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Can Cash Be a Ventilator for Firms Suffering from COVID-19? Evidence from Stock Market in Japan

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Can Cash Be a Ventilator for Firms Suffering from COVID-19? Evidence from Stock Market in Japan*

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Abstract

This paper explores how cash can mitigate adverse COVID-19 shocks to firms using an event-study methodology and the financial data from firms listed on the Tokyo Stock Exchange. We find that firms with more cash, less debt, and larger scale suffered less from the pandemic during the entire event window. We also find that the pandemic reduced the value of future investment opportunities the firms might invest in. Finally, we show that the variations in stock returns reflecting firm-specific factors become relatively smaller than that induced by market returns as cash holdings increase.

Keywords:COVID-19, cash holdings, stock returns, event study, precautionary demand
JEL Classification:G14,G32

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1 Introduction

In the absence of frictions in financial markets, cash in normal times does not contribute to firm value. However, in an emergency, such as when a firm faces an unexpected adverse shock, cash can support a firm's value. In many cases under such an environment, firms find it difficult to raise external funding, so the more cash they hold, the more likely they are to survive because they can pay off their debts and pay their workers.

The ongoing COVID-19 pandemic continues to have negative impacts not only on people's health but also on the economy. The total number of COVID-19 infections in Japan has increased rapidly since the beginning of March (Figure 1) As with the rest of the world, Japan's stock prices plummeted as the negative impact of COVID-19 on the economy became apparent; e.g., the TOPIX index fell about 500 points in a month from about 1,700 in early February. This was the first decline since October 2008, when the global financial crisis hit the economy.

This paper explores how cash saved firms suffering from the COVID-19 pandemic by investigating stock price reactions to the pandemic. Firms can reserve their cash either for investment in profitable projects that have not been implemented or for payment of their debts that are coming due when they face a cash-flow shortfall. We argue that cash holdings enabled firms to mitigate adverse shocks to their stock prices. We also find that it allowed them to maintain the value of their investment opportunities. To test these hypotheses, we use an event-study methodology and the financial data from firms listed on the Tokyo Stock Exchange.

As an event, the COVID-19 pandemic has several features. First, the COVID-19 outbreak was exogenous, unpredictable, and spread rapidly throughout the world in a short period of time. Second, during the early stages of the outbreak, investors were likely to be unaware that it would become a pandemic and have a significant negative impact on the economy because our knowledge of COVID-19 is limited. Thus, the COVID-19 pandemic has specific advantages and disadvantages compared with the economic shocks typically considered in the literature. The COVID-19 shock serves as an ideal setting to test the causal link between corporate cash holdings and asset prices because the event was exogenous and unpredictable. Using the pandemic as the event, we can rule out the issue of endogeneity that the firms may change their cash holdings because of large stock price fluctuations. Confounding events can be ignored because the outbreak of an infectious disease is an independent event. These are the advantages. However, it is difficult for us to determine the event date and window exactly because we knew little about the virus in the early stage of the pandemic and it is an ongoing event. Even if we exclude the impact of the market returns, the covariance of the abnormal returns across firms may not be zero because the event date is common to all firms. Those are the disadvantages.

Taking the advantages and overcoming the disadvantages of the COVID-19 pandemic as the event, we empirically analyze the role of cash in mitigating adverse shocks to stock prices. Following the standard procedure for event studies, we identified the event date, the event window, and the estimation window. As it is difficult to identify a single event date for the COVID-19 pandemic, we selected two event dates, January 30 and March 2. On the first event date, the World Health Organization (WHO) declared a "Public Health Emergency of International Concern," and the Governor of the Bank of Japan issued an emergency statement on the second event date. The event windows run from each event date to April 30. The estimation window run from January 4 to December 30 in 2019. We then use the data for the estimation window to estimate the capital asset pricing model (CAPM), and then use the estimated parameters to calculate the abnormal returns for the event window. From the abnormal returns, the cumulative abnormal returns are calculated, and we find that the pandemic had a negative impact on stock prices. We consider the role of cash by regressing the cumulative abnormal returns on the cash holding ratio and other variables representing firm attributes. Finally, some further analyses are performed.

Our empirical findings are as follows. First, we find a positive relation between cash holdings and abnormal returns for Japanese firms over the period from January 30 to April 30, which implies that cash holdings enable firms to mitigate the adverse shock to their stock price. The result is robust to alternative specifications for regression equations. The same result is observed over the period from March 2 to April 30. However, cash did not have an effect if the event window is limited to the period from January 30 to February 28.

Second, we also show that the pandemic reduced the value of future investment opportunities gauged by the market-to-book ratio. We do not find any significantly positive relation between the market-to-book ratio and the abnormal returns, suggesting that firms with a higher ratio experienced large drops in their stock prices. Combining the second finding with the first one offers an interesting insight: e.g., for some time after the COVID-19 outbreak occurred, investors understood that it would have a negative impact only on some firms. In particular, it would be difficult for firms with valuable investment opportunities to undertake these investments. But as the COVID-19 outbreak spread, investors changed their perceptions toward the outbreak causing an economy-wide negative cash flow shock.

Third, we find that the variations in stock returns reflecting firm-specific factors become relatively smaller as cash holdings increase. Variations in returns on each stock can be divided into those driven by common risk factors reflected in the market returns and those reflecting firm-specific factors. As the pandemic is a global event rather than a firm-specific event, the pandemic affects stock returns not only through firm-specific factors, but also through the market stock returns. We explore how much of the observed variation in the stock returns for each firm can be explained by the variation in the firm-specific factors and by the variation in the market returns. That finding is consistent with our first finding because firms with more cash can mitigate the effects of the adverse shock on their stock prices, resulting in less variation reflecting firm-specific factors.

Our paper relates to the recent literature on corporate liquidity management policies. As the literature on corporate liquidity management including cash holdings is extremely broad, we only present a brief discussion here[1]. If financial markets are perfect, the firms' liquidity decision is irrelevant to their firm value. But when firms face frictions in financial markets, it is worth exploring the optimal cash holding for firms. This literature has developed in two main directions.[2] The first direction relates to the "precautionary demand for cash"; i.e., cash holdings are effective as a precautionary hedge against the possibility that capital market frictions prevent the firms from obtaining external financing. The second direction is "cash holdings from an agency perspective." According to this argument, managers hold cash for greater discretion in management or for private benefit. Many empirical studies provide evidence of the benefits to firms of holding cash to hedge against uncertainty. Bates, Kahle, and Stulz (2009) find a growing demand for liquidity to buffer cash flow shocks as the reason for the increase in cash held by US firms. In other words, holding cash allows firms to maintain financial flexibility and minimize the damage of financial distress caused by adverse cash flow shocks. Holding cash also allows firms to quickly accept projects that have a positive net present value. For example, Almeida, Campello, and Weisbach (2004) develop a model that provides empirical evidence showing financially constrained firms hold more cash than unconstrained firms, which suggests that firms hold more cash for investment. Duong et al. (2020) find that US firms increase their cash holdings in response to greater economic policy uncertainty.

[1] See Almeida et al. (2014) for a survey of the literature.

[2] Theories of liquidity management such as Holmstrom and Tirole (1998) and Tirole (2006), e.g., provide a unifying framework to help understand the main results of the literature for liquidity management, and show that information asymmetries between management and capital markets make liquidity valuable.

The 2007–2009 global financial crisis highlighted the role of cash held by firms. Several studies have explored how the crisis has changed the management policies of firms. For example, Duchin, Ozbas, and Sensoy (2010) find that US firms ran out of cash during the crisis and that investment after the crisis is positively related to cash reserves. In addition, Campello, Graham, and Harvey (2010) show that firms tend to postpone or suspend their investment plans when capital markets are tightened. COVID-19 is the first major adverse shock to the global economy since the global financial crisis. However, the two are different in terms of the nature of the event: i.e., the financial crisis was a negative shock to external funding provided by financial institutions, whereas COVID-19 was an exogenous shock unrelated to financial institutions.

Our event-study methodology follows Faulkender and Wang (2006), and Wagner, Zeckhauser, and Ziegler (2018). Faulkender and Wang (2006) study the cross-sectional variation in the marginal value of firms' cash holdings resulting from different corporate monetary policies. What they have in common with our study is that they regress the excess returns, which are constructed by subtracting the benchmark returns from the observed returns, on various variables, including cash. However, the difference is that they do not determine a specific event date, but instead view any unexpected change in cash holdings as an event. Another difference is that while the events considered in their study are firm-specific, the event examined in our study is common to all firms. Many of the events covered in the event studies are firm-specific; thus, the event dates differ for different firms. However, several recent event studies considered political events and ensured event days are common across all firms. For example, Wagner, Zeckhauser, and Ziegler (2018) investigate stock market reactions to the outcome of the election for the 45th President of the United States of America and find evidence that a cross-section of stock returns after the election reflects expectations of a major corporate tax reduction.[3]

Our paper makes several contributions to the literature. First, this is an early economic analysis of the effects of COVID-19 implemented using observed data. As COVID-19 is an ongoing event, some economic impacts may be yet unknown. However, stock market data can provide a sense of how investors understood the event and we can derive some policy implications from our results for the issues that currently need to be resolved. Second, because the COVID-19 outbreak is an exogenous event,

[3] Liu, Shu, and Wei (2017) also investigate this issue through the impact of political uncertainty on asset prices using the Bo Xilai political scandal in 2012 in China as an exogenous shock event and find that the scandal caused a significant drop in stock prices, especially for firms that are more politically sensitive.

the effect of cash on firm value can be measured without concern about endogeneity. Third, when an event affects stock returns through both common risk factors and firm-specific factors, we propose a simple statistic that measures the relative influence of firm-specific factors.

The remainder of the paper is organized as follows. Sections 2 describes some key events related to COVID-19 in Japan. Section 3 explains hypothesis development and Section 4 presents the empirical strategy and data. Section 5 reports the empirical results and Section 6 considers further research issues. Section 7 concludes the paper.

2 Key Events Linked to COVID-19 in Japan

This section describes some key events linked to COVID-19 in Japan. Table 1 provides a timeline of the major events.

The Ministry of Health, Labor and Welfare (MHLW) confirmed the first infected person in Japan on January 15. Although the number of patients in Japan was limited until February, the number of infections has increased rapidly since the beginning of March. The number of deaths has continued to rise since the first was reported on February 13.

On February 1, the Japanese Government stepped up preventive measures against COVID-19 by classifying it as a legally designated infectious disease. In the case of severe infection, the government can legally order infected patients to be placed in a hospital and impose restrictions on their work activities to prevent further virus outbreak. Furthermore, on February 25, the MHLW announced its "Basic Policies for Novel Coronavirus Disease Control," which summarizes the measures that are currently being taken and some possible future measures that may be taken.

Despite all the measures taken, the number of COVID-19 patients kept surging throughout March (Figure 1). Following the Diet's approval of legislation authorizing Prime Minister Abe to declare a state of emergency, the Prime Minister declared a state of emergency covering Tokyo, Osaka, and five other prefectures on April 7.[4] Under a state of emergency, the prefectural governor may require residents to stay indoors.[5] It would also allow for the expropriation of land for the construction of temporary medical

[4]The Government defines a state of emergency as "a situation in which the capacity to provide medical care will reach its limit and people's lives and health will be put at risk unless measures are taken."

[5]They may also call for the temporary closure or curtailment of schools and other public facilities. If such a facility does not respond to a request, the prefecture will be able to publish the name of the facility to ensure that measures are implemented.

facilities to treat the rapidly growing number of patients. The provision allows suppliers of medicines and food to order the sale to the authorities or to forcefully procure goods from companies that refuse to do so. On April 16, the Prime Minister expanded the state of emergency to cover the entire country. This policy revision reflected continued growth in the number of infections in Japan in April and an understanding that efforts to contain the virus were needed at the national level.

While the number of COVID-19 infections was limited in January and February, the Japanese economy began to suffer. This was partly because Japanese firms were forced to suspend operations in China. Another reason is that the Chinese government prohibited all outbound group travel, which resulted in sharp declines in profits for Japan's retail and tourism sectors. As a result, a firm filed for bankruptcy on February 25, which marks the first business failure in Japan linked to the COVID-19 outbreak. Since March, the virus has had a serious negative impact on the Japanese economy. For example, some Japanese automakers have been forced to close some of their plants and change their production plans. The consumer confidence survey carried out by the Cabinet Office reported that the Consumer Confidence Index in March 2020 was 30.9, down 7.4 points from the previous month.

To mitigate the adverse economic impact of COVID-19, the Prime Minister pledged to implement emergency spending packages. The first round of measures disbursed ¥15.3 billion in early February and the second one ¥270 billion in early March. These measures included employment subsidies and zero-interest loans without collateral to small and mid-sized companies. On April 7, the Government announced its "Emergency Economic Measures for Response to COVID-19" stimulus package worth 108 trillion yen, which is equivalent to 20% of Japan's GDP. The package allows a one-year tax moratorium worth ¥26 trillion and spends ¥6 trillion on cash grants for affected small and midsize companies, and households in need. It also includes interest-free unsecured loans and allows recurring debts to be refinanced as interest-free loans.

The Bank of Japan (BOJ) also stepped up its quantitative and qualitative monetary easing policy. On March 2, the Governor of the BOJ issued an emergency statement and pledged that the BOJ would strive to provide ample liquidity and ensure stability in financial markets through appropriate market operations and asset purchases.[6]

[6]The BOJ has offered to buy 500 billion yen ($4.6 billion) of government bonds in a repurchase agreement to provide liquidity to market participants. Furthermore, on March 16, the BOJ pledged to buy exchange-traded funds and other risky assets at twice the current pace.

3 Hypothesis Development

The theory of optimal firm cash holdings predicts that a role of cash is a precautionary hedge against adverse shocks. In the presence of an unexpected shock, firms would use their cash reserves to mitigate a decline in cash flow because raising funds externally in such a situation would be costly or impossible. If the firms run out of cash or are unable to raise external funds, they will be forced to sell their essential assets or liquidate, resulting in a significant decline in their firm values. The widely accepted conclusion of the literature is that cash remains the best instrument for certain groups of firms even if other options such as debt capacity, derivatives, and lines of credit are also available.[7] Given the impact of COVID-19 on the economy, we expect that the stock prices of firms with more cash did not fall as much as those of firms with less cash.

(H1) *The more cash a firm holds, the less impact COVID-19 had on its stock price.*

Firms facing financial frictions incur higher costs in raising external funding. Firms with investment opportunities are therefore more likely to abandon these valuable projects if the cost of raising external funding is high and internal funding is insufficient. A large literature begun by Fazzari, Hubbard, and Petersen (1988) provides evidence in support of this hypothesis. Moreover, Almeida, Campello, and Weisbach (2004) show that financially constrained firms systematically save cash from their cash flow, while unconstrained firms do not. Based on these results, Acharya, Almeida, and Campello (2007) categorized constrained firms based on the correlation between cash flow and investment opportunities. They show that when investment opportunities arise when operating cash flow is relatively low, financially constrained firms save cash rather than pay down debt. However, unconstrained firms and constrained firms with a high correlation between investment opportunities and high cash flows pay down debt rather than save cash. Some studies such as Sufi (2009), Campello, Graham, and Harvey (2010) and Lins, Servaes, and Tufano (2010) find that lines of credit and cash are used for different purposes.[8] They show that nonoperational cash guards against future cash flow shocks in bad times, while credit lines give firms the option to exploit future investment opportunities available in good times. In Japan, Sasaki (2016) shows that the motivation of firms for holding excess cash is not only to prepare for future cash

[7]See Almeida et al. (2014).

[8]Lines of credit are also sources of liquidity, but this paper focuses its analysis solely on cash. This is because it is not possible to obtain the information on lines of credit for all firms, as even publicly traded companies are not required to disclose information on lines of credit agreements.

flow shortfalls, but also to prepare for future investment opportunities that have not been implemented. This argument motivates our second hypothesis:

(H2) *The more cash a firm holds, the less impact COVID-19 had on the value of its investment opportunities.*

4 Empirical Strategy and Data

To investigate the effects of the COVID-19 pandemic as an unexpected adverse shock to Japanese firms, we use the event-study methodology suggested by Campbell, Lo, and MacKinlay (1997) to measure the decline in market value of firms listed on the Tokyo Stock Exchange, which is an estimate of the market's valuation of the impact of the pandemic on the firms' value. The procedure for the analysis is as follows. First, the event date is identified. Then, we determine on the event window. Finally, abnormal returns are calculated based on the CAPM.

4.1 Event Date

The COVID-19 pandemic as an event has unique several features compared with the events that the literature typically considers. First, the outbreak of COVID-19 was exogenous, unpredictable, and spread rapidly throughout the world in a short period of time.

Second, because we know very little about COVID-19, the uncertainty of its impact on the economy is high. It is believed to be the first major pandemic since the Spanish Flu in 1918. The WHO certified the 2009 Swine Flu as a pandemic, but governments at that time did not implement measures such as voluntary restraints on overseas travel, border closures, or even lockdowns of major cities. Therefore, it is difficult to predict the impact of a pandemic on the economy based on past experiences.

We adopt two event days in our analysis because the above characteristics lead us to the difficulty of limiting the event date to a specific single day.[9] The first event date is January 30, when the WHO declared a "Public Health Emergency of International Concern" by acknowledging the outbreak of COVID-19 as a serious event endangering international public health. At that point, however, investors may not have been aware that COVID-19 would have a negative impact on the economy. The second event date is March 2, the day the Governor of the BOJ issued an emergency statement informing that it might pursue a further easing of monetary policy. The emergency economic

[9] In Appendix, we provide other evidence we used to determine the event date.

measures themselves could have a positive impact on stock prices. However, Japan has not had any experience in implementing economic policies on the grounds of infectious diseases since World War II, which suggests that COVID-19 is an unprecedented infectious disease and could have a negative impact on stock prices.

4.2 Event Window

We analyze three different sets of cumulative abnormal returns: the first from January 30 to the end of April, the second from March 2 to the end of April, and the third from January 30 to February 26. [10] The first set corresponds to the first event date. How the market was digesting information about the impact of COVID-19 on the economy over time can be understood by analyzing the cumulative abnormal returns over this period. The second set corresponds to the second event date. Since the second event day, investors may have been aware of the coming recession. Thus, the impact of the coming recession on stock prices can be understood by analyzing the cumulative abnormal returns over this period. For both sets, the last day of the event window is April 30. While this choice for the end point is somewhat arbitrary, the pandemic is an ongoing event, so it makes sense to use as much of the available data as possible. To confirm the robustness of the estimated results, we analyze the impact of COVID-19 on stock prices using the cumulative abnormal returns from January 30 to February 26. Between the first event date and the second event date, COVID-19 may have been perceived as serious, but not a disease that would negatively affect the economy. If such a perception existed, the negative shocks to the economy would be temporary and small in magnitude; thus, cash would play a limited role in mitigating the decline in stock prices.

4.3 Abnormal Returns

To measure stock market reactions to the COVID-19 pandemic, we calculate abnormal returns using the CAPM.

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + \epsilon_{it} \tag{1}$$

where R_{it} is the return for firm i on date t , R_{ft} is the risk-free rate on date t, R_{mt} is the market return on date t, α_i is a constant for firm i, β_i is the beta for firm i, and ϵ_{it}

[10] Note that the method of identifying the event window in this paper follows that adopted by Wagner (2018). Typically, the event window in this paper is set for a certain period of time before or after the event date, whereas Wagner (2018) only sets the event window for a certain period of time after the event.

is an error term with mean 0 and variance $\sigma^2_{\epsilon_i}$.

We estimate β_i in equation (1) for each firm i using ordinary least squares (OLS) for the period from January 4, 2019 to December 30, 2019 (estimation window). We then compute the abnormal return for firm i on date t, AR_{it}, after January 6, 2020, the next business day following the last day of the estimation window. To this end, we subtract the normal return, NR_{it}, from daily excess returns on each stock where NR_{it} is defined as follows.

$$NR_{it} = \hat{\alpha}_i + \hat{\beta}_i(R_{mt} - R_{ft}) + R_{ft} \tag{2}$$

$\hat{\alpha}_i$ is the estimated α_i and $\hat{\beta}_i$ is that of β_i in equation (1), respectively. The cumulative abnormal returns during the event window are obtained as follows.

$$CAR_i(T_1, T_2) = \sum_{t=T_1}^{T_2} AR_{it} \tag{3}$$

where $CAR_i(T_1, T_2)$ is the cumulative abnormal returns for firm i from T_1 to T_2, T_1 is the first day of the event window and T_2 is the last day of it.

4.4 Empirical Design

To evaluate the effect of cash holdings on staving off a stock price decline, we regress CAR on a variable representing firms' cash holdings (*Cash*), the other firm-specific characteristics, and industry dummy variables. The cash variable is calculated by dividing "cash and deposits" on the balance sheet by "total assets." To test hypothesis H1, we examine the coefficient of cash. If it is positive, the empirical result is consistent with *H1*.

Control variables include the market-to-book ratio of the firm (*MB*), cash flow (*CF*), firm leverage (*Leverage*), short-term debt ratio (*Short*), and total assets (*Size*). *MB* is measured by the ratio of the market value of the firm's total assets to their book value, where the market value of the firm's total assets is calculated by evaluating only the value of common stock minus treasury stock at the firm's stock price on December 30, 2019. *CF* is the cash-flow-to-assets ratio, measured as the cash flow over total assets. *Leverage* is defined as the ratio of "total liabilities" to total assets. *Short* is defined as total amount of borrowings from financial institutions and corporate bonds due within one year divided by total liabilities. Size is the logarithm of total assets.

To test hypothesis *H2*, we add the interaction term of *Cash* and *MB* (*Cash* MB*) as an explanatory variable. The coefficient on the interaction term reflects the *Cash*-dependent effect in the sensitivity, which measures the extent to which a firm's stock price after the event date reacts to the value of the firm at the end of 2019. An estimated positive coefficient of the interaction term would be evidence in support of hypothesis *H2*.

4.5 Data

The sample for this paper includes firms listed on the first and second sections, and the Mothers market of the Tokyo Stock Exchange, excluding the financial and insurance sectors. We also exclude firms from our sample if their stocks were not traded for even one business day in 2019. After applying these filters, we have a sample of 2468 firms, but then drop firms whose cash flow data are not reported when it is used as a control variable.

The stock and financial data, except the risk-free rate, are taken from Nikkei Financial-Quest. The stock prices are adjusted for splits and net dividends. The risk-free rate is the interest rate on Japanese government bonds with a 10-year maturity.[11] All rates of return are translated on a daily basis. We use the most current accounting data as of December 30, 2019 for all firms.

Table 2 presents descriptive statistics for the variables used in this paper. The cross-sectional mean of CAR over the entire period is -0.0437. Therefore, it can be said that COVID-19 has negative impacts on stock prices on average. However, the results are different between the early period (from January 30 to February 28) and the middle–late period (from March 2 to April 30). While the mean CAR for the early period is negative, it is positive for the middle–late period, which means that the negative impacts on stock prices are severe for the early period and are mild for the middle–late period. Note that raw returns during the middle–late period are not necessarily positive because CARs in this paper are calculated excluding the factor that correlates with the market return.

According to Surveys for the Financial Statements Statistics of Corporations by Industry conducted by the Ministry of Finance in Japan, cash and deposits account for about 12% of total assets for all industries except finance and insurance. The average for Cash in this paper is 23%, which is considerably larger than that ratio. This reflects the large values of Cash in relatively small firms because it is a simple mean.[12]

[11] The risk-free rate is taken from the website of Ministry of Finance, Japan, see `https://www.mof.go.jp/english/jgbs/reference/interest_rate/index.htm`

[12] The correlation coefficient between *Cash* and total assets is -0.05.

5 Empirical Results

5.1 Univariate Analysis

Figure 2 plots univariate comparisons of average cumulative standardized abnormal returns (CSAR) after January 6, 2020, the business day following the last day of the estimation window.[13] Here, the quintile is sorted based on *Cash*. The figure presents the average CSAR for Category 1 as the first quintile (the cash-richest group), Category 5 as the fifth quintile (the cash-poorest group), and all firms. The outbreak of COVID-19 was evident in January, but it was not until mid-February that stocks plummeted. This result suggests that the markets needed about two weeks to digest the information associated with the outbreak and the economy. This figure also shows that there has been substantial variation in the way the stock prices of companies with different cash holdings have reacted. The Category 1 CSAR was positive until mid-January, whereas the Category 5 CSAR has remained negative since the beginning of January. It is worth noting that in February, the Category 1 CSAR was significantly below the Category 5 CSAR. By mid-March, the CSAR was trending upward, but the Category 1 CSAR was still below the Category 5 CSAR. The variations of CSAR for the two groups are particularly striking and counterintuitive, which might not be consistent with *H1*. We will discuss this issue in Section 5.2 when we examine the results of the regression analysis.

5.2 Results from Regression Analysis

This section investigates the cross-section of stock price responses to the COVID-19 pandemic using regression analysis. We examine whether cash holdings affected the cross-section of stock returns, over the entire period (from January 30 to April 30), over the middle–late period, and over the early period. Table 3 presents the empirical results of regressions of individual CARs on *Cash* and the control variables for the entire period. In addition to *MB, CF, Leverage, Short, Size*, and *Cash* MB*, the control variables include industry dummies and interaction terms of industry dummies and *Cash*. All specifications are estimated by OLS.

The estimated coefficients of cash are significantly positive at the 1% level in all but one case (result in column (9)), which implies that cash-rich firms are fairly valued, all

[13] Cumulative standardized abnormal returns (CSAR) for firm i are defined as $CAR_i(T_1, T_2)/\sigma_i(T_1, T_2)$, where $\sigma_i(T_1, T_2)$ is the standard deviation of CAR for firm i between T_1 and T_2.

other things being equal. These results are consistent with *H1*, but not with the result from the univariate analysis. The reason why the results of the regression analysis differ from those of the univariate analysis is that the univariate analysis includes the industry-specific factors. Note that the explanatory variables in some equations include interaction terms for cash and industry dummies. The estimates of the coefficients of *Cash* are those for the benchmark industry (here, the services industry), an industry for which the industry dummy variable does not equal one, thus the estimates of these coefficients are not significantly positive for all industries. Still, about 20% of firms belong to industries for which the estimates are significantly negative, which does not significantly change our argument.[14]

Cash may be regarded as a measure of the difficulty of obtaining external financing rather than a measure of excess funds. This is because the more difficult it is to raise external funding in the face of a negative cash flow shock, the stronger the precautionary demand for cash will be. However, that interpretation is unlikely to be applicable to our results. The reason for this is that, if that interpretation is correct, we would expect the estimated coefficients on *Cash* to be insignificant. When a firm needs funds in an emergency, those with a substantial amount of cash will fund their operations with cash on hand, whereas those with little cash will need to raise money externally. Therefore, it should have no impact on CAR at all, as both types of firms can obtain the necessary funds. However, Table 3 presents no such evidence, with one exception. In other words, *Cash* should be interpreted as an index of excess funds.

The majority of the estimated coefficients of *MB* are insignificant. The exception is a result in column (7) in which estimated coefficients of *MB* is significantly negative at the 10% level. *MB* is a variable that represents the investment opportunities of a firm. If the pandemic caused firms to lose their investment opportunities, the firms with larger *MB* should experience more severe stock price drops. Therefore, the insignificance of the coefficient on *MB* means that stock prices fell uniformly amid the pandemic, regardless of the investment opportunities of the firm.

The estimated coefficients of *CF* are all insignificant. If the estimated coefficients on cash flow were positive, firms that performed well before the COVID-19 outbreak would have been able to stave off a decline in their stock price because they would have been expected to perform relatively well after the outbreak. However, such an effect is not observed here.

The estimated coefficients of *Leverage* are significantly negative in all cases. The

[14]The industries where the estimates are significantly negative are Food, Other Manufacturing, Construction, Trading, Retail, Air Transportation, and Electric Power. See Appendix A.2 for details.

common intuition about the coefficient for *Leverage* is that firms with higher leverage are riskier, which means that they have a higher probability of default. In the presence of default, the firms are forced to sell their essential assets and incur the cost of an inefficient liquidation. Our results are consistent with this intuition because the stock price of such firms with a high probability of default are undervalued in the market. The absolute values of the estimated coefficients for *Leverage* are smaller than those of *Cash*, which provides the following insight. Let us assume that a firm issues additional debt and all the funds raised are held in cash, making the firm's *Leverage* and *Cash* both increase by one point. According to the estimates in column (13), the impact on CAR is different between *Leverage* and *Cash.* A one percentage point increase in *Leverage* lowers CAR by 17 basis points, while a one percentage point increase in *Cash* raises CAR by 21 basis points. In other words, it would be more valuable to increase cash holdings by one dollar than to reduce debt by one dollar; thus, cash is not negative debt in an emergency. This result is consistent with Acharya, Almeida, and Campello (2007), who show that financially constrained firms prefer more cash to less debt if their hedging needs are high.

The estimated coefficients of *Short* are negative in all cases, but only two cases are significant. *Short* is a variable that indicates the need for funds within one year. Our results are not robust, but are consistent with the theory of refinancing risk; i.e., firms with more short-term debt have a higher risk of refinancing and a higher likelihood of failure.[15]

Following Faulkender and Wang (2006), *Size* is added as a control variable.[16] Larger firms are considered to be better known to investors and have better access to capital markets than smaller firms. Therefore, they have fewer constraints on raising funds for investment. It is also believed that there are economies of scale in liquidity management, and, given that the other conditions are equal, the larger firms can save more cash and its equivalent. The estimated coefficients of *Size* are significantly positive in all cases, which provides evidence in support of those hypotheses.

We find that the estimated coefficient of *Cash* MB* is not significant, suggesting that the hypothesis *H2* is not supported. Even when this interaction term is added as an explanatory variable, the estimates of the coefficients in column (13) are very similar to the estimates in column (12). Thus, we find that stock prices fell uniformly with or

[15]Harford, Klasa, and Maxwell (2014) find that firms can reduce refinancing risk by increasing their cash holdings and saving cash from cashflow. Even if a firm cannot refinance, cash holdings makes its likelihood of failure smaller.

[16]We use total assets for *Size*, whereas Faulkender and Wang (2006) use sales.

without investment opportunities at the end of last year, and do not observe that cash holdings prevented the loss of those investment opportunities.

Table 4 shows the empirical results of regressions for the middle–late period, using the same specifications as those for the entire period. The results are similar to those for the entire period.[17] The one exception is that the estimated coefficients of *Size* are significantly negative here, whereas they are significantly positive for the entire period. One interpretation of the similarity between the results in Tables 3 and 4 is that the shocks that occurred on the event days had a similar impact on the economy, although the event days were different between them. However, the spread of the COVID-19 is an ongoing event; i.e., as of January 30, investors may not yet have been able to fully digest all of the related information. This suggests that the results for the entire period strongly reflect the results for the middle–late period, even though they had different impacts on the economy. To see which interpretation is more plausible, we performed the same regression analysis for the early period, from January 30 to February 28.

Table 5 shows the empirical results of the regressions for the early period, with the same specifications as before. A difference from previous results is that more than half of the estimates of the coefficients for *Cash* are not significant and one coefficient is negative, making these empirical results for the early period not robust.[18]

The estimated coefficients of *MB* are all negative, although only two of the four cases are significant. This suggests that the greater the growth opportunities firms had prior to the COVID-19 outbreak, the lower their stock prices fell in February. In other words, the market interpreted the economic impact of COVID-19 as the loss of a potential investment opportunity that firms had held at that time. *Cash* MB* is added as an explanatory variable to the equation in column (12), and the estimation results are presented in column (13). Not only is the coefficient of this interaction term not significant, but the coefficients of *Cash* and *MB*, which were significant in column (12), are no longer significant in column (13). The reason for this is as follows. We find that the correlation coefficient between *Cash* and the interaction term is 0.515 and that between *MB* and the interaction term is 0.927, which means that *MB* and the interaction term vary in almost exactly same way. It is likely that this very high correlation caused the explanatory power of each explanatory variable to disappear in the regression analysis.

[17]The industries with the significantly negative estimates for *Cash* are Food, Pulp, Other Manufacturing, Construction, Trading, Retail, Air Transportation, and Telecommunication. See Appendix A.2 for this issue.

[18]The industries with the significantly negative estimates for *Cash* are Medicine, Rubber, Trading, and Electric Power. See Appendix A.2 for this issue.

Table 6 shows the results of regressing *MB* on *Cash*, which indicate that the more cash that a firm holds, the higher the stock market valuation of the firm. This result has the following implications for firms' cash holdings. Firms did not hold cash as "free cash flow" for managers to make inefficient investments discussed by Jensen (1986). Our understanding is consistent with Dittmar and Mahrt-Smith (2007) who show that firms facing greater uncertainty could have more cash holdings in the case of less agency conflicts between managers and shareholders.[19]

It is also likely that the purpose of holding large amounts of cash was to prepare for investments in high-value projects that might occur in the future. Let us assume that all of a firm's cash holdings were based on a precautionary demand against a negative cash flow shock. If this hypothesis is correct, following an unexpected negative cash flow shock because of COVID-19, the firm's value should not decline significantly because the firm can hedge that shock using the cash it holds. In this case, it is expected that the regression analysis in this paper will give positive estimates of the coefficients of *MB*, but the estimates we obtain here are different. That is, while all firms held cash based on preliminary demands to hedge negative cash flow risk, we can determine that the purpose of holding cash for cash-rich firms included investing in high-value projects.

6 Further Investigation

Although typical event studies assume that events are firm-specific, COVID-19 as an event has an economy-wide impact and the TOPIX index has been on a downward trend since January 2020 (Figure 1). Therefore, the effect of COVID-19 on stock prices should be reflected not only in the abnormal returns, but also the normal returns, i.e., the returns that can be explained by CAPM. This leads us to the following question. How much of the observed variation in the stock returns over the period of the event window can be explained by the variation in the abnormal returns and how much by the variation in the normal returns?

To answer these questions, we construct the following variable.

$$VR_i = \frac{Var(AR_i)}{Var(AR_i) + Var(NR_i)} \tag{4}$$

where $Var(AR_{it})$ and $Var(NR_{it})$ are the variance of the abnormal returns and that of the normal returns for firm i, respectively. VR_i is distributed between 0 and 1, and the larger the ratio of $Var(AR_{it})$ to the variance of observed stock returns for firm i, the

[19]Pinkowitz, Stulz, and Williamson (2006) provide evidence in support of the hypothesis that minority shareholders' cash holdings are smaller in countries with weaker investor protection.

larger VR_i is. We calculate VR_i for each firm i using the data over the entire period. Figure 3 shows that VR_i between about 0.4 and 1 is distributed almost uniformly, which implies that different firms have different relative magnitudes of the variance in their abnormal returns.

We then regressed VR_i on *Cash* and the industry dummy variables. Table 7 shows that the estimates of the coefficient on *Cash* are significantly negative. This result is consistent with the results in Table 2, suggesting that firms with higher *Cash* have smaller VR, and thus a relatively lower share of abnormal return variance in the total variance of each security's returns. This is because the higher a firm's *Cash* is, the less volatile its stock return is, as higher *Cash* can keep the abnormal rate of return from declining.

Table 8 shows some of the estimates of the coefficients when VR is regressed on the industry dummy variables, using data for the five largest industries ($Top5$) and five smallest industries ($Bottom5$). We estimated three different equations: the first equation's explanatory variables are the industry dummy variables only, the second equation's are the industry dummy variables and *Cash*, and the third equation's are the industry dummy variables, *Cash*, and the interaction terms of industry dummy variables and *Cash*. The results are robust regardless of the specification. On the one hand, the results suggest that the $Bottom5$ industries are strongly affected by fluctuations in the market returns; thus, there is a need for economic policies that support the entire industry because the stock prices of the firms in these industries strongly reflect the effects of macro shocks. On the other hand, the results suggest that the $Top5$ industries are strongly influenced by firm-specific factors; thus, different support measures are needed for each firm's attributes rather than for the industry as a whole.

7 Conclusion

We examine how cash mitigated the adverse COVID-19 shock to firms using the event-study methodology and financial data from firms listed on the Tokyo Stock Exchange. We find that firms with more cash, less debt, and larger scale suffered less from the pandemic during the entire event window. We also find that the pandemic reduced the value of future investment opportunities of the firms. It is shown that the variations reflecting firm-specific factors become relatively smaller as cash holdings increase.

Our results also raise important questions for future research. We show that cash did not prevent a decline in the value of potential investment opportunities. However, we are unable to determine from this result whether the value of the investment opportunity itself has declined, or whether the investment opportunity still exists but is seen as difficult to implement because of insufficient funds. In order to solve this problem, we need indexes of the difficulty for firms in obtaining external financing, as well as data on the actual amount of investment by firms.

Another issue is the design of optimal insurance against negative shocks caused by the epidemic. The implication of the results from the paper is that firms that hold cash can cope to some extent with negative firm-specific shocks, but it is difficult to respond to negative macro shocks. However, self-insurance, i.e., cash holdings, is not always the best way to prevent negative firm-specific shocks. This is because a firm's large cash holdings in normal times reduce the probability that it will invest in profitable projects. In fact, Duchin, Ozbas, and Sensoy (2010) find that US firms reduced their investment expenditure and increased cash held after the global crisis. Therefore, there is a need for a system that provides some degree of insurance against individual corporate shocks.

Appendix

A.1. Google Search for Coronavirus and Recession

Figure A shows the number of Google searches for "coronavirus" in Japanese from January to April 2020. The first peak in the graph is observed on January 30, reflecting the WHO declaration of a "Global Health Emergency" on January 30. The second peak came in late March, when people expected the disease to have a higher probability of becoming a pandemic, partly because the government had formulated its "Basic Policies for Novel Coronavirus Disease Control" and partly because the number of infected people in Japan had begun to rise rapidly, exceeding 100. The word was searched most often on April 4, when people were waiting for Prime Minister Abe to declare a state of emergency.

To identify the point at which people began to think that the coronavirus might have a negative impact on the economy, we also report data for Google searches for "recession" in Japanese in Figure A. Searches for the word have increased since mid-February, suggesting that Japanese were beginning to realize around this time that the coronavirus could have a negative impact on the economy. The first peak in the search for "recession" is observed on February 28, three days after the first business failure in Japan following the COVID-19 outbreak.

These results indirectly confirm plausibility of our choice of the event dates. While

COVID-19 has attracted enormous attention since early February, Japanese have been aware of the potential negative impact of COVID-19 on the economy since March.

A.2. Industries with Significantly Negative Estimated Coefficients for *Cash*

Table A reports the estimated coefficients of the interaction terms between industry dummy and *Cash*, and those of *Cash* adjusted by the estimates of the interaction terms. The estimated coefficients of the interaction terms between *Cash* and *MB* were not significant in any of the equations (13) from Table 3 to Table 5. Therefore, we report the estimated coefficients of the interaction terms based on equation (12) in each table. Because of the large number of industries, we report here only those industries in which the estimated coefficient was significantly negative. In addition, we also report the estimated total coefficients of *Cash* for each industry, adjusted by the estimated coefficients of the interaction terms. For example, the estimated total coefficient of Food, -0.1581, is equal to the sum of the one for *Cash*,0.1660, and the one for the interaction term, -0.3242. The number in parentheses next to the name of the coefficient represents the number of firms in that industry. As this table shows, the number of firms belonging to industries in which the adjusted cash coefficient is significantly negative is 521 in Table 3, 404 in Table 4, and 84 in Table 5.

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Table 1 Timeline of Key Events Linked to COVID-19 in Japan

Jan. 15:	The Ministry of Health, Labor and Welfare confirmed the first infected person in Japan.
Feb. 1:	Government classified COVID-19 as a legally designated infectious disease.
Feb. 13:	The first confirmed fatality in Japan was reported.
	Government announced the first emergent package to support economy.
Feb. 25:	Basic Policies for Novel Coronavirus Disease Control
	decided by the Headquarters for Novel Coronavirus Disease Control.
	The first business failure in Japan following the COVID-19 outbreak
Mar. 2:	Governor of BOJ issued an emergency statement.
Mar. 13:	The Diet approved legislation authorizing the Prime Minister to declare a state of emergency.
Apr. 7:	The Prime Minister declared a state of emergency covering major city areas such as Tokyo.
	Government adopted Emergency Economic Measures for Response to COVID-19.
Apr. 16:	The Prime Minister expanded the state of emergency to cover the whole country.

Table 2 Descriptive Statistics

	Obs	Min	P25	Mean	Median	P75	Max	Stdev
Dependent variables								
CAPM-adj CAR from Jan 30 to Apr 30(*CAR130430*)	2468	-0.9630	-0.1722	-0.0437	-0.0249	0.0962	1.0940	0.2225
CAPM-adj CAR from Mar 2 to Apr 30(*CAR302430*)	2468	-0.9010	-0.0684	0.0240	0.0255	0.1163	1.3462	0.1605
CAPM-adj CAR from Jan 30 to Feb 28(*CAR130228*)	2468	-0.6674	-0.1401	-0.0677	-0.0554	0.0128	0.9205	0.1330
CAPM								
Beta	2468	-1.8688	0.6806	0.9889	0.9651	1.2762	2.5858	0.4335
Explanatory Variable								
Cash	2468	0.0005	0.1053	0.2319	0.1827	0.3070	0.9835	0.1793
Control variables								
MB	2468	-1.3676	1.2850	2.2044	1.5572	2.2120	62.2814	2.6985
CF	2427	-0.7694	0.0450	0.0819	0.0821	0.1229	0.5457	0.0951
Leverage	2467	0.0180	0.3050	0.4516	0.4500	0.5930	1.7670	0.1940
Short	2468	0.0000	0.0206	0.1362	0.0972	0.2048	0.8343	0.1402
Size	2468	6.0497	9.7314	10.9379	10.8866	12.0490	19.4721	1.8442

This table reports the descriptive statistics for the variables used in the empirical analysis. Here, the observations (Obs), minimum (Min), Mean, Median, maximum (Max), and standard deviation (Stdev) are reported in addition to the first and third quartiles (P25 and P75). These dependent variables (*CAR130430*, *CAR302430* and *CAR130228*) are the cumulative excess rate of return for the three periods (January 30 to April 30, March 2 to April 30, and January 30 to February 28) calculated in equation (3).The *Beta* of CAPM is calculated with the data from January to December 2019, which is the estimated window based on equation (1). *Cash* is calculated by dividing "cash and deposits" on the balance sheet by "total assets." *MB* is measured by the ratio of the market value of the firm's total assets to their book value, where the market value of the firm's total assets is calculated by evaluating only the value of common stock minus treasury stock at the firm's stock price on December 30, 2019. *CF* is the cash-flow-to-assets ratio, measured as cash flow over total assets. *Leverage* is defined as the ratio of "total liabilities" to total assets. *Short* is defined as total borrowings from financial institutions and corporate bonds due within one year divided by total liabilities. MB is measured by the ratio of the market value of the firm's total assets to their book value, where the market value of the firm's total assets is calculated by evaluating only the value of common stock minus treasury stock at the firm's stock price on December 30, 2019. CF is the cash-flow-to-assets ratio, measured as the cash flow over total assets. Leverage is defined as the ratio of "total liabilities" to total assets. Short is defined as total borrowings from financial institutions and corporate bonds due within one year divided by total liabilities. *Size* is the logarithm of total assets.

Table 3 Regression Results: *CAR130430* (CAR from Jan 30 to Apr 30)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(12)	(12)	(13)
Const	-0.1563***	-0.1035***	-0.1058***	-0.0114***	-0.0776***	-0.2136***	-0.1513***	-0.1633***	-0.0537**	-0.1354***	-0.3999***	-0.2816***	-0.3014***
(tstat)	-7.9901	-7.6030	-6.3194	-0.5023	-6.1942	-3.3985	-7.6968	-8.0129	-2.1179	-6.8301	-9.9904	-6.3211	-6.3479
Cash	0.1336***						0.1644***	0.1497***	0.0526	0.1171**	0.2079***	0.1660***	0.2066***
(tstat)	2.8319						3.3471	3.0532	1.0651	2.5016	4.3205	3.1604	2.7992
MB		-0.0010					-0.0047*					-0.0032	0.0030
(tstat)		-0.3525					-1.7182					-0.9354	0.4285
CF			-0.0091					0.0097				-0.0809	-0.0831
(tstat)			-0.0879					0.1482				-1.1935	-1.2262
Leverage				-0.2269***					-0.1724***			-0.1722***	-0.1685***
(tstat)				-4.4045					-5.9598			-5.7289	-5.5171
Short					-0.2765***					-0.1397***		-0.0155	-0.0157
(tstat)					-3.5424					-3.9707		-0.4082	-0.4134
Size						0.0111*					0.0225***	0.0215***	0.0216***
(tstat)						1.8185					7.5748	6.9919	7.0352
*Cash*MB*													-0.0120
(tstat)													-0.8198
Obs	2468	2468	2427	2467	2468	2468	2468	2427	2467	2468	2468	2427	2427
Adj R^2	0.1037	0.1009	0.0971	0.1095	0.1033	0.1177	0.1060	0.1070	0.1189	0.1102	0.1254	0.1426	0.1428
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cash × *Indust*	Yes	NO	NO	NO	NO	NO	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control × *Indust*		Yes	Yes	Yes	Yes	Yes	NO	NO	NO	NO	NO	NO	NO

This table shows the results of the regression using the cumulative excess return (*CAR130430*) for the period January 30 to April 30. See the footnotes in Table 2 for a description of each variable. *Industry* is the industry dummy variable, *Cash* × *Indust* is the interaction term of industry dummy and *Cash*, and *Control* × *Indust* is the interaction term of each variable and industry dummy in single regressions other than *Cash*. The t-statistics (tstat) are based on White-corrected robust standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4 Regression Results: *CAR302430* (CAR from Mar 2 to Apr 30)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(12)	(12)	(13)
Const	-0.0404 ***	0.0041	0.0173	0.0827 ***	0.0328 ***	0.0981 **	-0.0403 ***	-0.0434 ***	0.0149 ***	-0.0370 ***	0.0193	0.0763 **	0.0595 *
(tstat)	-3.0416	0.4338	1.4788	5.3496	3.8256	2.3654	-2.9941	-3.1059	0.8304	-2.7181	0.6976	2.4887	1.7611
Cash	0.1502 ***						0.1506 ***	0.1733 ***	0.1066 ***	0.1476 ***	0.1320 ***	0.1102 ***	0.1445 ***
(tstat)	4.6475						4.3798	5.1869	3.1393	4.5620	3.9724	3.0001	2.7331
MB		0.0031					-0.0001					0.0002	0.0054
(tstat)		1.6415					-0.0283					0.0701	0.9604
CF			-0.0125					-0.0412				-0.0524	-0.0543
(tstat)			-0.1634					-0.8275				-0.9956	-1.0284
Leverage				-0.1605 ***					-0.0925 ***			-0.0952 ***	-0.0921 ***
(tstat)				-4.6025					-4.2388			-4.0105	-3.8230
Short					-0.1675 ***					-0.0225		-0.0035	-0.0036
(tstat)					-3.0345					-0.8264		-0.1179	-0.1239
Size						-0.0086 **					-0.0055 ***	-0.0057 ***	-0.0057 **
(tstat)						-2.1421					-2.6080	-2.5909	-2.5664
*Cash*MB*													-0.0101
(tstat)													-0.9189
obs	2468	2468	2427	2467	2468	2468	2468	2427	2467	2468	2468	2427	2427
Adj R^2	0.0859	0.0693	0.0767	0.0822	0.0697	0.0773	0.0855	0.0921	0.0943	0.0858	0.0880	0.1025	0.1028
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cash × *Indust*	Yes	NO	NO	NO	NO	NO	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control × *Indust*		Yes	Yes	Yes	Yes	Yes	NO	NO	NO	NO	NO	NO	NO

This table shows the results of the regression using the cumulative excess return (*CAR302430*) for the period March 2 to April 30. See the footnotes in Table 2 for a description of each variable. *Industry* is the industry dummy variable, *Cash* × *Indust* is the interaction term of industry dummy and *Cash*, and *Control* × *Indust* is the interaction term of each variable and industry dummy in single regressions other than *Cash*. The t-statistics (tstat) are based on White-corrected robust standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5 Regression Results: *CAR130228* (CAR from Jan 30 to Feb 28)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(12)	(12)	(13)
Const	-0.1158***	-0.1077***	-0.1232***	-0.0941***	-0.1104***	-0.3117***	-0.1110***	-0.1199***	-0.0686***	-0.0983***	-0.4192***	-0.3579***	-0.3610***
(tstat)	-10.214	-14.748	-13.392	-6.6575	-14.533	-7.5846	-9.9287	-10.206	-4.4792	-8.4535	-17.848	-13.719	-13.1223
Cash	-0.0166						0.0138	-0.0236	-0.0540*	-0.0304	0.0759***	0.0558*	0.0621
(tstat)	-0.5651						0.4556	-0.8008	-1.7478	-1.0390	2.6052	1.7994	1.5819
MB		-0.0041***					-0.0046***					-0.0033***	-0.0024
(tstat)		-3.5645					-4.1576					-2.6076	-0.7496
CF			0.0034					0.0509				-0.0285	-0.0288
(tstat)			0.0635					1.3900				-0.7979	-0.8058
Leverage				-0.0664**					-0.0799***			-0.0769***	-0.0764***
(tstat)				-2.1534					-4.5102			-4.3671	-4.2772
Short					-0.1090**					-0.1172***		-0.0121	-0.0121
(tstat)					-2.2722					-5.5934		-0.5372	-0.5384
Size						0.0197***					0.0280***	0.0272***	0.0272***
(tstat)						4.9791					15.592	14.654	14.6820
*Cash*MB*													-0.0019
(tstat)													-0.2959
obs	2468	2468	2427	2467	2468	2468	2468	2427	2467	2468	2468	2427	2427
Adj R^2	0.1142	0.1245	0.1159	0.1057	0.1168	0.2136	0.1210	0.1197	0.1232	0.1275	0.2095	0.2246	0.2243
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cash × *Indust*	Yes	NO	NO	NO	NO	NO	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control × *Indust*		Yes	Yes	Yes	Yes	Yes	NO	NO	NO	NO	NO	NO	NO

This table shows the results of the regression using the cumulative excess return (*CAR130228*) for the period January 30 to February 28. See the footnotes in Table 2 for a description of each variable. *Industry* is the industry dummy variable, *Cash* × *Indust* is the interaction term of industry dummy and *Cash*, and *Control* × *Indust* is the interaction term of each variable and industry dummy in single regressions other than *Cash*. The t-statistics(tstat) are based on White-corrected robust standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6 Results of Regressing MB on Cash

	MB	
const	0.8231	***
tstat	10.0892	
Cash	5.9567	***
tstat	21.3991	
Obs	2468	
Adj R^2	0.1563	

This table shows the result of a single regression of *MB* on *Cash*.The t-statistics(tstat) are based on White-corrected robust standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7 Regression Results: Variance Ratio

	Variance Ratio(VR)					
	(1)		(2)		(3)	
const	0.6069	***	0.6471	***	0.6702	***
tstat	77.2223		51.1703		40.2924	
Cash			-0.1087	***	-0.1712	***
tstat			-4.9675		-5.1159	
Obs	2468		2468		2468	
Adj R^2	0.4519		0.4579		0.4593	
Industry	Yes		Yes		Yes	
Cash × *Indust*	NO		NO		Yes	

This table shows the results of regressing VR on *Cash* and Industry dummy variables, where VR is calculated by dividing the variance of the abnormal returns ($VAR(AR)$) by the sum of the variance of the abnormal returns ($VAR(AR)$) and the variance of the normal returns ($VAR(NR)$) (equation (4) in the text).The t-statistics (tstat) are based on White-corrected robust standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8 Regression Coefficients for Industry Dummy: Bottom 5 and Top 5

Bottom 5		
Table7 (1)	Table7 (2)	Table7 (3)
Marine Products	Marine Products	Marine Products
(-0.4236)	(-0.4549)	(-0.5047)
Mining	Mining	Mining
(-0.3705)	(-0.3906)	(-0.4337)
Construction	Construction	Construction
(-0.3299)	(-0.3483)	(-0.4004)
Food	Food	Food
(-0.2574)	(-0.2811)	(-0.3301)
Fiber	Fiber	Fiber
(-0.171)	(-0.1982)	(-0.2467)

Top 5		
Table7 (1)	Table7 (2)	Table7 (3)
Gas	Gas	Gas
(0.3543)	(0.3220)	(0.2907)
Electric Power	Electric Power	Electric Power
(0.3514)	(0.3193)	(0.2877)
Warehouse	Warehouse	Warehouse
(0.3340)	(0.3116)	(0.2698)
Air Transportation	Air Transportation	Air Transportation
(0.3265)	(0.3042)	(0.2633)
Shipping	Shipping	Shipping
(0.3255)	(0.2954)	(0.2590)

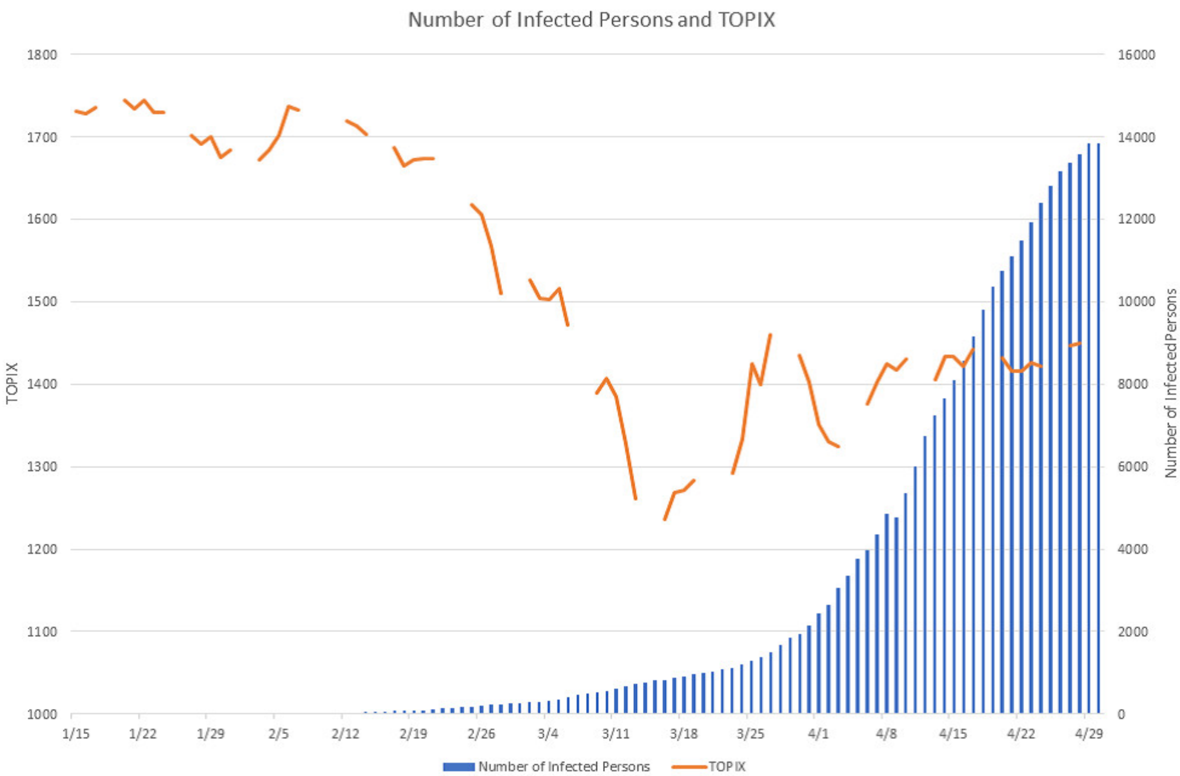
This table summarizes the five industries with small industry dummy regression coefficients (Bottom 5) and five industries with large regression coefficients (Top 5) for each regression equation in Table 7. Parentheses under each industries indicate the size of the coefficient.

Table A Industry Dummy

	Table3 (12)		Table4 (12)		Table5 (12)			Table3 (12)		Table4 (12) Total coefficients		Table5 (12)	
Cash	0.1660	***	0.1102	***	0.0558	*							
t stat	3.1604		3.0001		1.7994								
*Cash**Food dummy (92)	-0.3242		-0.4389				Food	-0.1581		-0.3287			
t stat	-2.4303	**	-4.4803	***			F stat	1.5196		11.6686	***		
*Cash**Pulp dummy (12)			-1.0534				Pulp			-0.9432			
t stat			-2.4800	**			F stat			4.9483	**		
*Cash**Medicine dummy (57)					-0.1737		Medicine					-0.1180	
t stat					-2.4003	**	F stat					3.1773	*
*Cash**Rubber dummy (14)					-0.4214		Rubber					-0.3657	
t stat					-2.3918	**	F stat					4.3828	**
*Cash**Other Manufacturing dummy (67)	-0.2885		-0.2373				Other Manufacturing	-0.1224		-0.1270			
t stat	-1.7730	*	-1.8174	*			F stat	0.6103		0.9992			
*Cash**Construction dummy (112)	-0.4388		-0.2967				Construction	-0.2728		-0.1864			
t stat	-2.9649	***	-3.3621	***			F stat	3.7674	*	5.1338	**		
*Cash**Trading dummy (208)	-0.3895		-0.2282		-0.1613	**	Trading	-0.2235		-0.1180		-0.1055	
t stat	-2.8224	***	-2.5167	**	-2.1200		F stat	2.8714	*	1.8772		2.1304	
*Cash**Retail dummy (184)	-0.5156		-0.4038				Retail	-0.3496		-0.2936			
t stat	-4.0809	***	-4.4016	***			F stat	8.7598	***	11.5427	***		
*Cash**Air Transportation dummy (4)	-0.6705		-0.4394				Air Transportation	-0.5044		-0.3292			
t stat	-4.3084	***	-3.0668	***			F stat	11.2528	***	5.5129	**		
*Cash**Telecommunication dummy (28)			-0.4152				Telecommunication			-0.3050			
t stat			-1.9239	*			F stat			2.0163			
*Cash**Electric Power dummy (13)	-1.1288				-0.9658		Electric Power	-0.9628				-0.9100	
t stat	-2.2449	**			-3.8397	***	F stat	3.6863	*			13.2045	**

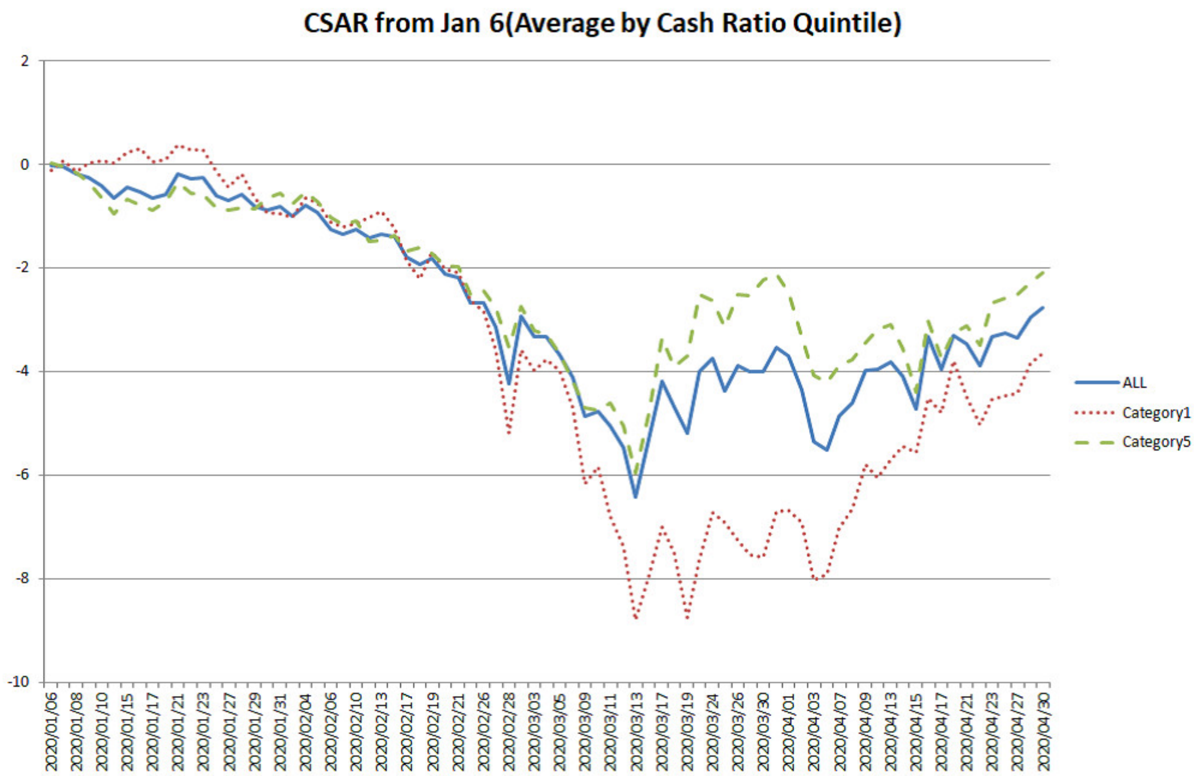
The left-hand side of this table reports the coefficients of the interaction terms of cash and industry dummies in the regression equation in column (12) of Tables 3, 4 and 5. Because of the large number of industries, we report here only those industries for which the estimated coefficient was significantly negative. The number in parentheses next to the name of the coefficient represents the number of firms in that industry. The t-statistics (t stat) are based on White-corrected robust standard errors. The right-hand side of this table reports the sum of the coefficients of *Cash* and the coefficients of the interaction terms for each industry and the F-statistic (F stat) that tests the null hypothesis that the sum is zero. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Figure 1 Number of Infected Persons in Japan and TOPIX



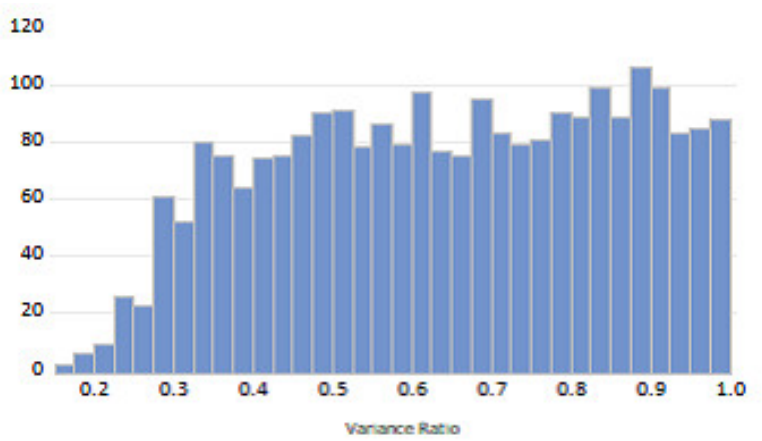
This figure shows the closing price of TOPIX from January to April 2020 (line, left axis) and the number of infected persons in Japan (bar graph, right axis).

Figure 2 CSAR from Jan 6 (average by cash ratio quintile)



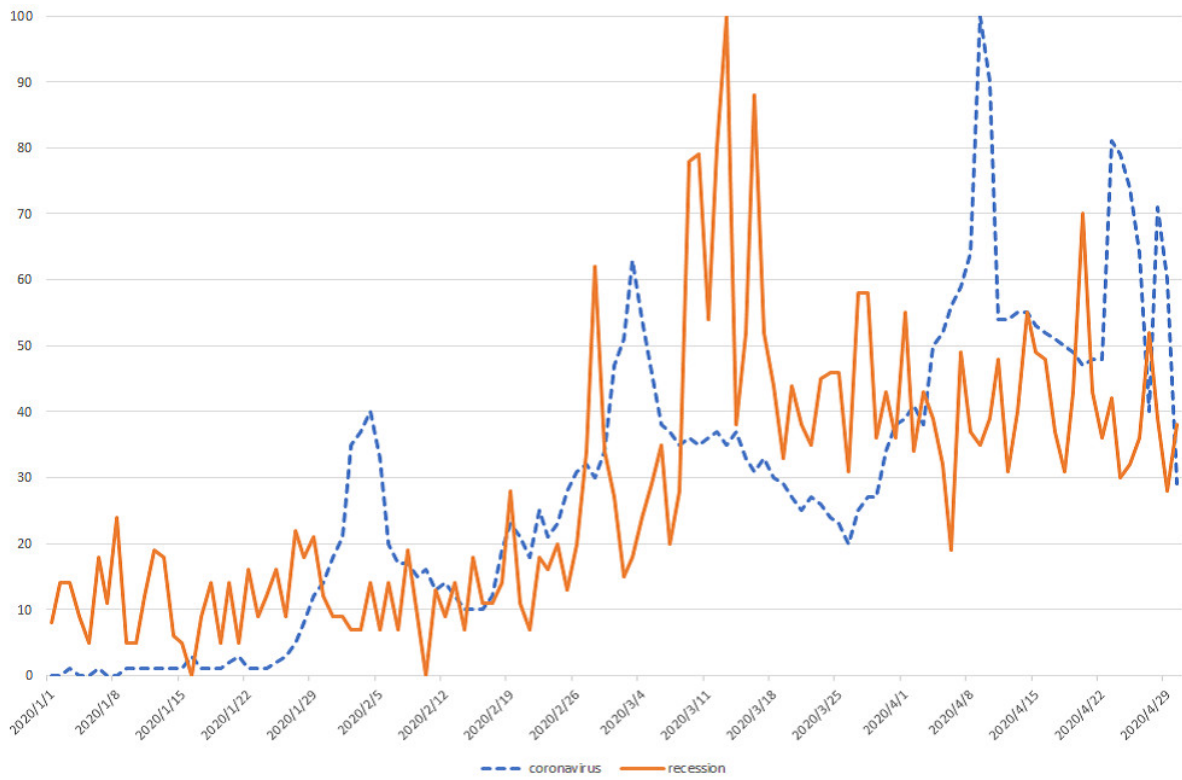
This graph shows univariate comparisons of average cumulative standardized abnormal returns (CSAR) after January 6, 2020, the business day following the last day of the estimation window. Here, the quintile is sorted based on Cash. The figure presents the average CSAR for Category 1 as the first quintile (cash-richest group), Category 5 as the fifth quintile (the cash-poorest group), and all firms.

Figure 3 Histogram of Variance Ratio



This graph shows the distribution of the variance ratio (VR) calculated by dividing the variance of the abnormal returns ($VAR(AR)$) by the sum of the variance of the abnormal returns ($VAR(AR)$) and the variance of the normal returns ($VAR(NR)$) (equation (4) in the text).

Figure A Number of Searches for "Coronavirus" and "Recession"



This figure summarizes the changes in the number of searches for "Coronavirus" and "Recession" in Japan. The maximum value for this period is set to 100 as the reference value.