **(-2.96)** | (-1.45) | **(2.05)** |
| New COVID Deaths | **0.086** | **0.470** | -0.025 | 0.021 | **0.038** | **0.828** | **-0.133** | **-0.033** | -0.015 | 0.049 |
| | **(3.68)** | **(2.46)** | (-1.00) | (0.73) | **(2.32)** | **(2.76)** | **(-1.92)** | **(-2.51)** | (-1.50) | (1.38) |
| Total COVID Deaths | **0.660** | **0.288** | **0.812** | **-0.432** | 0.0.82 | **0.555** | **1.087** | **-0.014** | -0.057 | 0.213 |
| | **(7.64)** | **(2.27)** | **(10.51)** | **(-3.73)** | (1.13) | **(2.92)** | **(3.81)** | **(-2.46)** | (-1.29) | (1.41) |
| ICU COVID Patients | **0.515** | 0.803 | -0.011 | **0.293** | **0.283** | **2.282** | **-1.028** | **-0.122** | **-0.074** | **0.374** |
| | **(19.41)** | (1.02) | (-0.20) | **(5.11)** | **(10.56)** | **(2.29)** | **(-8.29)** | **(-4.40)** | **(-3.32)** | **(5.25)** |
| Hospitalized COVID Patients | **0.449** | 0.803 | 0.070 | **0.165** | 0.212 | **2.282** | **-0.696** | **-0.106** | **-0.069** | **0.249** |
| | **(27.61)** | (1.02) | (1.56) | **(3.32)** | (9.00) | **(2.29)** | **(-6.31)** | **(-4.73)** | **(-3.88)** | **(4.12)** |

Panel B: Vaccination Period Analysis

| Variables | Top 10 Cryptocurrencies Price Return as Dependent Variable | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Model 7 | Model 8 | Model 9 | Model 10 |
| Δ Crypto Volatility Index | | | | | | | | | | |
| MSCI World Index Return | | | | | | | | | | |
| One-Year Risk-Free Rate | | | | | | | | | | |
| Crypto Trading Volume | | | | | | | | | | |
| New COVID Cases | **-0.047** | **0.051** | **-0.018** | **-0.042** | **-0.039** | **-0.057** | **-0.034** | **-0.062** | **0.054** | **-0.062** |
| | **(-9.52)** | **(2.16)** | **(-3.28)** | **(-4.52)** | **(-6.52)** | **(-7.16)** | **(-3.84)** | **(-3.10)** | **(2.20)** | **(-11.09)** |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Total COVID Cases** | **-0.205** | **-0.005** | **-0.172** | **-1.019** | **-0.241** | **-0.832** | **-0.651** | **0.034** | 0.009 | **-0.366** |
| | **(-4.52)** | **(-0.27)** | **(-3.83)** | **(-17.10)** | **(-4.67)** | **(-14.80)** | **(-9.61)** | **(1.98)** | (0.45) | **(-7.18)** |
| **New COVID Deaths** | **-0.030** | -0.035 | **-0.021** | -0.005 | **-0.031** | **-0.033** | **-0.037** | 0.011 | -0.035 | **-0.022** |
| | **(-6.06)** | (-1.58) | **(-4.25)** | (-0.60) | **(-5.56)** | **(-4.28)** | **(-4.50)** | (-0.60) | (-1.50) | **(-3.61)** |
| **Total COVID Deaths** | -0.140 | **0.080** | 0.120 | **-0.257** | -0.101 | **-0.161** | **-0.863** | -0.006 | **0.112** | **-0.809** |
| | (-1.39) | **(1.84)** | (1.21) | **(-2.37)** | (-0.87) | **(-2.47)** | **(-5.40)** | (-0.16) | **(2.46)** | **(-7.30)** |
| **ICU COVID Patients** | **-0.144** | -0.034 | **0.078** | -0.028 | **-0.136** | **-0.112** | **-0.124** | 0.025 | -0.033 | -0.091 |
| | **(-6.56)** | (-0.78) | **(7.26)** | (-1.38) | **(-12.21)** | **(-6.59)** | **(-6.93)** | (0.67) | (-1.59) | (-0.77) |
| **Hospitalized COVID Patients** | **-0.165** | -0.002 | **-0.081** | -0.100 | **-0.149** | **-0.170** | **0.154** | **0.019** | 0.023 | -0.142 |
| | **(-20.36)** | (-0.47) | **(-7.34)** | (-0.49) | **(-3.29)** | **(-4.10)** | **(8.56)** | **(4.42)** | (0.43) | (-1.18) |

This table presents the regression results of the top 10 cryptocurrencies' prices and COVID-19 variables. The regression models present the effect of COVID-19 variables on cryptocurrency price return after controlling for financial market variables. Each model represents an induvial cryptocurrency result. The variables are defined in Table 1 legend. The regression estimates are reported in the upper part, and t-statistics are in parenthesis.

among cryptocurrencies. Katsiampa (2017) shows, using GARCH models, that volatility in Bitcoin arises from the short- and long-run component of the conditional variance. Therefore, we account for this behavior and examine the impact covid variables have on the returns of cryptocurrencies. The distribution of variables is non-normal, heteroskedasticity is present, and return variables are stationary. These statistics motivate the choice of an autoregressive error model, i.e., GARCH (1, 1). A VAR model is unsuitable in our analysis since it ignores heteroskedasticity.

A GARCH (1,1) model with a t-distribution is used to estimate the marginal distribution for the return series. Similar to prior multivariate regressions, we include control variables in our autoregressive error model that also controls for endogeneity. Table 6 presents the results of this model. Panel A of Table 6 shows that all covid variables except total covid cases and deaths positively and significantly influence cryptocurrency index returns. Even the sign of total covid cases estimate is positive; however, when the same regression analysis is performed during the vaccination period, we find that total covid cases and deaths are positive and significant. Hospitalized and icu covid estimates are negative and significant. Overall, the results suggest that the role of covid cases has become imprecise after vaccination started. GARCH parameters (including the asymmetry term) are generally significant, and the equations are well specified regarding residual ARCH and other specification errors.

For the robustness of our analysis, we perform several robustness tests. We use four GARCH models to verify the sensitivity of our findings. Prior studies note that GARCH orders are crucial in models. The role of higher orders is checked based on Akaike Information Criterion. Finally, we use several higher-order GARCH-M models, such as GARCH-M (2,1), GARCH-M (1,2), and GARCH-M (2,2). Table 7 shows the results of these models.

We analyze the GARCH model results in Panel A of Table 7. GARCH-M (2, 1) shows that all covid variables except total covid cases are positive and significant. Similar results show for GARCH (2, 2) except in total covid deaths. In the case of GARCH (1, 2), new covid deaths, icu covid patients, and hospitalized covid patients are positive and significant. Lastly, the EGARCH model is employed to verify the sensitivity of GARCH results. The outcomes of the EGARCH model are similar to various GARCH model conclusions.

## Table 6: Time-Series Regression Model

Panel A: Pre-Vaccination Period Analysis

| **Variables** | **Cryptocurrencies Index Return as Dependent Variable** | | | | | |
|---|---|---|---|---|---|---|
| | **New COVID Cases** | **Total COVID Cases** | **New COVID Deaths** | **Total COVID Deaths** | **ICU COVID Patients** | **Hospitalized COVID Patients** |
| **Δ Crypto Volatility Index** | 0.015<br>(1.10) | 0.029<br>(1.56) | 0.013<br>(0.93) | 0.019<br>(1.37) | **-0.045**<br>**(-2.65)** | **-0.035**<br>**(-2.17)** |
| **MSCI World Index Return** | **2.366**<br>**(28.49)** | **2.421**<br>**(25.30)** | **2.482**<br>**(32.43)** | **2.507**<br>**(27.63)** | **2.458**<br>**(11.31)** | **2.156**<br>**(9.85)** |
| **One-Year Risk-Free Rate** | 0.113<br>(1.44) | **-0.113**<br>**(-1.75)** | -0.137<br>(-1.18) | **-0.347**<br>**(-2.60)** | **-0.326**<br>**(-5.68)** | **-0.315**<br>**(-5.73)** |
| **Crypto Trading Volume** | **0.073**<br>**(4.34)** | **0.075**<br>**(4.50)** | **0.068**<br>**(3.88)** | **0.065**<br>**(3.29)** | **-0.059**<br>**(-3.49)** | **-0.039**<br>**(-2.49)** |
| **COVID Cases** | **0.038**<br>**(4.54)** | 0.009<br>(1.58) | **0.021**<br>**(2.75)** | -0.020<br>(-0.28) | **0.305**<br>**(12.07)** | **0.267**<br>**(13.10)** |
| Intercept | **-7.672**<br>**(-11.43)** | **-8.096**<br>**(-11.84)** | **-8.301**<br>**(-12.06)** | **-8.329**<br>**(-11.82)** | **-6.545**<br>**(-4.66)** | **-5.192**<br>**(-3.74)** |
| $R$ Square | 84.45% | 83.35% | 84.04% | 83.48% | 89.73% | 90.58% |

Panel B: Vaccination Period Analysis

| **Variables** | **Cryptocurrencies Index Return as Dependent Variable** | | | | | |
|---|---|---|---|---|---|---|
| | **New COVID Cases** | **Total COVID Cases** | **New COVID Deaths** | **Total COVID Deaths** | **ICU COVID Patients** | **Hospitalized COVID Patients** |
| **Δ Crypto Volatility Index** | 0.026<br>(1.52) | 0.025<br>(1.50) | 0.026<br>(1.49) | 0.024<br>(1.48) | 0.024<br>(1.39) | 0.025<br>(1.41) |
| **MSCI World Index Return** | **2.867**<br>**(18.37)** | **1.629**<br>**(6.79)** | **2.875**<br>**(18.31)** | **0.958**<br>**(3.90)** | **2.836**<br>**(18.15)** | **2.825**<br>**(17.95)** |
| **One-Year Risk-Free Rate** | **-0.095**<br>**(-9.82)** | **-0.253**<br>**(-9.89)** | **-0.093**<br>**(-8.80)** | **-0.297**<br>**(-13.03)** | **-0.111**<br>**(-9.22)** | **-0.102**<br>**(-9.85)** |
| **Crypto Trading Volume** | **0.093**<br>**(8.87)** | **0.075**<br>**(7.13)** | **0.093**<br>**(8.66)** | **0.073**<br>**(7.26)** | **0.085**<br>**(7.75)** | **0.087**<br>**(7.94)** |
| **COVID Cases** | -0.074<br>(-1.06) | **0.182**<br>**(1.67)** | 0.002<br>(0.26) | **0.240**<br>**(2.68)** | **-0.028**<br>**(-2.31)** | **-0.024**<br>**(-2.03)** |
| Intercept | **-1.045**<br>**(-9.76)** | **-0.529**<br>**(-4.08)** | **-1.055**<br>**(-9.85)** | **-0.161**<br>**(-1.19)** | **-1.005**<br>**(-9.27)** | **-0.998**<br>**(-9.09)** |
| $R$ Square | 67.84% | 69.93% | 67.40% | 72.00% | 68.06% | 67.99% |

The regression model estimates time series data in which the effects of the regressor variables are distributed across time.

$$CryIndRet_t = \alpha + \sum_{i=0}^{p} \beta_i COVID - 19\ Cases_{t=i} + \sum_{i=0}^{j} \gamma\ Control\ Variables_{t=i} + \ \dots\dots\ + \varepsilon_t$$

$CryIndRet_t$ is the Cryptocurrencies Index proxied using the top 10 cryptocurrencies by market capitalization. COVID-19 cases are the log-transformed cases per million population. Control Variables are the change in the Crypto Volatility Index, World Equity represented by the MSCI World Index, the One-year U.S. treasury bill, the trading volume of cryptocurrencies, and an error term. The variables are defined in Table 1 legend. The regression estimates are reported in the upper part, and t-statistics are in parenthesis.

## Table 7: GARCH Model

Panel A: Pre-Vaccination Period Analysis

| **Variables** | **Cryptocurrencies Index Return as Dependent Variable** | | | |
|---|---|---|---|---|
| | **GARCH (2, 1)** | **GARCH (1, 2)** | **GARCH (2, 2)** | **EGARCH (1, 1)** |
| **New COVID Cases** | **0.038** | 0.063 | **0.029** | 0.021 |
| | **(5.34)** | (1.55) | **(4.13)** | (0.21) |
| | $R^2$ = 84.42% | $R^2$ = 84.33% | $R^2$ = 82.94% | $R^2$ = 78.22% |
| **Total COVID Cases** | 0.091 | 0.027 | 0.084 | **0.049** |
| | (0.50) | (0.92) | (1.37) | **(2.30)** |
| | $R^2$ = 82.01% | $R^2$ = 79.18% | $R^2$ = 83.26% | $R^2$ = 73.01% |
| **New COVID Deaths** | **0.073** | **0.153** | **0.201** | **0.100** |
| | **(1.79)** | **(3.52)** | **(3.21)** | **(4.59)** |
| | $R^2$ = 82.09% | $R^2$ = 85.61% | $R^2$ = 84.01% | $R^2$ = 73.17% |
| **Total COVID Deaths** | **0.148** | 0.104 | -0.026 | 0.013 |
| | **(4.17)** | (1.49) | (-0.37) | (0.19) |
| | $R^2$ = 81.48% | $R^2$ = 87.29% | $R^2$ = 83.45% | $R^2$ = 76.43% |
| **ICU COVID Patients** | **0.305** | **0.288** | **0.305** | 0.288 |
| | **(11.91)** | **(17.95)** | **(12.52)** | (1.12) |
| | $R^2$ = 89.70% | $R^2$ = 88.14% | $R^2$ = 89.73% | $R^2$ = 87.65% |
| **Hospitalized COVID Patients** | **0.265** | **0.279** | **0.266** | **0.292** |
| | **(15.79)** | **(15.13)** | **(15.64)** | **(2.92)** |
| | $R^2$ = 90.29% | $R^2$ = 89.82% | $R^2$ = 90.45% | $R^2$ = 87.81% |

Panel B: Vaccination Period Analysis

| **Variables** | **Cryptocurrencies Index Return as Dependent Variable** | | | |
|---|---|---|---|---|
| | **GARCH (2, 1)** | **GARCH (1, 2)** | **GARCH (2, 2)** | **EGARCH (1, 1)** |
| **New COVID Cases** | -0.007 | **-0.037** | -0.007 | **-0.040** |
| | (-0.83) | **(-13.49)** | (-0.80) | **(-11.23)** |
| | $R^2$ = 67.84% | $R^2$ = 65.93% | $R^2$ = 67.80% | $R^2$ = 66.28% |
| **Total COVID Cases** | **0.282** | **0.271** | **0.281** | **0.187** |
| | **(5.01)** | **(17.00)** | **(4.99)** | **(1.01)** |
| | $R^2$ = 69.93% | $R^2$ = 68.78% | $R^2$ = 69.99% | $R^2$ = 67.29% |
| **New COVID Deaths** | 0.002 | **-0.010** | 0.001 | **-0.010** |
| | (0.19) | **(-3.73)** | (0.17) | **(-4.11)** |
| | $R^2$ = 67.40% | $R^2$ = 66.35% | $R^2$ = 67.38% | $R^2$ = 66.09% |
| **Total COVID Deaths** | **0.540** | **0.395** | **0.538** | **0.398** |
| | **(7.63)** | **(20.52)** | **(7.58)** | **(16.96)** |
| | $R^2$ = 72.00% | $R^2$ = 69.96% | $R^2$ = 69.99% | $R^2$ = 68.15% |
| **ICU COVID Patients** | **-0.028** | **-0.129** | **-0.027** | **-0.135** |
| | **(-1.80)** | **(-22.46)** | **(-1.77)** | **(-52.63)** |
| | $R^2$ = 68.06% | $R^2$ = 62.46% | $R^2$ = 68.04% | $R^2$ = 60.58% |
| **Hospitalized COVID Patients** | -0.024 | **-0.207** | -0.023 | -0.161 |
| | (-1.59) | **(-37.67)** | (-1.56) | (-0.90) |
| | $R^2$ = 67.99% | $R^2$ = 62.17% | $R^2$ = 67.96% | $R^2$ = 53.78% |

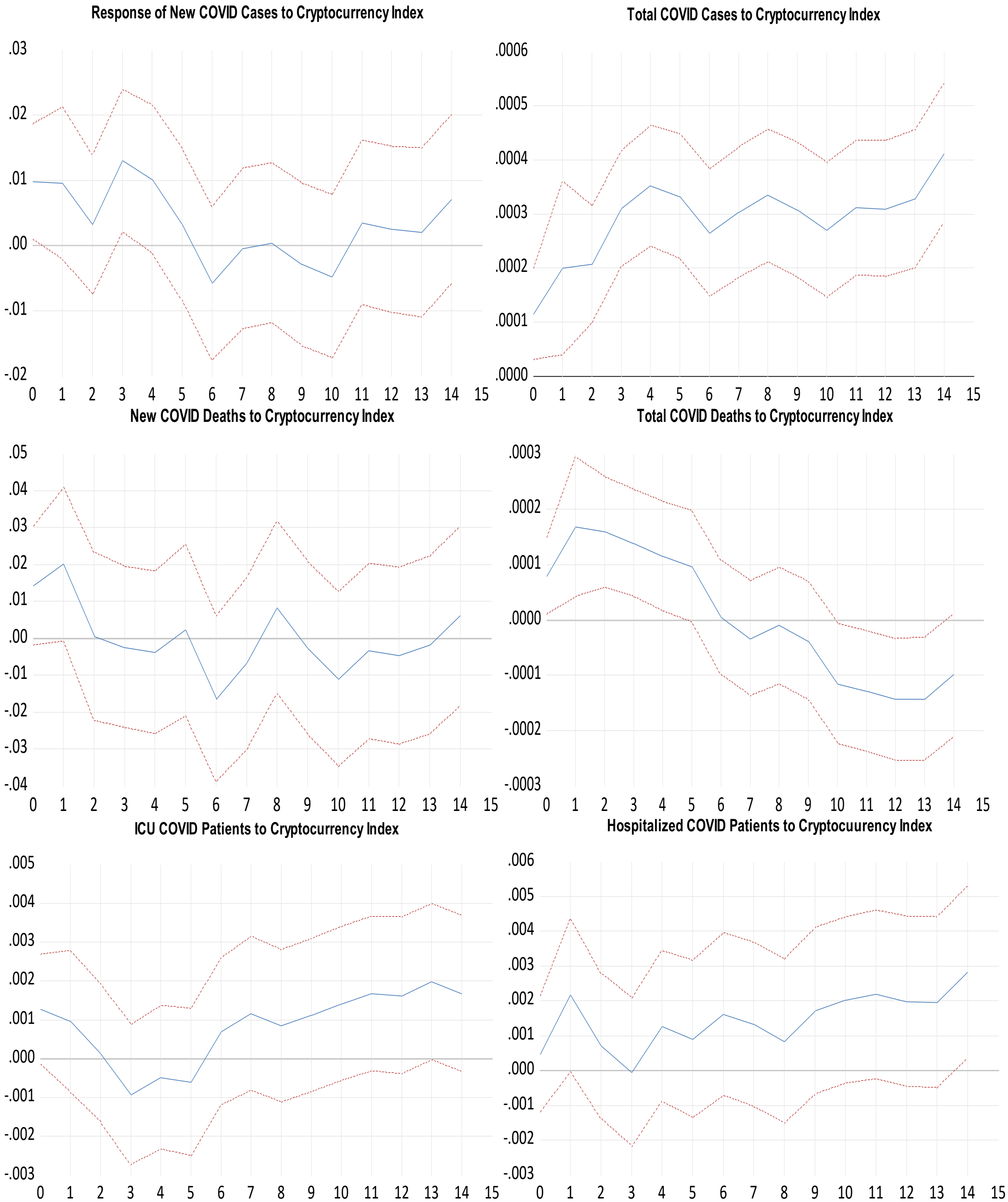
This table reports the effect of COVID-19 variables on cryptocurrencies from alternative GARCH models.

$$CryIndRet_t = \alpha + \sum_{i=0}^{p} \beta_i COVID - 19\ Cases_{t=i} + \sum_{i=0}^{j} \gamma\ Control\ Variables_{t=i} + \dots\dots + \varepsilon_t$$

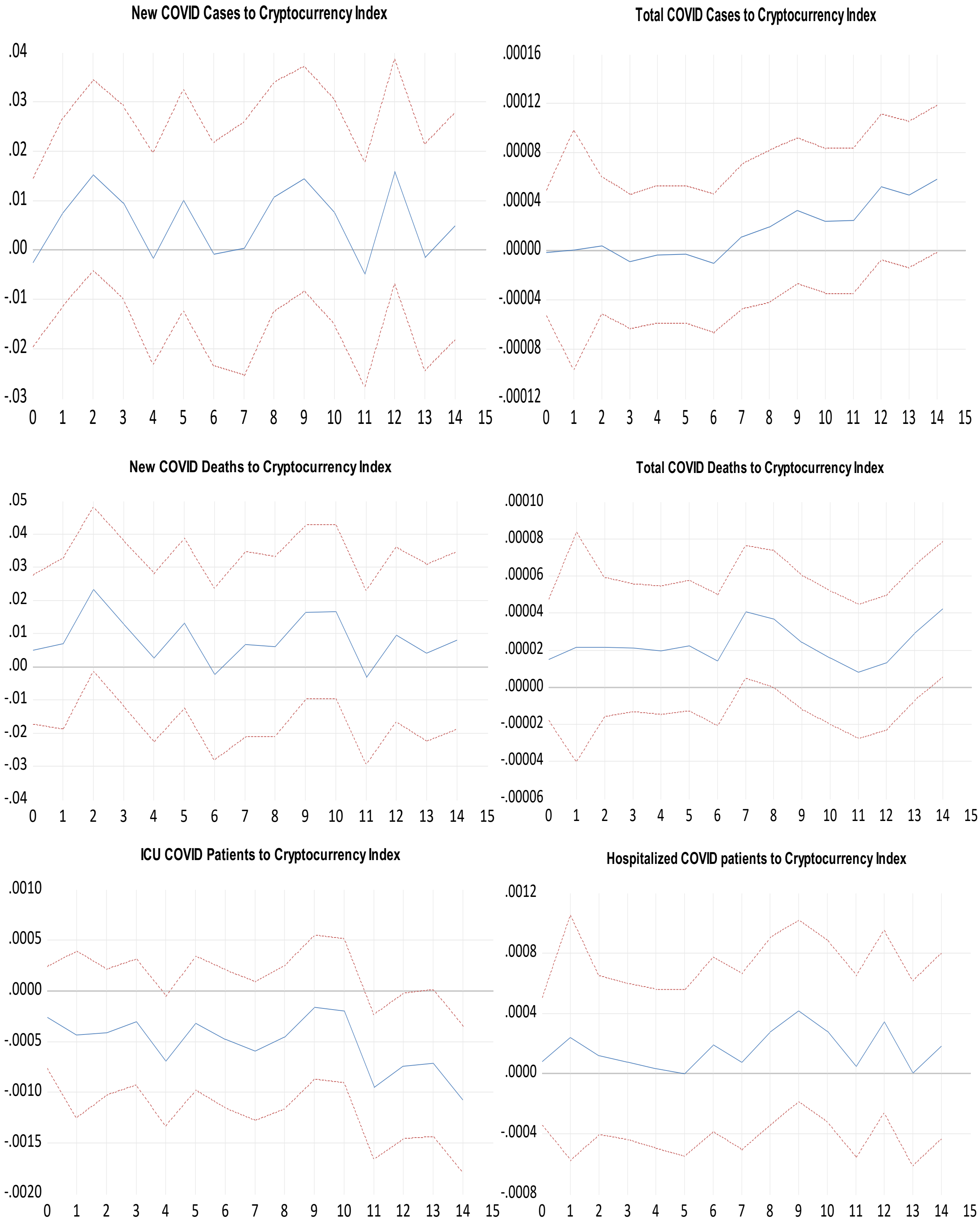
GARCH-M orders, p, and q are set to (2,1), (1,2), and (2,2). These models report the results in columns 2 to 4. Column 5 reports the exponential GARCH (EGRACH) with the mean version of the model. We estimate the model using the quasi-maximum likelihood function (QMLF) of Bollerslev and Wooldridge (1992) to obtain robust estimates of the standard errors. We only report the coefficients relating to COVID-19 variables. Moreover, these models contain all controls. Numbers in parentheses are t-statistics.

**Figure 5: Impulse Response Function**

Panel A: Impulse Response Function during Pre-Vaccination Period



Panel B: Impulse Response Function during Vaccination Period




This figure measures the response of COVID-19 variables on cryptocurrency index returns.

When we look at the as reported in Panel B of Table 7 shows the GARCH model results during the vaccination period. We find that the new covid deaths variable is significant and positive in all GARCH models, while icu covid patients are positive and significant in three models except in GARCH (1, 2). Thus, similar to prior results, we find that covid proxies are not so specifically related to cryptocurrency returns during vaccination. This application conveys that our primary conclusions are unaltered, and the findings persist on different modeling tests.

Lastly, we use the impulse response function (IRF) to measure the response of COVID-19 variables on the cryptocurrency index returns and their reactions. The impulse response functions are based on local projections based on Jorda (2009). They do not require an estimation or specific specification of the unknown multivariate dynamic system. Since the coefficients of the impulse response function can have a serial correlation, leading to a broader marginal error band, the function applies a conditional error band to mitigate the variability arising out of serial correlation. Figure 5 exhibits the impulse response functions measuring the response of COVID-19 variables to a shock in cryptocurrency index returns. Panel A of Figure 5 indicates that COVID-19 generates positive shocks in cryptocurrency returns. It shows that the shocks dissipate slowly and disappear in a week during the pre-vaccination period. Panel B of Figure 5 indicates that the effect of COVID-19 variables on the cryptocurrency returns becomes slightly lower. Once the vaccination has started and restrictions on commercial activities loosened up, the investors are less concerned about the COVID-19 economic woes and looking for alternative investment opportunities.

## V Concluding Remarks

Cryptocurrency markets are of great importance to both investors and financial markets. The pandemic crisis presents a new perspective for investors and portfolio managers for asset pricing and risk management. In this paper, we evaluate the COVID-19 impact in explaining cryptocurrency returns. The leading ten cryptocurrencies are analyzed based on trading volume and market capitalization, representing the cryptocurrency market. The sample period runs from January 22, 2020, to August 31, 2022. For a better understanding of the behavior of cryptocurrencies during the pandemic, the study is conducted on two sub-sample periods: the pre-vaccination sub-period (from January 22, 2020, to December 10, 2020) and the vaccination sub-period (from December 11, 2020, to August 31, 2022), thus analyzing the COVID-19 measures.

The findings show that cryptocurrency returns are significantly affected by the COVID-19 pandemic and are most visible during the pre-vaccination period. Even during vaccination, COVID-19 is a statistically significant determinant of cryptocurrency returns. The intraday price movement shows a negative relationship during the vaccination period in contrast to cryptocurrency returns. Our main contribution to the literature is the direct measures of COVID-19 measures used in the study and their influence on the behavior of cryptocurrencies.

Our findings suggest that COVID-19 has influenced the cryptocurrency market, but its influence varies depending on the size of the currency during vaccination. These results show apparent differences in the impact of changes in the smaller size of currencies. We argue that more major currencies have higher liquidity and more investor participation, bringing market efficiency and risk adjustment as an academic interpretation of the cryptocurrency market behavior. These findings can help policymakers and investors understand that financial markets value a sound health policy. The implications of our research could instigate further research into the role of health policies in the financial markets.

## Limitation of the Paper

This paper uses only the top 10 cryptocurrencies. Some currencies are not directly traded against fiat money in small exchanges. It can bring inaccuracy in pricing and volume. Crypto exchanges are decentralized and traded 24 hours across globally. The data provided by Investing.com is aggregated from many exchanges and denominated in U.S. dollars. The data aggregation process may also lead to ballpark pricing. However, this is a crucial starting avenue for future research in decentralized financial markets. The findings of the paper devise trading strategies for long-term investment.

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## Appendix 1

Top 10 cryptocurrencies used in this study are as follow:

| **Cryptocurrency** | **Market Capitalization as on September 01, 2022** | **Weight** |
|---|---|---|
| Bitcoin | $368,616,658,388 | 48.07% |
| Ethereum | $159,717,882,226 | 20.83% |
| Tether | $67,952,277,033 | 8.86% |
| USD | $47,261,155,810 | 6.16% |
| BNB | $46,058,751,565 | 6.01% |
| XRP | $22,936,407,710 | 2.99% |
| Binance | $21,053,447,315 | 2.75% |
| Cardano | $14,624,881,010 | 1.91% |
| Solana | $11,582,275,936 | 1.51% |
| Polkadot | $7,054,526,600 | 0.92% |

# Insurance Contracting with Adverse Selection and Moral Hazard

Zhiqiang Yan and Hongbok Lee [1]


## Abstract

The asymmetric information problem has been widely discussed in the context of insurance markets. Most of previous research treats adverse selection and moral hazard separately, though it is possible that they may coexist and interact with each other. In this paper, we build a principal-agent model to examine optimal contracts in a competitive insurance market facing adverse selection and moral hazard simultaneously. We apply the change-of-variable method and the Kuhn-Tucker conditions to solve the optimization programs. Our model brings richer separating Nash equilibria than pure moral hazard and pure adverse selection models, although separating Nash equilibria may not exist. It also retains some properties, for example, no full insurance and the positive correlation between insurance coverage and risk type, in those benchmark models. Our study on comparative statics indicates that, under some conditions and with some exceptions, the optimal indemnity and premium decrease with disutility from effort, increase with potential loss and decrease with the initial wealth of the insured.


**Keywords**: Insurance contracting; Adverse selection; Moral hazard

**JEL Classification:** G22

## I Introduction

Insurance markets are well-known to be plagued with two types of asymmetric information problems: adverse selection and moral hazard. Under adverse selection, people are characterized by different levels of risk. High risk people, knowing that they are more likely to have an accident in the future, tend to purchase contracts with more complete coverage. However, in the context of moral hazard, people first choose different contracts due to exogenous reasons, and then they are faced with different incentive schemes: those who end up facing a contract with more complete coverage will have less incentive to adopt more cautious behaviors, which may result in higher probability of accident. Inspired by the seminal works of Arrow (1963) and Akerlof (1970), there is a flourishing literature that has theoretically examined the adverse selection problem (see, e.g., Rothschild and Stiglitz, 1976; Jean-Baptiste and Santomero, 2000) and the moral hazard problem (see, e.g., Pauly, 1974; Stiglitz, 1977; Shavell, 1979; Lambert, 1983; Smith and Stutzer, 1995). While we recognize their importance, most of these previous studies on asymmetric information take these two polar cases as mutually exclusive. In reality, however, it is possible that moral hazard and adverse selection can coexist in the same market and interact with each other. The approach to deal with each problem separately may provide us with limited or even biased information. In this paper, we develop a one-period principal-agent model with the simultaneous presence of moral hazard and adverse selection in a competitive insurance market. We analyze the characteristics of possible separating Nash equilibria and perform a comparative study to

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investigate the effects of external shocks, such as initial wealth and potential loss, on contract design. Though we focus on insurance contracts in this paper, our model framework can be readily applied to other areas, such as financial contracts and labor contracts.

One important work on adverse selection is by Rothschild and Stiglitz (1976). They prove that in a competitive market with adverse selection only, a separating equilibrium (in a Nash sense) could exist, and that, in equilibrium, high-risk individuals self-select into a contract with full insurance coverage at a higher unit price, whereas low-risk individuals self-select into a contract with partial coverage at a lower unit price. However, a separating equilibrium may not exist under certain conditions. Stiglitz (1977) extends the Rothschild-Stiglitz model to the case of monopoly. In the monopolistic equilibrium, high-risk individuals purchase full insurance, while low-risk individuals purchase partial or no insurance. Cooper and Hayes (1987) investigate optimal multi-period insurance contracts with experience rating in both monopolistic and competitive environments. They demonstrate that, in both settings, the contract for high-risk individuals does not reflect their loss experience, whereas the contract for low-risk individuals does.

Under adverse selection, high-risk individuals are more likely to choose a contract with more complete coverage. The pure moral hazard model discovers a similar pattern between risk and coverage from an inverted causality, as people choose different contracts first. A person having better coverage and, therefore, weaker incentives will be less cautious, and hence becomes the riskier one (Arnott and Stiglitz, 1988).

Pauly (1974) investigates the moral hazard problem in a competitive setting. By assuming that insurance price is uniform over the quantity of insurance purchased, he shows that the first best solution is not feasible. Shavell (1979) argues that some imperfect information about the insured’s level of care can still be useful and partial coverage is generally optimal in this context. Lambert (1983) examines the moral hazard problem in a two-period model. He demonstrates that an agent’s compensation in the second period should depend on her performance in both periods, no matter whether she is pre-committed to the long-term contract or not. This implies that insurance companies should use both experience rating and retrospective rating to control moral hazard problems. Smith and Stutzer (1995) introduce aggregate uncertainty into the analysis of moral hazard problems. They show that insurance coverage varies across aggregate states, and insurance companies should offer less coverage to provide a greater incentive to mitigate the moral hazard problem in states where moral hazard is most costly.

To our best knowledge, there are only a few theoretical papers addressing insurance contracts when moral hazard and adverse selection coexist. Whinston (1983) considers a single-period social insurance model in a monopolistic setting with moral hazard and adverse selection, and demonstrates that the optimal equilibrium is a pooling one. Stewart (1994) assumes that agents only differ in their marginal costs of loss prevention effort and characterizes a separating reactive equilibrium (versus Nash equilibrium as in Rothschild and Stiglitz, 1976) in a competitive insurance market with both moral hazard and adverse selection. He shows that, in equilibrium, the adverse selection and moral hazard problems partially offset each other such that welfare losses are sub-additive. Jack (2002) examines the existence of pure strategy equilibria in health insurance markets that exhibit both *ex ante* adverse selection and *ex post* moral hazard. The *ex post* moral hazard in his paper is also labeled as hidden information moral hazard, in which insurers cannot observe the state of the world that occurs ex post. In contrast, it is hidden action moral hazard that we study in this paper, where individuals can take unobservable actions (efforts) that affect the probability distribution over states of nature. Huang, Liu and Tzeng (2010) graphically illustrate the separating Nash equilibria in the simultaneous presence of hidden confidence and hidden action on self-protection. They find that hidden overconfidence can result in advantageous selection in a perfectly competitive market. Gottlieb and Moreira (2014) introduce adverse selection in a standard moral hazard model, where agents are risk-averse and not subject to limited liability constraints. They characterize the solution and find that the optimal mechanisms are quite different from environments featuring only moral hazard or adverse selection. More recently, Chade and Swinkels (2021) analyze a principal-agent problem with moral hazard and adverse selection. They attempt to disentange moral hazard from adverse selection by utilizing a decoupling procedure that treats moral hazard and adverse selection sequentially. Gottlieb and Moreira (2022) study a principlal-agent model with moral hazard and adverse selection, where agents are risk-neutral and have limited liability. Under a multiplicative separability condition, they find that a single contract should be offered in the optimal mechanism.

Our paper is most allied with Laffont and Martimort (2002) and Chassagnon and Chiappori (1997). We follow the model setup in these two papers. Basically, we assume that there are two sorts of insureds differing *ex ante* according to their risk types. Each type could privately choose a discrete loss prevention effort level, and they both suffer from a disutility when exerting an effort. The insured's risk type or her effort level is private information and can not be observed by the insurer. Therefore, the insurer's task is to design optimal contracts to incentivize the insured to exert effort and truthfully report her type. In this setup, the probability of no loss depends on both the risk type and the effort level of the insured. Therefore, it is possible that by exerting an effort, a high-risk individual achieves a higher probability of no loss than a low-risk one who makes no effort.

Laffont and Martimort (2002) investigate insurance contracts in this context by assuming a monopolistic and risk-neutral insurer. Therefore, they maximize the insurer's expected profit by selecting the contracts offered to the high- and low-risk individuals, subject to participation constraints, adverse selection constraints, and moral hazard constraints. However, the insurance market is not monopolistic. Instead, it is often viewed as an archetypical example of a perfectly competitive market. The assumption of monopoly greatly simplifies the contract design problem as we only need to solve one optimization program. In a competitive market with two or more risk types, insurers' expected profits on each type of contracts are driven to zero. Hence, insurance contracts should maximize each type of insured's expected utility subject to the above mentioned constraints plus zero expected profit constraints. There are more than one constrained optimization programs to be solved in order to find the equilibrium, if it exists. In this paper, we extend the work of Laffont and Martimort (2002) to a competitive insurance market and characterize each possible equilibrium in detail.

Chassagnon and Chiappori (1997) examine insurance contracts with perfect competition in the presence of moral hazard and adverse selection as well. They find that, in the context of discrete effort levels, there are three types of separating Nash equilibria (in the sense of Rothschild and Stiglitz, 1976) and no pooling Nash equilibrium. Separating Nash equilibria may not exist under certain conditions. Furthermore, they extend the model to the case of continuous effort levels, and claim that pooling Nash equilibria are possible in this context. Our paper differs from Chassagnon and Chiappori (1997) in two major aspects. First, Chassagnon and Chiappori (1997) use the techniques of correspondence and sequences to characterize the equilibria. In this paper, we apply more straightforward mathematical techniques, that is, the change-of-variable method (Laffont and Martimort 2002) together with the Kuhn-Tucker conditions, to solve the optimization programs and find the equilibria. Second, Chassagnon and Chiappori (1997) allow zero effort from the insured under the optimal insurance contract in their model, whereas we require that the optimal insurance contracts always induce the insured to exert efforts, which results in different sorts of equilibria.

We find that there are five possible types of separating Nash equilibrium contracts based on our model setup, although separating Nash equilibria may not exist. The optimal contracts with both adverse selection and moral hazard retain some features in the pure adverse selection model and the pure moral hazard model. In equilibrium, the optimal contracts need to have the high-risk individual bear less risk than the low-risk one in order to reduce her incentive to lie on her type, as indicated in the pure adverse selection model. Consequently, the high-risk individual is offered more complete coverage but pays a higher unit price. Also, both types are offered partial insurance coverage as in the pure moral hazard model. In addition, the pure moral hazard model dominates in the sense that no agent in our model can obtain a coverage higher than that in the pure moral hazard model.

We further conduct a comparative analysis on each possible equilibrium. More specifically, we examine the effects of disutility, potential loss, and initial wealth on the optimal contracts offered to each risk type respectively. We find that, in general, the optimal premium and indemnity written on both types of contracts decrease with disutility, increase with potential loss, and decrease with initial wealth. However, some assumptions need to be made and some exceptions still exist. By comparing with the standard results from pure adverse selection and pure moral hazard models, we show that the mixed results in our model arise from the coexistence of moral hazard and adverse selection. Hence caution is needed in order to characterize the optimal contracts in our model.

The remainder of this paper is organized as follows. We describe the model framework in section 2 and brief the model with pure adverse selection and the model with pure moral hazard in section 3. We then develop a model with coexistence of adverse selection and moral hazard in the context of perfect competition, and graphically characterize possible separating Nash equilibria in section 4. We present the results of comparative analysis in section 5. Concluding remarks come in section 6.

## II A Principal-Agent Model

### The Model Setup

Following the literature, we assume that there are two parties in the insurance contract: a risk-neutral insurer group (or principals) and a risk-averse insured group (or agents). We assume that insurance markets are competitive and thus each insurer is constrained to earn zero expected profit. The insured has an initial wealth $w$ and possesses von Neumann-Morgenstern utility function $u(w)$ with $u' > 0$ and $u'' < 0$ for all $w \in \mathbb{R}_+$.

In the simultaneous presence of moral hazard and adverse selection, defining an agent's risk type is a little tricky. In the standard adverse selection setting, the separation of high and low-risk types is clear-cut: a high-risk agent has a higher probability of accident, and vice versa. However, after introducing the moral hazard problem into the model of pure adverse selection, a high-risk agent may expend more effort to reduce her probability of accident, leading to a lower probability of accident than a low-risk agent who makes less or no effort. This possibility alone complicates traditional definitions of risk types.

A common approach taken in the literature (Stewart, 1994; Chassagnon and Chiappori, 1997) is to define an agent as a high-risk type if the agent's probability of accident is higher than that of the other type of agent, given the same level of effort. In Stewart (1994), the probability function of avoiding a loss is continuous and identical across agents, but one type of agent has a higher marginal cost of effort, which makes her a high-risk type. Chassagnon and Chiappori (1997) define the probability of accident in a similar fashion except that they use a discrete probability function.

In this paper, to make things simpler, we use a discrete probability function as in Chassagnon and Chiappori (1997). Assume that there are two types of agents who differ *ex ante* in their risk types $\theta \in \Theta = \{\underline{\theta}, \overline{\theta}\}$, where $\overline{\theta}$ represents a high-risk type and $\underline{\theta}$ corresponds to a low-risk type.[2] The two risk types are independently distributed, the distribution of which is common knowledge to both agents and principals. Both types of agents can choose to either make effort or not, i.e., the effort $e \in \{0,1\}$.

Therefore, the probability of no loss $\pi(\theta, e)$ is a function of an agent's risk type $\theta$ and the agent's loss prevention effort $e$. For the sake of simplicity, we suppress the notation to $\pi_e$ with overline (or underline) on $\pi$ to indicate that the agent is of a high- (or low-) risk type. Then, with probability $1 - \pi_e$ the agent incurs an accident loss with the amount equal to $l$. We assume that the loss $l$ is so large that it is always optimal for the insurer to induce the insured to expend effort. It is natural to assume $\underline{\pi}_e > \overline{\pi}_e$ for every $e \in \{0,1\}$. Moreover, we rule out the non-generic case $\overline{\pi}_1 = \underline{\pi}_0$ to avoid peculiar equilibria. By exerting effort $e$, an agent suffers disutility $\psi(e)$, with $\psi(1) = \psi$ and $\psi(0) = 0$. To be more analytically tractable, we assume that the utility function is separable in wealth and effort, which essentially assumes away the non-convexity problem in the indifference curves and the zero expected profit curves.[3] In order to avoid the limited liability problem, we assume that the initial wealth $w$ is greater than the potential accident loss $l$, i.e., $w > l$.

An insurer offers an insured a menu of insurance contracts, $\delta = \{P, I\}$, where $P$ is the premium paid to the insurer and $I$ is the indemnity less the premium if a loss claim is filed. The equilibrium in question will be a pure Nash equilibrium (i.e., a simultaneous game equilibrium) instead of a Stackelberg equilibrium (i.e., a sequential game equilibrium). Because a pooling Nash equilibrium does not exist in the adverse selection and moral hazard model in the context of discrete effort levels (Chassagnon and Chiappori, 1997), we only consider contracts supporting separating Nash equilibria in the following analysis.

A separating Nash equilibrium should be characterized by the following conditions: (1) for each contract, an insurer will earn zero expected profit. Otherwise, rival competitors can undercut the insurer and make a profit until the expected profit goes to zero; (2) since we assume that premium is actuarially fair, according to standard results of insurance economics, these risk-averse agents will always be better off by purchasing insurance (Mossin, 1968; Smith, 1968).

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[2] We use overline (or underline) on a variable or an incentive constraint associated with the high- (or low-) risk type, respectively.

[3] We refer interested readers to Arnott and Stiglitz (1983) for detailed discussion.

## Constrained Utility Maximization

In a competitive insurance market, each contract maximizes an agent's expected utility

$$V = \max_{\{P,I\}} \pi_1 u(w-P) + (1-\pi_1)u(w-l+I) - \psi$$

subject to the agent's participation constraint, adverse selection constraint, moral hazard constraint, and the principal's zero expected profit constraint. We formulate these constraints in this section.

*Participation Constraint (PC)*

A type $\theta$ agent's participation constraint is:

$$V \geq U_0(\theta, e) \equiv \max_{e\in\{0,1\}} \pi_e u(w) + (1-\pi_e)u(w-l) - \psi(e),$$

where $U_0(\theta, e)$ is the reservation utility of the type $\theta$ agent without insurance.

It is natural to assume that

$$u(w) - u(w-l) \geq \frac{\psi}{\Delta\,\pi}$$

where $\Delta\,\pi = \pi_1 - \pi_0$.[4] This assumption means that the type $\theta$ agent will exert a positive effort if she is self-insured, which is consistent with the previous assumption that it is optimal for a principal to induce an agent to expend a positive effort due to the magnitude of claim $l$. With perfect competition and no transaction costs, risk-averse agents will always prefer insurance to self-insurance. Thus, the participation constraint is automatically satisfied.

*Moral Hazard Constraint (MH)*

Inducing the type $\theta$ agent to exert effort requires the following moral hazard incentive constraint to be satisfied:

$$\pi_1 u(w-P) + (1-\pi_1)u(w-l+I) - \psi \geq \pi_0 u(w-P) + (1-\pi_0)u(w-l+I),$$

which can be reduced to

$$u(w-P) - u(w-l+I) \geq \frac{\psi}{\Delta\,\pi}.$$

*Adverse Selection Constraint (AS)*

Here we need to analyze the adverse selection constraint for the low- and high-risk types, respectively.

To induce the high-risk agent to truthfully report her type, the following adverse selection incentive constraint must be met:

$$\overline{\pi}_1 u\left(w-\overline{P}\right) + (1-\overline{\pi}_1)u\left(w-l+\overline{I}\right) - \psi \geq \max_{e\in\{0,1\}} \overline{\pi}_e u\left(w-\underline{P}\right) + (1-\overline{\pi}_e)u\left(w-l+\underline{I}\right) - \psi(e).$$

[4] This assumption is automatically satisfied based on the moral hazard constraint.

To simplify the problem, we assume that, by exerting effort, the high-risk agent can increase her probability of no loss more effectively, i.e.,

$$\Delta \underline{\pi} < \Delta \overline{\pi}.$$

Together with the moral hazard constraint for the low-risk type, this condition implies that the moral hazard constraint for a high-risk type is easier to satisfy than that for a low-risk type. That is,

$$u\left(w-\underline{P}\right)-u\left(w-l+\underline{I}\right)>\frac{\psi}{\Delta \overline{\pi}},$$

or,

$$\overline{\pi}_1 u\left(w-\underline{P}\right)+(1-\overline{\pi}_1)u\left(w-l+\underline{I}\right)-\psi \geq \overline{\pi}_0 u\left(w-\underline{P}\right)+(1-\overline{\pi}_0)u\left(w-l+\underline{I}\right).$$

Therefore, the high-risk agent will always expend effort even if she lies and chooses the contract $\underline{\delta}=\{\underline{P},\underline{I}\}$. The adverse selection constraint of the high-risk agent then becomes

$$\overline{\pi}_1 u\left(w-\overline{P}\right)+(1-\overline{\pi}_1)u\left(w-l+\overline{I}\right)-\psi \geq \overline{\pi}_1 u\left(w-\underline{P}\right)+(1-\overline{\pi}_1)u\left(w-l+\underline{I}\right)-\psi.$$

Similarly, the low-risk agent's adverse selection incentive constraint is:

$$\underline{\pi}_1 u\left(w-\underline{P}\right)+\left(1-\underline{\pi}_1\right)u\left(w-l+\underline{I}\right)-\psi \geq \max_{e\in\{0,1\}} \underline{\pi}_e u\left(w-\overline{P}\right)+\left(1-\underline{\pi}_e\right)u\left(w-l+\overline{I}\right)-\psi(e).$$

For the low-risk agent to exert effort while choosing the contract $\overline{\delta}=\{\overline{P},\overline{I}\}$, we must have

$$\underline{\pi}_1 u\left(w-\overline{P}\right)+\left(1-\underline{\pi}_1\right)u\left(w-l+\overline{I}\right)-\psi \geq \underline{\pi}_0 u\left(w-\overline{P}\right)+\left(1-\underline{\pi}_0\right)u\left(w-l+\overline{I}\right),$$

which can be reduced to

$$u\left(w-\overline{P}\right)-u\left(w-l+\overline{I}\right)\geq\frac{\psi}{\Delta \underline{\pi}}.$$

We will prove later that it does not hold.

*Zero Profit Constraint (ZPC)*

The assumption of competitive insurance markets implies that a principal earns zero expected profit on every contract offered in equilibrium. Thus, given a contract $\delta=\{P,I\}$ offered to the type $\theta$ agent, we have

$$\pi_1 P-(1-\pi_1)I=0$$ [5]

[5] By introducing moral hazard problems, the zero profit curve (and the indifference line) are partitioned into two portions. The zero profit curve above the moral hazard line is $\pi_1 P-(1-\pi_1)I=0$ and it becomes $\pi_0 P-(1-\pi_0)I=0$ when it is below the moral hazard line. We only present the upper portion of the zero profit curve here since we assume the optimal insurance contract will always induce the agent to exert an effort.

## Change-of-Variable Method

When it comes to solve the optimization problem, a technical difficulty arises. That is, the maximization program may not be concave because the concave utility function appears on both sides of moral hazard constraints and adverse selection constraints, which renders the traditional Kuhn-Tucker method invalid.[6] To resolve this issue, we follow the change-of-variable method proposed by Laffont and Martimort (2002). Define $u_a = u(w - l + I)$ and $u_n = u(w - P)$, which represent the agents' utility levels whether a loss occurs or not. Denote the inverse function of $u(\cdot)$ by $h = u^{-1}$. $h(\cdot)$ is an increasing and strictly convex function ($h' > 0$ and $h'' > 0$), because $u' > 0$ and $u'' < 0$ by assumption. Using these new variables, we can obtain that $I = -w + l + h(u_a)$ and $P = w - h(u_n)$. Therefore, the utility maximization problem for the high-risk agent can be written as

$$\overline{V} = \max_{\{\overline{u}_n, \overline{u}_a\}} \overline{\pi}_1 \overline{u}_n + (1 - \overline{\pi}_1)\overline{u}_a - \psi$$

subject to the following constraints,

$$\begin{cases} \overline{MH}:\ \overline{u}_n - \overline{u}_a \geq \dfrac{\psi}{\Delta\,\overline{\pi}} \\ \overline{AS}:\ \ \overline{\pi}_1\overline{u}_n + (1-\overline{\pi}_1)\overline{u}_a - \psi \geq \overline{\pi}_1\underline{u}_n + (1-\overline{\pi}_1)\underline{u}_a - \psi \\ \underline{AS}:\ \ \underline{\pi}_1\underline{u}_n + \left(1-\underline{\pi}_1\right)\underline{u}_a - \psi \geq \max\limits_{e\in\{0,1\}} \underline{\pi}_e\overline{u}_n + \left(1-\underline{\pi}_e\right)\overline{u}_a - \psi(e) \\ \overline{ZPC}:\ \overline{\pi}_1\left(w - h(\overline{u}_n)\right) - (1-\overline{\pi}_1)\left(-w + l + h(\overline{u}_a)\right) = 0 \end{cases}$$

We can formulate the constrained optimization problem for the low-risk agent in a similar fashion. With the change of variables, the objective function, the adverse selection and moral hazard constraints are now linear, and the zero profit constraint becomes concave. This implies that the Lagrangian function is concave, and thus we can apply the Kuhn-Tucker procedure to solve the optimization problem.

After changing variables, the zero expected profit curve for a type $\theta$ agent is given by

$$\pi_1\left(w - h(u_n)\right) - (1-\pi_1)\left(-w + l + h(u_a)\right) = 0.$$

According to the implicit function theorem, we can obtain,

$$\frac{\partial u_n}{\partial u_a} = -\frac{1-\pi_1}{\pi_1}\frac{h'(u_a)}{h'(u_n)},$$

and

---

[6] Let $f$ be a function of many variables with continuous partial derivatives of first and second order on the convex open set $S$ and denote the Hessian of $f$ at the point $x$ by $H(x)$. Then $f$ is concave if and only if $H(x)$ is negative semi-definite for all $x \in S$. $H(x)$ is negative semi-definite if and only if all the $k$-th order principal minors of $A$ are non-positive if $k$ is odd and non-negative if $k$ is even. For the moral hazard constraints, the first order principal minors are $u''(w - P) < 0$ and $-u''(w - l + I) > 0$, the second order principal minor is $-u''(w - p)u''(w - l + I) < 0$. Therefore, the moral hazard constraints are not concave. We can check the adverse selection constraints similarly and neither of them is concave.

$$\frac{\partial^2 u_n}{\partial u_a^2} = -\frac{1-\pi_1}{\pi_1}\frac{\pi_1\big(h'(u_n)\big)^2 h''(u_a) + (1-\pi_1)\big(h'(u_a)\big)^2 h''(u_n)}{\pi_1\big(h'(u_n)\big)^3}.$$

Since $h' > 0$ and $h'' > 0$, we have $\partial u_n / \partial u_a < 0$ and $\partial^2 u_n / \partial u_a^2 < 0$. Therefore, each zero expected profit curve passes the uninsured point $E = \big(u(w-l), u(w)\big)$ and decreases at an increasing rate. Meanwhile, the zero expected profit curve gets flatter as the probability of no claim $\pi(\cdot)$ increases.

Note that the slope of an agent's indifference line is $-\frac{1-\pi_1}{\pi_1}$. We can obtain $\frac{1-\pi_1}{\pi_1}\frac{h\prime(u_a)}{h\prime(u_n)} \leq \frac{1-\pi_1}{\pi_1}$ because of $\frac{h\prime(u_a)}{h\prime(u_n)} \leq 1$, i.e, the slope of the zero profit curve is equal to or smaller than that of the indifference curve (in absolute terms). Therefore, for a type $\theta$ agent, the indifference line can cross the zero expected profit curve from above at any point (and they only cross once), except at the point $u_a = u_n$ where these two curves are tangent to each other.

## III Pure Adverse Selection and Pure Moral Hazard

Before we go into details about our model of adverse selection and moral hazard, we first briefly present the standard models of pure adverse selection and pure moral hazard respectively, which serve as two benchmarks.

### The Model with Pure Adverse Selection (PAS)

The competitive pure adverse selection model is proposed and characterized in great detail in Rothschild and Stiglitz (1976). They assume that risk type is an agent's private information but principals are able to observe the actions of agents, or effort that agents exert to prevent losses. Because of the assumption of perfect competition, contracts offered to each agent should maximize the agent's expected utility subject to the adverse selection constraint of each risk type and the zero expected profit constraint.

Therefore, for a type $\overline{\theta}$ agent, the optimal contract in equilibrium should maximize the agent's expected utility

$$\max_{\{\overline{u}_n, \overline{u}_a\}} \overline{\pi}_1 \overline{u}_n + (1-\overline{\pi}_1)\overline{u}_a - \psi$$

subject to the following constraints,

$$\begin{cases} \overline{AS}: & \overline{\pi}_1\overline{u}_n + (1-\overline{\pi}_1)\overline{u}_a - \psi \geq \overline{\pi}_1\underline{u}_n + (1-\overline{\pi}_1)\underline{u}_a - \psi \\ \underline{AS}: & \underline{\pi}_1\underline{u}_n + \big(1-\underline{\pi}_1\big)\underline{u}_a - \psi \geq \underline{\pi}_1\overline{u}_n + \big(1-\underline{\pi}_1\big)\overline{u}_a - \psi \\ \overline{ZPC}: & \overline{\pi}_1\big(w - h(\overline{u}_n)\big) - (1-\overline{\pi}_1)\big(-w + l + h(\overline{u}_a)\big) = 0 \end{cases}$$

It is well-known that, in the presence of pure adverse selection, high-risk agents self-select into a full insurance contract but pay a higher unit price for insurance coverage, while low-risk agents choose a partial insurance contract but pay a lower unit price, as illustrated in Figure 1.

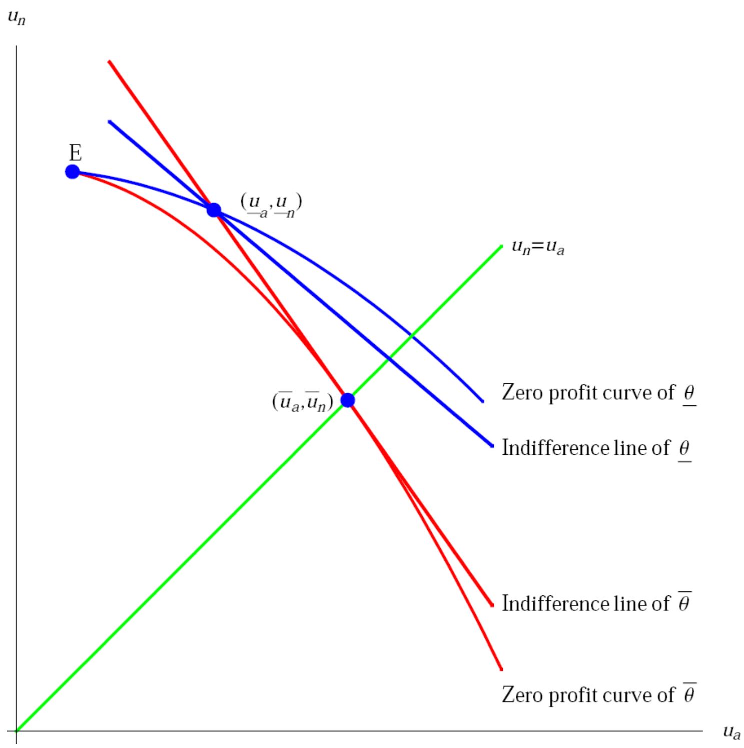


Figure 1: The Case of Pure Adverse Selection

Intuitively, the two adverse selection constraints indicate that $(\overline{u}_a, \overline{u}_n)$ must lie on or to the left of the indifference line of type $\underline{\theta}$ and $(\underline{u}_a, \underline{u}_n)$ must lie on or to the left of the indifference line of type $\overline{\theta}$. Since $\overline{\pi}_1 < \underline{\pi}_1$, the indifference line of type $\overline{\theta}$ is steeper than that of type $\underline{\theta}$. Therefore, we can shift the indifference line of type $\underline{\theta}$ rightward until it crosses the intersection of the indifference line of type $\overline{\theta}$ and the zero expected profit curve of type $\underline{\theta}$. The adverse selection constraint of type $\overline{\theta}$ must be binding and that of type $\underline{\theta}$ can never be binding. In order to maximize her expected utility, the high-risk agent's contract must be achieved at the point where type $\overline{\theta}$'s indifference line is tangent to her zero profit curve, which occurs at the point where $\overline{u}_n = \overline{u}_a$. The low-risk agent's contract is given by the intersection of type $\underline{\theta}$'s zero-profit curve and type $\overline{\theta}$'s indifference line.

### The Model with Pure Moral Hazard (PMH)

In the case of pure moral hazard, an agent's risk type is publicly observable, but an agent's actions or loss prevention efforts are her private information. Since an agent's risk type is assumed to be observable by a principal, it is adequate to formally analyze one type of agent's equilibrium contract. Here we take a high-risk type as an example. Because of the perfect competition among insurers, the equilibrium contract offered to type $\overline{\theta}$ agent should maximize the agent's expected utility,

$$\max_{\{\overline{u}_n, \overline{u}_a\}} \overline{\pi}_1 \overline{u}_n + (1 - \overline{\pi}_1)\overline{u}_a - \psi$$

subject to the following constraints,

$$\begin{cases} \overline{MH}: \overline{u}_n - \overline{u}_a \geq \dfrac{\psi}{\Delta \overline{\pi}} \\ \overline{ZPC}: \overline{\pi}_1\big(w - h(\overline{u}_n)\big) - (1 - \overline{\pi}_1)\big(-w + l + h(\overline{u}_a)\big) = 0. \end{cases}$$

According to the moral hazard constraint, the high-risk agent exerts effort when the contract is above the moral hazard line $\overline{u}_n = \overline{u}_a + \frac{\psi}{\Delta \overline{\pi}}$, whereas she makes no effort when the contract is below the line. Therefore, the indifference line and the zero profit curve are segmented into two parts by the moral hazard line. It is obvious that the agent achieves maximum utility at the intersection of the upper part of the zero profit curve and the moral hazard line. Hence, a principal offers a partial insurance contract to an agent in the context of pure moral hazard as illustrated in Figure 2.

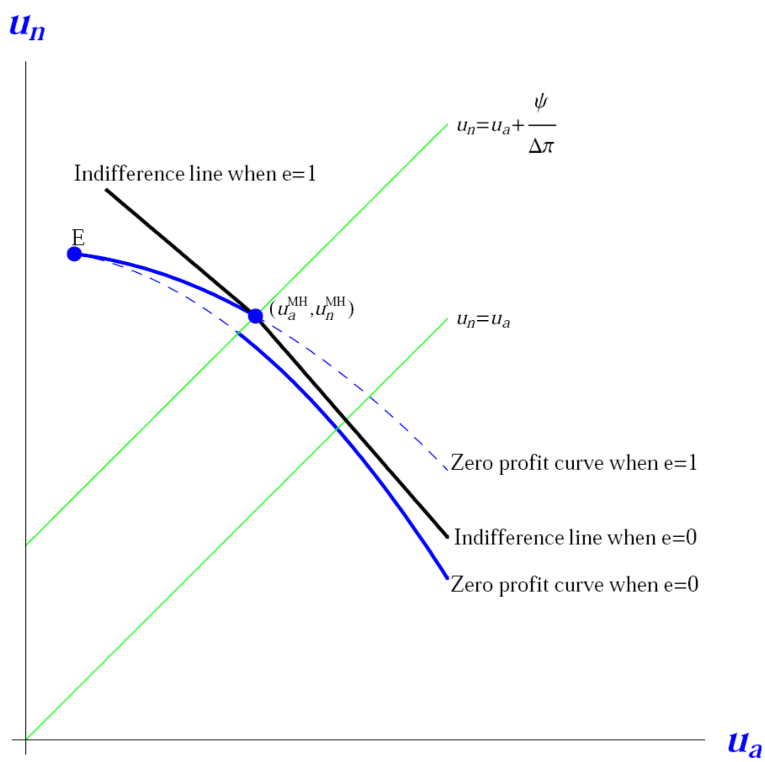


Figure 2: The Case of Pure Moral Hazard

## IV Coexistence of Adverse Selection and Moral Hazard

When it comes to contract design, the majority of studies in the literature treat moral hazard and adverse selection separately. A few technical issues such as non-convex programming and random coverage (Winter, 2000) may be responsible for it. In this paper, by applying the change-of-variable technique and assuming a separable utility function in wealth and effort, we use the Kuhn-Tucker method to solve the maximization problem.

We use $\lambda_{MH}$, $\lambda_{AS}$, and $\lambda_Z$ to denote the respective multipliers on the moral hazard constraint, the adverse selection constraint, and the zero profit constraint. The Lagrangian function of type $\overline{\theta}$ is:

$$
\begin{aligned}
\mathcal{L} = \quad & \max_{\{\overline{u}_n,\overline{u}_a\}} \overline{\pi}_1\overline{u}_n + (1-\overline{\pi}_1)\overline{u}_a - \psi \\
& +\overline{\lambda}_{MH}\left[\overline{u}_n - \overline{u}_a - \frac{\psi}{\Delta\,\overline{\pi}}\right] \\
& +\overline{\lambda}_{AS}\left[\overline{\pi}_1\overline{u}_n + (1-\overline{\pi}_1)\overline{u}_a - \psi - \overline{\pi}_1\underline{u}_n - (1-\overline{\pi}_1)\underline{u}_a + \psi\right] \\
& +\underline{\lambda}_{AS}\left[\underline{\pi}_1\underline{u}_n + \left(1-\underline{\pi}_1\right)\underline{u}_a - \psi - \underline{\pi}_{\underline{e}}\overline{u}_n - \left(1-\underline{\pi}_{\underline{e}}\right)\overline{u}_a + \psi\left(\underline{e}\right)\right] \\
& +\overline{\lambda}_Z\left[\overline{\pi}_1\left(w - h(\overline{u}_n)\right) - (1-\overline{\pi}_1)\left(-w + l + h(\overline{u}_a)\right)\right]
\end{aligned}
$$

Differentiating the Lagrangian function regarding $\overline{u}_n$ and $\overline{u}_a$ respectively, we can get the following first order conditions:

$$\frac{\partial\mathcal{L}}{\partial\overline{u}_n} = \quad \overline{\pi}_1\left(1+\overline{\lambda}_{AS}\right) + \overline{\lambda}_{MH} - \underline{\lambda}_{AS}\underline{\pi}_{\underline{e}} - \overline{\lambda}_Z\overline{\pi}_1 h'^{(\overline{u}_n)} = 0 \tag{1}$$

$$\frac{\partial\mathcal{L}}{\partial\overline{u}_a} = \quad (1-\overline{\pi}_1)\left(1+\overline{\lambda}_{AS}\right) - \overline{\lambda}_{MH} - \underline{\lambda}_{AS}\left(1-\underline{\pi}_{\underline{e}}\right) - \overline{\lambda}_Z(1-\overline{\pi}_1)h'^{(\overline{u}_a)} = 0 \tag{2}$$

By $(1)\times(1-\overline{\pi}_1) - (2)\times\overline{\pi}_1$, we can obtain

$$\overline{\lambda}_{MH} + \underline{\lambda}_{AS}\left(\overline{\pi}_1 - \underline{\pi}_{\underline{e}}\right) = \overline{\lambda}_Z\overline{\pi}_1(1-\overline{\pi}_1)[h'(\overline{u}_n) - h'(\overline{u}_a)] \tag{3}$$

A close examination of Equation (3) leads to the results in Lemma 1. The proof can be found in the Appendix.

**Lemma 1**. *In equilibrium, if equilibrium exists, we must have* $\frac{\psi}{\Delta\overline{\pi}} \le \overline{u}_n - \overline{u}_a < \frac{\psi}{\Delta\underline{\pi}} \le \underline{u}_n - \underline{u}_a$. *In addition, the type* $\underline{\theta}$ *agent will not exert effort when she selects the type* $\overline{\theta}$ *agent's contract, that is,* $\underline{e} = 0$.

Intuitively, we can interpret $u_n - u_a$ as the risk level borne by the agent. If $u_n - u_a = 0$, i.e., $(u_n, u_a)$ is on the full insurance line, the agent does not bear any risk. Lemma 1 tells us that, to prevent the high-risk agent from pretending that she is a low-risk type, the insurer would let the high-risk agent bear less risk than the low-risk agent, i.e., $\overline{u}_n - \overline{u}_a < \underline{u}_n - \underline{u}_a$.

According to Lemma 1, $\underline{e} = 0$, then Equation (3) becomes:

$$\overline{\lambda}_{MH} + \underline{\lambda}_{AS}\left(\overline{\pi}_1 - \underline{\pi}_0\right) = \overline{\lambda}_Z\overline{\pi}_1(1-\overline{\pi}_1)[h'(\overline{u}_n) - h'(\overline{u}_a)] \tag{4}$$

Because $\overline{\lambda}_Z > 0$, $\overline{\lambda}_{MH} \ge 0$, $\underline{\lambda}_{AS} \ge 0$, and $\overline{u}_n > \overline{u}_a$, we can easily obtain Lemma 2 from Equation (4).

**Lemma 2**. $\overline{\lambda}_{MH}$ and $\underline{\lambda}_{AS}$ *can not equal zero simultaneously. In other words, at least one of the moral hazard constraints of the type* $\overline{\theta}$ *agent and the adverse selection constraint of the type* $\underline{\theta}$ *agent is binding.*

Therefore, there are three pairs of $\left(\overline{\lambda}_{MH}, \underline{\lambda}_{AS}\right)$, which are summarized below:

*Case H1*: $\overline{\lambda}_{MH} = 0$ and $\underline{\lambda}_{AS} > 0$, i.e., the moral hazard constraint of the high-risk type is not binding, while the adverse selection incentive constraint of the low-risk type is binding.

*Case H2*: $\overline{\lambda}_{MH} > 0$ and $\underline{\lambda}_{AS} = 0$, i.e., the moral hazard constraint of the high-risk type is binding, but the adverse selection incentive constraint of the low-risk type is not binding.

*Case H3*: $\overline{\lambda}_{MH} > 0$ and $\underline{\lambda}_{AS} > 0$, i.e., both the moral hazard constraint of the high-risk type and the adverse selection incentive constraint of the low-risk type are binding.

Similar to the derivation of Equation (3) for the high-risk type, we can obtain the following equation for the low-risk type:

$$\underline{\lambda}_{MH} + \overline{\lambda}_{AS}(\underline{\pi}_1 - \overline{\pi}_1) = \overline{\lambda}_Z \underline{\pi}_1 (1 - \underline{\pi}_1)[h'(\underline{u}_n) - h'(\underline{u}_a)] \tag{5}$$

Lemma 3 follows directly from Equation (5).

**Lemma 3**. $\underline{\lambda}_{MH}$ and $\overline{\lambda}_{AS}$ *can not equal zero simultaneously. In other words, at least one of the moral hazard constraints of the type $\underline{\theta}$ agent and the adverse selection constraint of the type $\overline{\theta}$ agent is binding.*

There are also three possible pairs of $(\underline{\lambda}_M, \overline{\lambda}_{AS})$:

*Case L1*: $\underline{\lambda}_{MH} = 0$ and $\overline{\lambda}_{AS} > 0$, i.e., the moral hazard constraint of the low-risk type is not binding, while the adverse selection constraint of the high-risk type is binding.

*Case L2*: $\underline{\lambda}_{MH} > 0$ and $\overline{\lambda}_{AS} = 0$, i.e., the moral hazard constraint of the low-risk type is binding, but the adverse selection constraint of the high-risk type is not binding.

*Case L3*: $\underline{\lambda}_{MH} > 0$ and $\overline{\lambda}_{AS} > 0$, i.e., both the moral hazard constraint of the low-risk type and the adverse selection incentive constraint of the high-risk type are binding.

Because the utility levels of the two types of agents, $(\overline{u}_n, \overline{u}_a)$ and $(\underline{u}_n, \underline{u}_a)$, are interdependent in equilibrium, we need to take the first order conditions of both agents into consideration in determining the optimal contracts. Based on Lemma 2 and 3, there are nine possible combinations of those Lagrangian multipliers. Lemma 4 below further rules out four of them. Therefore, there are five possible separating Nash equilibria, which are summarized in Proposition 1. The proofs are provided in the Appendix.

**Lemma 4**. *We can not have both $\underline{\lambda}_{MH} > 0$ and $\underline{\lambda}_{AS} > 0$. In other words, the adverse selection constraint and the moral hazard constraint of type $\underline{\theta}$ can not be binding at the same time.*

**Proposition 1**. *In a competitive insurance market with the simultaneous presence of adverse selection and moral hazard, there are five possible types of separating Nash equilibria in the sense of Rothschild-Stiglitz as follows:*

- Only Adverse Selection: *both of the adverse selection constraints are binding, but none of the moral hazard constraints is binding.*
- Only Moral Hazard: *both of the moral hazard constraints are binding, but none of the adverse selection constraint is binding.*
- Strong Adverse Selection: *both of the adverse selection constraints are binding, but only the moral hazard constraint of the high-risk type is binding.*
- Strong Moral Hazard: *both of the moral hazard constraints are binding, but only the adverse selection constraint of the high-risk type is binding.*

- Local Asymmetric Information: *the adverse selection constraint and the moral hazard constraint of the high-risk type are binding, but none of the asymmetric information constraints of the low-risk type is binding.*

Through the analysis of different equilibria, we can easily observe that $(\overline{u}_a, \overline{u}_n)$ is closer to the full insurance line than $(\underline{u}_a, \underline{u}_n)$, which means the type $\overline{\theta}$ agent is offered more coverage and bears less risk. Note that the unit price of insurance can be derived directly from the binding zero expected profit constraint, i.e., $\frac{P}{I} = \frac{1-\pi_1}{\pi_1}$. Therefore, the type $\overline{\theta}$ agent is offered a higher unit price than the type $\underline{\theta}$ agent, based on the assumption $\overline{\pi}_1 < \underline{\pi}_1$. The following proposition summarizes our findings comparing optimal contracts in the presence of both moral hazard and adverse selection with those in the context of pure adverse selection or pure moral hazard.

**Proposition 2**. *In the simultaneous presence of adverse selection and moral hazard, the moral hazard problem dominates in the sense that optimal contracts provide insurance coverage at most equal to the amount of coverage offered in the case of pure moral hazard, depending on model structures. Moreover, more complete insurance coverage is offered to type $\overline{\theta}$ at a higher unit price. Specifically,*

- *when $\overline{\pi}_1 > \underline{\pi}_0$: the optimal contract offered to type $\underline{\theta}$ provides an insurance coverage less than that in the case of pure moral hazard, while the optimal contract offered to type $\overline{\theta}$ provides an insurance coverage equal to or less than that in the case of pure moral hazard.*
- *when $\overline{\pi}_1 < \underline{\pi}_0$: the optimal contract offered to type $\underline{\theta}$ provides an insurance coverage equal to or less than that in the case of pure moral hazard, while the optimal contract offered to type $\overline{\theta}$ provides an insurance coverage equal to that in the case of pure moral hazard.*

Proposition 2 implies that optimal contracts with the coexistence of adverse selection and moral hazard retain some properties in the pure moral hazard model and the pure adverse selection model. As in the pure moral hazard case, no agent can obtain full insurance coverage. As in the adverse selection case, the positive correlation between insurance coverage and riskiness of agents still holds.

Furthermore, when $\overline{\pi}_1 > \underline{\pi}_0$, the type $\overline{\theta}$ agent is relatively riskier in the sense that the probability of loss of type $\overline{\theta}$ is higher if both types of agents expend the same level of effort. However, if the type $\overline{\theta}$ agent exerts effort while the type $\underline{\theta}$ agent does not, the latter becomes riskier. This additional layer of adverse selection complicates the principal's job of contract design even further and reduces the amount of coverage offered to the type $\underline{\theta}$ agent. When $\overline{\pi}_1 < \underline{\pi}_0$, the type $\overline{\theta}$ agent is absolutely riskier no matter whether the type $\underline{\theta}$ agent expends effort or not. In this case, the highest possible amount of coverage, which occurs at the intersection of type $\overline{\theta}$'s zero profit curve and moral hazard line, is offered to the type $\overline{\theta}$ agent.

## V Comparative Statics

In this section, we conduct comparative analysis to investigate the effects of changing $\psi$ (disutility), $w$ (initial wealth), and $l$ (loss) on $I$ (optimal indemnity) and $P$ (optimal premium) for both risk types. The separating Nash equilibria are defined by a system of nonlinear equations, which can not be solved analytically. We, therefore, linearize the system of nonlinear equations by differentiation and apply Cramer's rule to compute the partial derivatives of insurance premium and indemnity with respect to disutility, initial wealth, and potential loss. Proposition 1 demonstrates five possible types of separating Nash equilibria, and the comparative statics of the optimal contracts in those five Nash equilibria for the low-risk type and the high-risk type are reported in Table 1 and 2, respectively, together with the comparative statics of the two baseline models of pure adverse selection and pure moral hazard.[7]

Table 1: Comparative Statics of Optimal Contract for Low-Risk Type

| Case | $\frac{\partial \underline{P}}{\partial \psi}$ | $\frac{\partial \underline{P}}{\partial l}$ | $\frac{\partial \underline{P}}{\partial w}$ | $\frac{\partial \underline{I}}{\partial \psi}$ | $\frac{\partial \underline{I}}{\partial l}$ | $\frac{\partial \underline{I}}{\partial w}$ |
|---|---|---|---|---|---|---|
| Case 1: Only adverse selection | - | + | - | - | + | - |
| Case 4: Local asymmetric information | - | + | ? | - | + | ? |
| Case 5: Only moral hazard | - | + | - | - | + | - |
| Case 6: Strong moral hazard | - | + | ? | - | + | ? |
| Case 7: Strong adverse selection | - | + | ? | - | + | ? |
| Pure adverse selection | 0 | + | ? | 0 | + | ? |
| Pure moral hazard | - | + | - | - | + | - |

Note: "-"/"+" means that the partial derivative is negative/positive, "0" means that the partial derivative equals zero, and "?" means that the partial derivative is undetermined.

Table 2: Comparative Statics of Optimal Contract for High-Risk Type

| Case | $\frac{\partial \overline{P}}{\partial \psi}$ | $\frac{\partial \overline{P}}{\partial l}$ | $\frac{\partial \overline{P}}{\partial w}$ | $\frac{\partial \overline{I}}{\partial \psi}$ | $\frac{\partial \overline{I}}{\partial l}$ | $\frac{\partial \overline{I}}{\partial w}$ |
|---|---|---|---|---|---|---|
| Case 1: Only adverse selection | - | ? | ? | - | ? | ? |
| Case 4: Local asymmetric information | - | + | - | - | + | - |
| Case 5: Only moral hazard | - | + | - | - | + | - |
| Case 6: Strong moral hazard | - | + | - | - | + | - |
| Case 7: Strong adverse selection | - | + | - | - | + | - |
| Pure adverse selection | 0 | + | 0 | 0 | + | 0 |
| Pure moral hazard | - | + | - | - | + | - |

Note: "-"/"+" means that the partial derivative is negative/positive, "0" means that the partial derivative equals zero, and "?" means that the partial derivative is undetermined.

**Comparative Statics for the PAS Model**

In the pure adverse selection model, the contract offered to the high-risk type is at the intersection of the full insurance curve, $\overline{P} + \overline{I} = l$, and its zero profit curve, $\overline{\pi}_1 \overline{P} = (1 - \overline{\pi}_1)\overline{I}$. Obviously, a

[7] The derivation of the partial derivatives is not reported in the paper but available upon request.

change in disutility or initial wealth has no effect on the high-risk type's contract, while an increase in the loss results in an increase in both $\overline{P}$ and $\overline{I}$.

As to the low-risk type, its contract is determined by the binding adverse selection constraint of the high-risk type and the zero profit curve of the low-risk type. The binding adverse selection constraint means that type $\overline{\theta}$ is indifferent between the two types of contracts, thus the marginal utility resulting from an increase in $\psi$ must be equal no matter whether she truthfully reports her type or not. Suppose an increase in $\psi$ by one unit causes the indemnity to change by $\triangle I$. If she chooses her own contract, one-unit increase in $\psi$ will change her expected utility by $(1-\overline{\pi}_1)\left[u'\left(w-l+\overline{I}\right)-u'\left(w-\overline{P}\right)\right]\triangle \overline{I}-1$; if she lies, her expected utility will change by $\left[(1-\overline{\pi}_1)u'\left(w-l+\underline{I}\right)-\frac{\overline{\pi}_1(1-\underline{\pi}_1)}{\underline{\pi}_1}u'\left(w-\underline{P}\right)\right]\triangle \underline{I}-1$. To make the marginal changes equal, $\underline{I}$ and $\overline{I}$ must move in the same direction.[8] Recall that an increase in disutility has no impact on the high-risk type's contract, so it does not affect the low-risk type's contract either.

Now we investigate the impact of potential loss on the low-risk agent's contract. Suppose an increase in the loss by one unit causes the indemnity to change by $\triangle I$. The expected utility changes by an amount of $(1-\overline{\pi}_1)\left[u'\left(w-l+\overline{I}\right)-u'\left(w-\overline{P}\right)\right]\triangle \overline{I}-(1-\overline{\pi}_1)u'\left(w-l+\overline{I}\right)$, if she truthfully reports her type, and by an amount of $\left[(1-\overline{\pi}_1)u'\left(w-l+\underline{I}\right)-\frac{\overline{\pi}_1(1-\underline{\pi}_1)}{\underline{\pi}_1}u'\left(w-\underline{P}\right)\right]\triangle \underline{I}-(1-\overline{\pi}_1)u'\left(w-l+\underline{I}\right)$, if she lies. We know that $\overline{I}$ increases with $l$. To make the marginal effects equal, we conclude that $\underline{I}$ increases with $l$ as well.

For one-unit increase in initial wealth $w$, if the high-risk agent truthfully reports her type, it can increase the expected utility by $\overline{\pi}_1 u'\left(w-\overline{P}\right)+(1-\overline{\pi}_1)u'\left(w-l+\overline{I}\right)$. If the high-risk agent pretends to be a low-risk type, the marginal benefit from the wealth change is $\overline{\pi}_1 u'\left(w-\underline{P}\right)+(1-\overline{\pi}_1)u'\left(w-l+\underline{I}\right)$. The difference between them measures the effect of $w$ on $\underline{I}$. Unless the marginal benefit from telling the truth is larger than that from lying on her type, an increase in initial wealth will decrease $\underline{I}$, and $\underline{P}$ accordingly.

**Comparative Statics for the PMH Model**

In the pure moral hazard model, the contract offered to the high- (low-) risk type is determined by its binding moral hazard constraint and zero profit constraint. We take the high-risk agent as an example in the following analysis. The binding moral hazard constraint, i.e., $u\left(w-\overline{P}\right)-u\left(w-l+\overline{I}\right)=\frac{\psi}{\Delta\overline{\pi}}$, implies that the risk borne by the high-risk agent, $\triangle \overline{u}=u\left(w-\overline{P}\right)-u\left(w-l+\overline{I}\right)$, is proportional to the disutility, $\psi$. An increase in the disutility $\psi$ indicates that type $\overline{\theta}$ needs to bear more risk, leading to a decrease in both $\overline{P}$ and $\overline{I}$.

When the loss increases (but $\psi$ remains unchanged), the risk borne by the high-risk agent increases if she keeps the same premium and indemnity as before. Therefore, the high-risk type have to increase $\overline{P}$ and $\overline{I}$ in order to keep the amount of risk unchanged.

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[8] Note that $u'\left(w-l+\overline{I}\right)-u'\left(w-\overline{P}\right)>0$ and $(1-\overline{\pi}_1)u'\left(w-l+\underline{I}\right)-\frac{\overline{\pi}_1(1-\underline{\pi}_1)}{\underline{\pi}_1}u'\left(w-\underline{P}\right)>0$, given $w-l+\overline{I}<w-\overline{P}$, $w-l+\underline{I}<w-\underline{P}$, $u''<0$ and $\overline{\pi}_1<\underline{\pi}_1$.

Now let us investigate the effect of initial wealth. Risk aversion implies that an increase in initial wealth results in a smaller increase in $u(w-\overline{P})$ than that in $u(w-l+\overline{I})$, given $w-\overline{P} > w-l+\overline{I}$. In other words, the risk borne by the high-risk agent goes down if she keeps the premium and indemnity unchanged. In order to offset this effect and keep the same amount of risk as before, the high-risk agent will demand less indemnity and thereby pay less premium.

**Comparative Statics for the ASMH Model**

In Cases 1, 4, and 5, there are exactly four equations and four unknown variables, i.e., $\underline{u}_n$, $\underline{u}_a$, $\overline{u}_n$, and $\overline{u}_a$ (see the proof of Proposition 1). All the other parameters ($\underline{\pi}_0$, $\underline{\pi}_1$, $\overline{\pi}_0$, $\overline{\pi}_1$, $\psi$, $w$, and $l$) are exogenous. We can compute the partial derivatives of $\underline{u}_n$, $\underline{u}_a$, $\overline{u}_n$, and $\overline{u}_a$ with respect to other parameters, based on the Cramer's rule. In Cases 6 and 7, there are five equations and we need to solve four unknowns ($\underline{u}_n$, $\underline{u}_a$, $\overline{u}_n$, and $\overline{u}_a$). Clearly, one of the other parameters must be endogenous and the choice of the endogenous variable surely affects the results of comparative statics in these two cases. The following analysis is based on the assumption that $\underline{\pi}_0$ is endogenous as it represents the simplest scenario.[9] We can compute the partial derivatives of $\underline{u}_n$, $\underline{u}_a$, $\overline{u}_n$, $\overline{u}_a$ and $\underline{\pi}_0$ with respect to other parameters in Cases 6 and 7. Recall the relationships: $P = w - h(u_n)$ and $I = -w + l + h(u_a)$. Using the chain rule, we can derive the partial derivatives of $\underline{P}$, $\underline{I}$, $\overline{P}$, and $\overline{I}$ with respect to other parameters.[10] Note that $P$ and $I$ change in the same direction as in the pure adverse selection or pure moral hazard model under the assumption that $\pi_1$ is exogenous.

Comparing the results in the pure adverse selection model and the pure moral hazard model with those in the model of both adverse selection and moral hazard, we can easily observe that the coexistence of adverse selection and moral hazard complicates the problem and generates some mixed results. First, Case 5 (only moral hazard) has the same comparative results as the pure moral hazard model. It is not surprising since in both models, if the equilibrium contracts exist, they must be jointly determined by the binding moral hazard and zero profit constraints, even though optimal contracts in Case 5 have to satisfy the adverse selection constraints as well. Second, in Cases 4, 6, and 7, the high-risk agent's contract is driven by the binding moral hazard constraint and therefore responds to external shocks in other parameters similarly as in the pure moral hazard model, while the contract offered to the low-risk agent is determined by the binding adverse selection constraint

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[9] If we choose $\underline{\pi}_0$ as the endogenous variable, the binding moral hazard constraint of type $\underline{\theta}$ in Case 6 and the binding adverse selection constraint of type $\underline{\theta}$ in Case 7 become redundant. $(\overline{u}_n, \overline{u}_a)$ is then determined by type $\overline{\theta}$'s binding moral hazard and zero profit constraints, and $(\underline{u}_n, \underline{u}_a)$ is determined by type $\underline{\theta}$'s binding zero profit constraint and type $\overline{\theta}$'s binding adverse selection constraint. Choosing any other variable as endogenous complicates our work of comparative analysis. If we choose $\underline{\pi}_1$ as the endogenous variable, for example, type $\overline{\theta}$'s contract remains unchanged as it is still determined by type $\overline{\theta}$'s binding moral hazard and zero profit constraints, but type $\underline{\theta}$'s contract will be jointly determined by type $\underline{\theta}$'s binding moral hazard and zero profit constraints and type $\overline{\theta}$'s binding adverse selection constraint.

[10] The partial derivatives computed in this way are expressed as functions of $h'(u_n)$ and $h'(u_a)$. We can express the partial derivatives in the forms of $u'(w-P)$ and $u'(w-l+I)$ once we notice the following relationships: $u'(w-P) = \frac{1}{h'(u_n)}$ and $u'(w-l+I) = \frac{1}{h'(u_n)}$.

of the high-risk type and thus behaves in the same manner as in the pure adverse selection model (except for the effect of disutility which affects the premium/indemnity of the high-risk agent and the low-risk agent in the same direction). Finally, Case 1 is the most complicated because the contracts are simultaneously determined by two binding adverse selection constraints. Hence, we cannot infer the results of comparative statistics of Case 1 from the pure adverse selection or the pure moral hazard model. The partial derivatives in this case can be derived following the procedure stated above. The results are rather mixed: the premium/indemnity profile of the low-risk type decreases with $\psi$, increases with $l$ and decreases with $w$; for the high-risk type, the premium/indemnity decreases with $\psi$, but the effect of $l$ or $w$ is uncertain. It is in sharp contrast to the standard result that people buy more insurance when they face higher potential loss in the future. So, caution has to be used to characterize optimal contracts when both adverse selection and moral hazard exist.

## VI Conclusion and Discussion

Since the early nineteen-seventies, the theoretical studies on contract theory have been explosive. Various optimal contracts are designed to deal with different asymmetric information problems, such as adverse selection and moral hazard. However, the majority of the asymmetric information literature treats adverse selection and moral hazard separately. In this paper, we consider a principal-agent model with the simultaneous presence of adverse selection and moral hazard in a competitive environment. To resolve the non-concavity issue in the optimization programming, we utilize the change-of-variable method proposed by Laffont and Martimort (2002), and then apply the Kuhn-Tucker method to solve the optimization programming. By analyzing the interaction between adverse selection and moral hazard, we find that there are several forms of separating Nash equilibria and graphically illustrate the characteristics of optimal contracts in each one of them. The equilibria in our paper are much richer than those in the pure adverse selection model and the pure moral hazard model, but retain some basic properties in these two benchmark models as well, such as no full insurance and the positive correlation between risk and coverage.[11] However, the equilibria may not exist. Even if an equilibrium exists, it may not be unique. A further examination of the conditions of existence and uniqueness of a separating Nash equilibrium may add new insight into our model. In addition, in the case of multiple equilibria, is there an equilibrium that Pareto-dominates all the others? These questions are beyond the scope of this paper but should be addressed in future research.

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[11] A common prediction of contract theory is the positive correlation property: everything being equal, people who face contracts with more comprehensive coverage should exhibit higher probability of accident. Therefore, if a data sample demonstrates a positive correlation between insurance coverage and accident occurrence, it implies the existence of asymmetric information. However, the positive correlation alone does not give us much insight into the nature of the underlying asymmetric information problems, as is well argued in the literature that the positive correlation can be the result of either adverse selection or moral hazard (Chiappori and Salanie, 2000, 2003), or even unobserved heterogeneous preferences (Meza and Webb, 2001). Proposition 1 of our paper implies that, in the simultaneous presence of adverse selection and moral hazard, the positive correlation property still holds.In addition, the comparative statics of the optimal contracts in our model predicts that the indemnity and premium decrease with disutility of effort, increase with potential loss, and decrease with the initial wealth of the insured, which may shed light on the regression analysis of insurance indemnity and/or premium.

One thing that makes the model with both adverse selection and moral hazard complicated is the insurer's inability to observe an agent's risk type and effort level. Therefore, the definition of "riskiness" alone is not an easy task. The low-risk agent may turn out to be even riskier if she is not incentivized to make effort. This simple possibility jeopardizes the Spence-Mirrless condition in the standard setup, and leads to more complex results (Chassagnon and Chiappori 1977, Laffont and Martimort 2002). In order to obtain more information on the "riskiness" of agents and provide corresponding incentive contracts, experience rating and retrospective rating are usually used. Further research on a more dynamic, two-period model based on these two rating approaches may be interesting.

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## Appendix: Proofs in the Case of Moral Hazard and Adverse Selection

***Proof of Lemma 1***. Assume $\underline{e} = 1$, i.e., type $\underline{\theta}$ exerts effort when she selects type $\overline{\theta}$'s contract $\overline{\delta} = \{\overline{P}, \overline{I}\}$. Then we must have $\overline{u}_n - \overline{u}_a \geq \frac{\psi}{\Delta \underline{\pi}}$. Given $\Delta\, \underline{\pi} < \Delta\, \overline{\pi}$ by assumption, we can obtain $\overline{u}_n - \overline{u}_a \geq \frac{\psi}{\Delta \underline{\pi}} > \frac{\psi}{\Delta \overline{\pi}} > 0$.

Since $h''(\cdot) > 0$ and $\overline{u}_n > \overline{u}_a$, we have $h'(\overline{u}_n) - h'(\overline{u}_a) > 0$. In addition, given $\overline{\pi}_1 < \underline{\pi}_1$ by assumption and $\underline{\lambda}_{AS} \geq 0$ and $\overline{\lambda}_Z > 0$ by definition, we can obtain from equation (3) that $\overline{\lambda}_M > 0$. This implies that, if $\underline{e} = 1$, the moral hazard constraint of type $\overline{\theta}$ is binding, i.e., $\overline{u}_n - \overline{u}_a = \frac{\psi}{\Delta \overline{\pi}}$. This contradicts the inequalities $\overline{u}_n - \overline{u}_a \geq \frac{\psi}{\Delta \underline{\pi}} > \frac{\psi}{\Delta \overline{\pi}}$. Therefore, we must have $\underline{e} = 0$, and $\overline{u}_n - \overline{u}_a < \frac{\psi}{\Delta \underline{\pi}}$. Combining this inequality with the two moral hazard constraints, we can easily get that $\frac{\psi}{\Delta \overline{\pi}} \leq \overline{u}_n - \overline{u}_a < \frac{\psi}{\Delta \underline{\pi}} \leq \underline{u}_n - \underline{u}_a$. ■

***Proof of Lemma 4***. Suppose $\underline{\lambda}_{MH} > 0$ and $\underline{\lambda}_{AS} > 0$, which means that both the moral hazard constraint and the adverse selection constraint of type $\underline{\theta}$ are binding, i.e.,

$$\underline{u}_n - \underline{u}_a = \frac{\psi}{\Delta\,\underline{\pi}},$$

$$\underline{\pi}_1 \underline{u}_n + \left(1 - \underline{\pi}_1\right)\underline{u}_a - \psi = \underline{\pi}_0 \overline{u}_n + \left(1 - \underline{\pi}_0\right)\overline{u}_a$$

These equations essentially imply that, in equilibrium, if an equilibrium exists, the optimal contract offered to type $\underline{\theta}$ is at the intersection of her moral hazard line and indifference line $\underline{V}\left(\underline{e} = 1\right)$, while the optimal contract offered to type $\overline{\theta}$ is at the intersection of type $\overline{\theta}$'s indifference line $\overline{V}(\overline{e} = 1)$ and type $\underline{\theta}$'s indifference line $\underline{V}\left(\underline{e} = 0\right)$. Moreover, the indifference line $\overline{V}(\overline{e} = 1)$ should cross the indifference line $\underline{V}\left(\underline{e} = 0\right)$ from above, otherwise type $\overline{\theta}$ will select type $\underline{\theta}$'s contract since it yields a higher utility level to the type $\overline{\theta}$ agent (i.e., type $\underline{\theta}$'s contract lies above type $\overline{\theta}$'s indifference line).

A steeper indifference line $\overline{V}(\overline{e} = 1)$ implies that $\frac{1-\overline{\pi}_1}{\overline{\pi}_1} > \frac{1-\underline{\pi}_0}{\underline{\pi}_0}$, which can be simplified as $\overline{\pi}_1 < \underline{\pi}_0$. It means that type $\overline{\theta}$ is absolutely riskier than type $\underline{\theta}$, regardless of the effort level. In addition, when $\overline{\pi}_1 < \underline{\pi}_0$, for every $u_a$, the zero profit curve of type $\underline{\theta}$ when $\underline{e} = 0$ is flatter than the zero profit curve of type $\overline{\theta}$ at $\overline{e} = 1$. In equilibrium, the zero profit curve of type $\underline{\theta}$ when $\underline{e} = 0$ can not cross type $\underline{\theta}$'s indifference line $\underline{V}\left(\underline{e} = 0\right)$ (at most, to be tangent), otherwise an insurer can always offer another contract that shifts type $\underline{\theta}$ agent's indifference line rightwards and make a profit herself as well. Therefore type $\overline{\theta}$'s zero profit curve when $\overline{e} = 1$ can not cross the indifference line $\underline{V}\left(\underline{e} = 0\right)$, because the zero profit curve of type $\underline{\theta}$ when $\underline{e} = 0$ is flatter than the zero profit curve of type $\overline{\theta}$ at $\overline{e} = 1$ and the former is at most tangent to the indifference line $\underline{V}\left(\underline{e} = 0\right)$. Hence, there is no point on the indifference line $\underline{V}\left(\underline{e} = 0\right)$ that can be an optimal contract offered to the type $\overline{\theta}$ agent. This completes the proof that $\underline{\lambda}_M > 0$ and $\lambda_{AL} > 0$ can not hold simultaneously in equilibrium.

***Proof of Proposition 1***. In this proof, we investigate every case in turn. When there is a Rothschild-Stiglitz Nash equilibrium, we illustrate the equilibrium in a figure.

*Case 1*: (Case H1)+ (Case L1), that is, $\overline{\lambda}_{MH} = 0$, $\underline{\lambda}_{AS} > 0$, $\underline{\lambda}_{MH} = 0$, and $\overline{\lambda}_{AS} > 0$. This case represents the *Only Adverse Selection* equilibrium in Proposition 1.

In this case, the two moral hazard constraints are not binding, but the two adverse selection incentive constraints are binding. Coupled with the two binding zero-profit constraints, we now have four equations to solve for the four unknowns $\overline{u}_n$, $\overline{u}_a$, $\underline{u}_n$, and $\underline{u}_a$:

$$\begin{cases} \overline{AS}\colon \overline{\pi}_1 \overline{u}_n + (1 - \overline{\pi}_1)\overline{u}_a - \psi = \overline{\pi}_1 \underline{u}_n + (1 - \overline{\pi}_1)\underline{u}_a - \psi \\ \underline{AS}\colon \underline{\pi}_1 \underline{u}_n + \left(1 - \underline{\pi}_1\right)\underline{u}_a - \psi = \underline{\pi}_0 \overline{u}_n + \left(1 - \underline{\pi}_0\right)\overline{u}_a \\ \overline{ZPC}\colon \overline{\pi}_1\left(w - h(\overline{u}_n)\right) - (1 - \overline{\pi}_1)\left(-w + l + h(\overline{u}_a)\right) = 0 \\ \underline{ZPC}\colon \underline{\pi}_1 \left(w - h\left(\underline{u}_n\right)\right) - \left(1 - \underline{\pi}_1\right) \left(-w + l + h\left(\underline{u}_a\right)\right) = 0 \end{cases}$$

It is difficult to analytically solve this system of equations without assuming the specific functional form of $h$. However, we can graphically demonstrate some features of the equilibrium contracts in Figure 3, if equilibria exist.

Since both of the adverse selection constraints are binding, $(\overline{u}_n, \overline{u}_a)$ should be at the intersection of type $\overline{\theta}$'s indifference line $\overline{V}(e=1)$ and type $\underline{\theta}$'s indifference line $\underline{V}(e=0)$, while $(\underline{u}_n, \underline{u}_a)$ should be at the intersection of type $\overline{\theta}$'s indifference line $\overline{V}(e=1)$ and type $\underline{\theta}$'s indifference line $\underline{V}(e=1)$. Furthermore, type $\overline{\theta}$'s zero profit curve should cross $(\overline{u}_n, \overline{u}_a)$, while type $\underline{\theta}$'s zero profit curve should cross $(\underline{u}_n, \underline{u}_a)$. From Figure 3, we can see that type $\underline{\theta}$'s indifference line $\underline{V}(e=0)$ crosses type $\overline{\theta}$'s indifference line $\overline{V}(e=1)$ from above, which leads to $\underline{\pi}_0 < \overline{\pi}_1$. $(\overline{u}_n, \overline{u}_a)$ and $(\underline{u}_n, \underline{u}_a)$ are above their respective moral hazard lines, which indicates that the amount of insurance offered to each type is even less than that offered in the case of pure moral hazard.

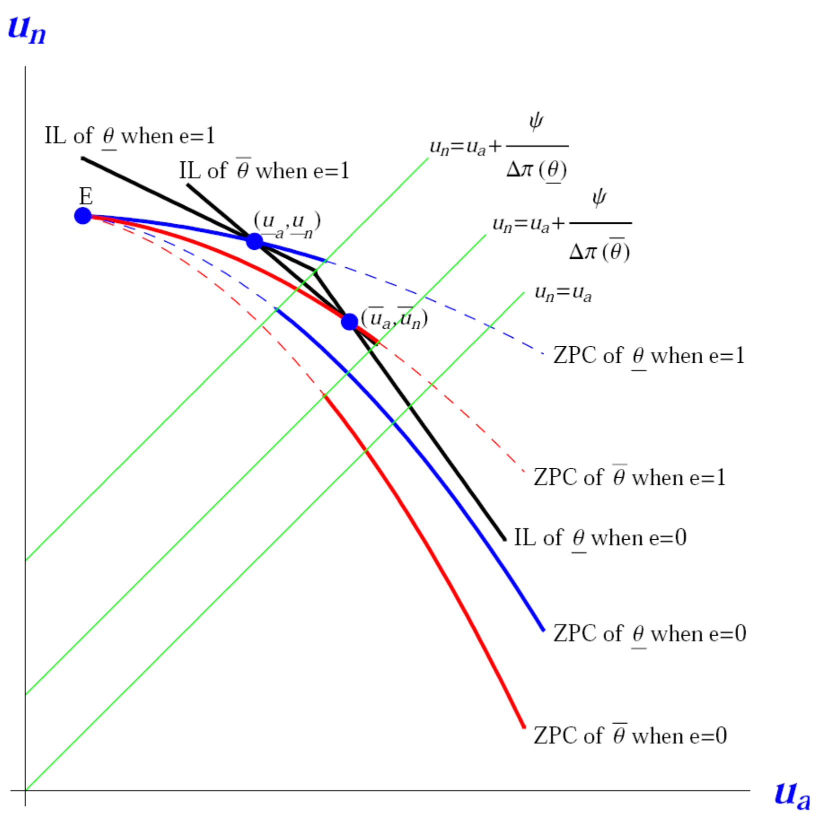


Figure 3: Case 1 of Adverse Selection and Moral Hazard

*Case 2*: (Case H1)+ (Case L2), that is, $\overline{\lambda}_{MH} = 0$, $\underline{\lambda}_{AS} > 0$, $\underline{\lambda}_{MH} > 0$, and $\overline{\lambda}_{AS} = 0$

In this case, the moral hazard constraint and the adverse selection constraint of type $\overline{\theta}$ are not binding, but those of type $\underline{\theta}$ are binding. According to *Lemma 2*, there is no equilibrium.

*Case 3*: (Case H1)+ (Case L3), that is, $\overline{\lambda}_{MH} = 0$, $\underline{\lambda}_{AS} > 0$, $\underline{\lambda}_{MH} > 0$, and $\overline{\lambda}_{AS} > 0$

In this case, the moral hazard constraint and the adverse selection constraint of type $\underline{\theta}$ are binding. Again, according to *Lemma 2*, there is no equilibrium.

*Case 4*: (Case H2)+ (Case L1), that is, $\overline{\lambda}_{MH} > 0$, $\underline{\lambda}_{AS} = 0$, $\underline{\lambda}_{MH} = 0$, and $\overline{\lambda}_{AS} > 0$. This case corresponds to the *Local Asymmetric Information* equilibrium in Proposition 1.

In this case, the moral hazard constraint and the adverse selection constraint of type $\overline{\theta}$ are binding, while none of the constraints of type $\underline{\theta}$ is binding. Combined with the two binding zero profit constraints, we have four equations with four unknowns:

$$\begin{cases} \overline{MH}: \overline{u}_n - \overline{u}_a = \dfrac{\psi}{\Delta\,\overline{\pi}} \\ \overline{AS}: \overline{\pi}_1\overline{u}_n + (1-\overline{\pi}_1)\overline{u}_a - \psi = \overline{\pi}_1\underline{u}_n + (1-\overline{\pi}_1)\underline{u}_a - \psi \\ \overline{ZPC}: \overline{\pi}_1\big(w - h(\overline{u}_n)\big) - (1-\overline{\pi}_1)\big(-w + l + h(\overline{u}_a)\big) = 0 \\ \underline{ZPC}: \underline{\pi}_1\left(w - h\left(\underline{u}_n\right)\right) - \left(1-\underline{\pi}_1\right)\left(-w + l + h\left(\underline{u}_a\right)\right) = 0 \end{cases}$$

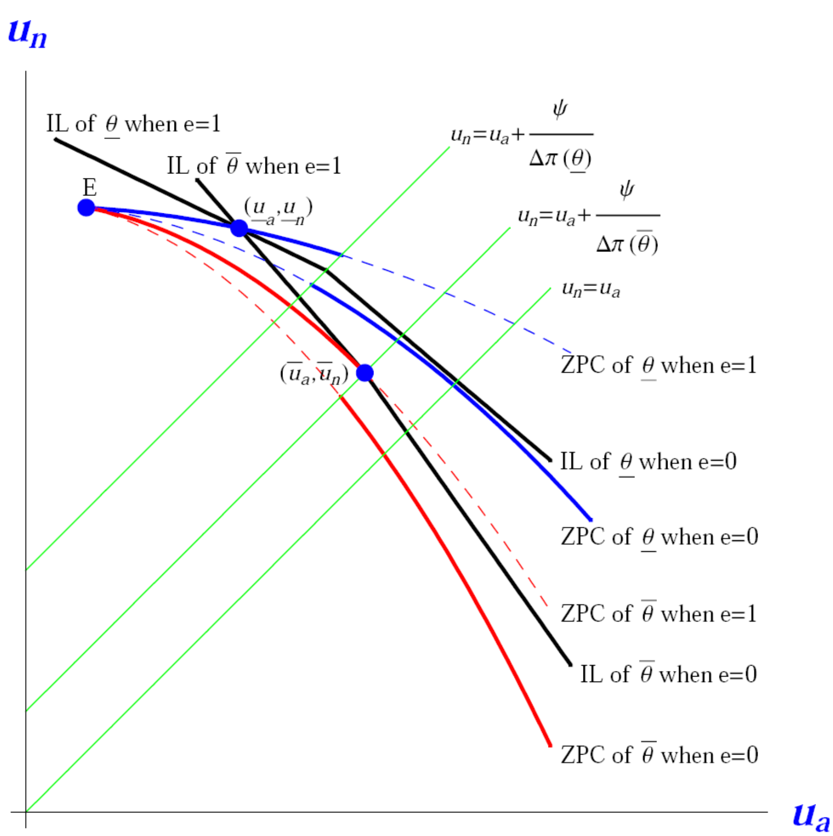


Figure 4: Case 4 of Adverse Selection and Moral Hazard

Since type $\underline{\theta}$'s moral hazard constraint is not binding but the adverse selection constraint of type $\overline{\theta}$ is binding, $(\underline{u}_a, \underline{u}_n)$ should locate above its moral hazard line and at the intersection of the indifference lines of the two types. As for $(\overline{u}_a, \overline{u}_n)$, since the moral hazard constraint of type $\overline{\theta}$ is binding, it is at the intersection of its indifference line and moral hazard line. Meanwhile, $(\overline{u}_a, \overline{u}_n)$ should be to the left of type $\underline{\theta}$'s indifference line, since the adverse selection constraint of type $\underline{\theta}$ is not binding. Figure 4 illustrates the possible equilibrium in this case. It is obvious that type $\overline{\theta}$

is offered the same contract as in the case of pure moral hazard, while type $\underline{\theta}$ is offered even smaller amount of insurance than that in the pure moral hazard case.

*Case 5*: (Case H2)+ (Case L2), that is, $\overline{\lambda}_{MH} > 0$, $\underline{\lambda}_{AS} = 0$, $\underline{\lambda}_{MH} > 0$, and $\overline{\lambda}_{AS} = 0$. This case represents the *Only Moral Hazard* equilibrium in Proposition 1.

In this case, both of the moral hazard constraints are binding, while none of the adverse selection constraints is binding. The two binding moral hazard constraints and the binding zero profit constraints give us a system of four equations with four unknowns:

$$\begin{cases} \overline{MH}: \overline{u}_n - \overline{u}_a = \dfrac{\psi}{\Delta\,\overline{\pi}} \\ \underline{MH}: \underline{u}_n - \underline{u}_a = \dfrac{\psi}{\Delta\,\underline{\pi}} \\ \overline{ZPC}: \overline{\pi}_1\big(w - h(\overline{u}_n)\big) - (1-\overline{\pi}_1)\big(-w + l + h(\overline{u}_a)\big) = 0 \\ \underline{ZPC}: \underline{\pi}_1\left(w - h(\underline{u}_n)\right) - (1-\underline{\pi}_1)\left(-w + l + h(\underline{u}_a)\right) = 0 \end{cases}$$

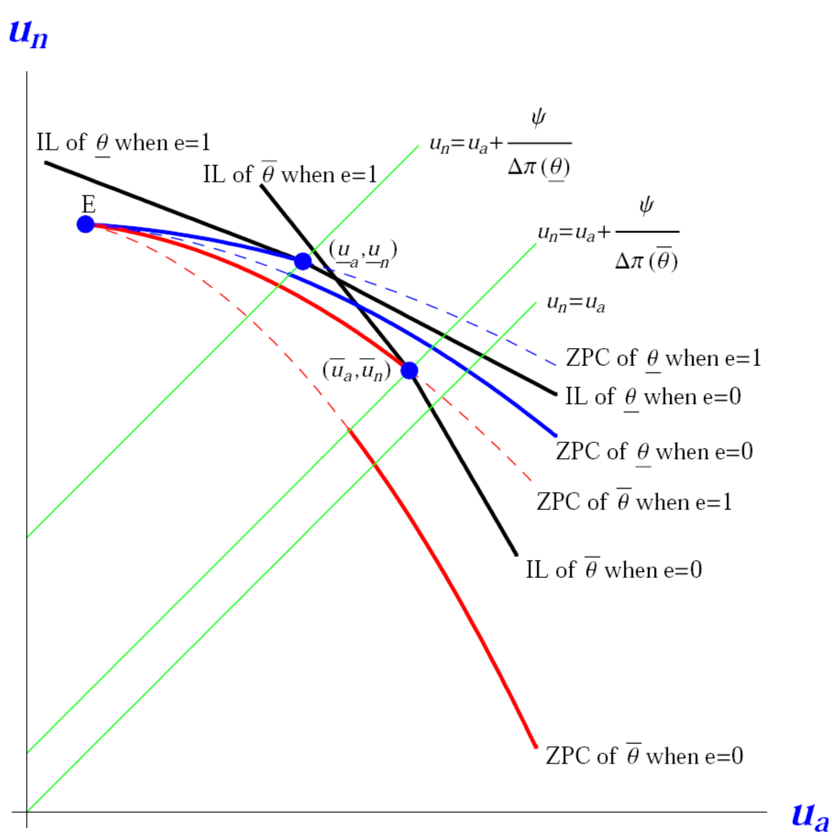


Figure 5: Case 5 of Adverse Selection and Moral Hazard

Since both of the moral hazard constraints are binding, $(\underline{u}_a, \underline{u}_n)$ and $(\overline{u}_a, \overline{u}_n)$ should be on their respective moral hazard lines, thus each agent is offered the same contract as in the case of pure moral hazard. Moreover, since both of the adverse selection constraints are not binding, the indifference line of the high-risk type $\overline{V}(e = 1)$ must cross the indifference line of the low-risk type $\underline{V}(e = 0)$from above, as illustrated in Figure 5. This implies $\underline{\pi}_0 > \overline{\pi}_1$, i.e., type $\overline{\theta}$ is absolutely riskier than type $\underline{\theta}$ no matter whether the latter expends effort or not.

*Case 6*: (Case H2)+ (Case L3), that is, $\overline{\lambda}_{MH} > 0$, $\underline{\lambda}_{AS} = 0$, $\underline{\lambda}_{MH} > 0$, and $\overline{\lambda}_{AS} > 0$. This case represents the *Strong Moral Hazard* equilibrium in Proposition 1.

In this case, both of the moral hazard constraints and type $\overline{\theta}$'s adverse selection constraint are binding, while type $\underline{\theta}$'s adverse selection constraint is not binding. Therefore, similar to Case 5, each agent is offered the same contract as in the case of pure moral hazard and type $\overline{\theta}$ is absolutely riskier than type $\underline{\theta}$. The only difference is that type $\overline{\theta}$ is now indifferent between the two contracts offered, whereas in Case 5, she strictly prefers her own contract. The equilibrium is illustrated in Figure 6.

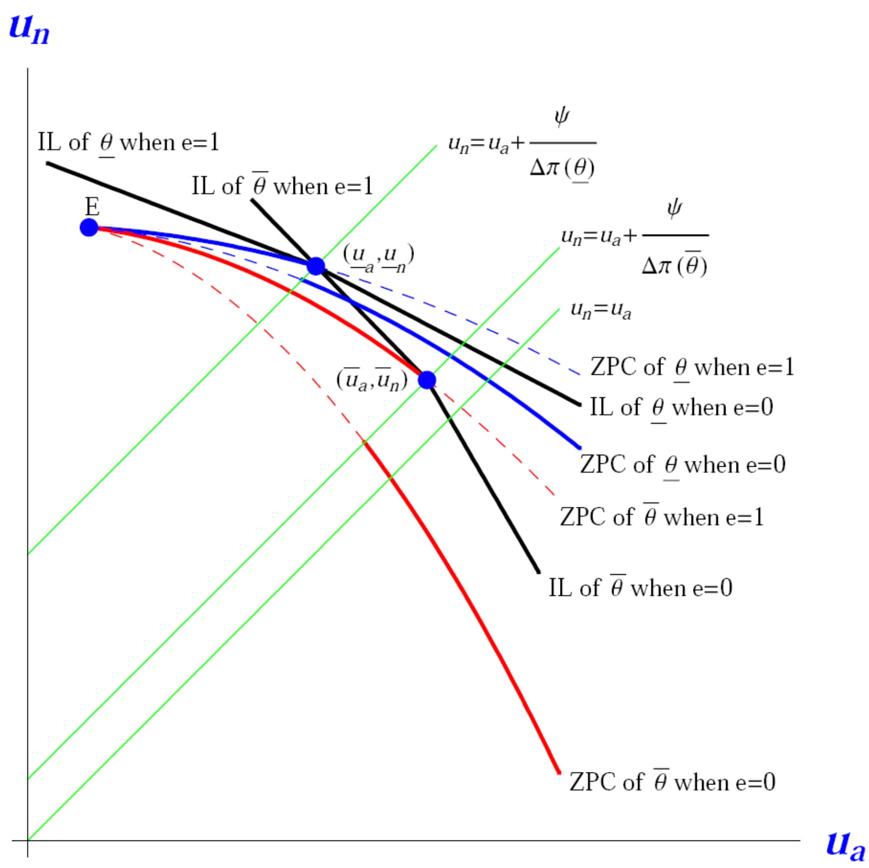


Figure 6: Case 6 of Adverse Selection and Moral Hazard

*Case 7*: (Case H3)+ (Case L1), that is, $\overline{\lambda}_{MH} > 0$, $\underline{\lambda}_{AS} > 0$, $\underline{\lambda}_{MH} = 0$, and $\overline{\lambda}_{AS} > 0$. This case corresponds to the *Strong Adverse Selection* equilibrium in Proposition 1.

In this case, both of the adverse selection constraints and type $\overline{\theta}$'s moral hazard constraint are binding, but type $\underline{\theta}$'s moral hazard constraint is not binding. Similar to Case 4, type $\overline{\theta}$ is offered the same contract as in the case of pure moral hazard, while type $\underline{\theta}$ is offered even smaller amount of insurance than that in the pure moral hazard case. One major difference between this one and Case 4 is that type $\underline{\theta}$ is now indifferent between the two contracts offered, whereas in Case 4, she strictly prefers her own contract. Also, two binding adverse selection constraints imply that the indifference curves of the two different types cross each other twice and thus $\underline{\pi}_0 < \overline{\pi}_1$. Figure 7 demonstrates the equilibrium in this case.

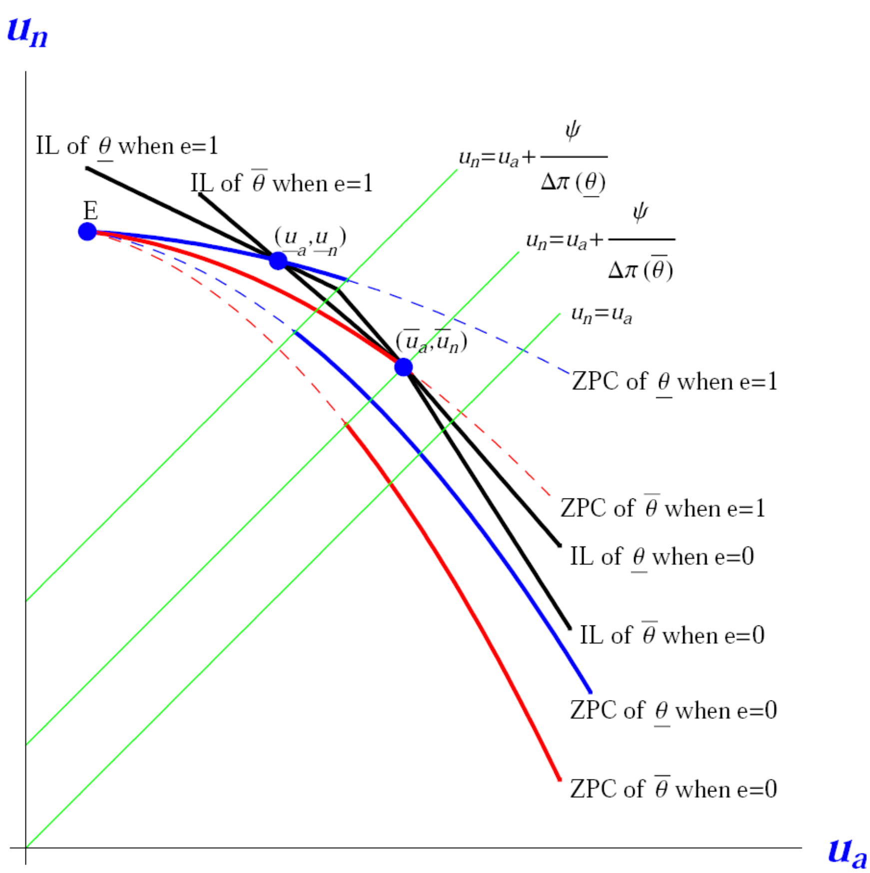


Figure 7: Case 7 of Adverse Selection and Moral Hazard

*Case 8*: (Case H3)+ (Case L2), that is, $\overline{\lambda}_{MH} > 0$, $\underline{\lambda}_{AS} > 0$, $\underline{\lambda}_{MH} > 0$, and $\overline{\lambda}_{AS} = 0$

In this case, both of the moral hazard constraints and type $\underline{\theta}$'s adverse selection constraint are binding, but type $\overline{\theta}$'s adverse selection constraint is not binding. According to *Lemma 2*, there is no equilibrium.

*Case 9*: (Case H3)+ (Case L3), that is, $\overline{\lambda}_{MH} > 0$, $\underline{\lambda}_{AS} > 0$, $\underline{\lambda}_{MH} > 0$, and $\overline{\lambda}_{AS} > 0$

In this case, all constraints are binding. According to *Lemma 2*, there is no equilibrium.

This completes the proof of Proposition 1. ■