Supply Chains and Shareholder Risk in Challenging Times: Evidence from the Coronavirus Crisis

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Abstract

In this paper, the S&P 500 stock returns during three key event periods in the coronavirus crisis are regressed on various explanatory variables. Focused on incorporating and operationalizing Supply Chain analysis into event studies, the paper aims to explain the returns using this novel approach together with traditional indicators such as liquidity, leverage, and industry effects. Results are split in market and book leverage, across raw returns, and Capital Asset Pricing Model adjusted Abnormal Returns. Using supply chain analysis, four different variables indicating international supply chain dependence are operationalized and regressed for each period. The results, 60 regressions in total, show that although financial leverage does not play a significant role, there is evidence that supply chain analysis can play a part in explaining increased risk in crises. Therefore, given the increasing ease at which supply chain data is available, supply chain analysis can play an innovative role in cross-sectional event studies. Furthermore, I find that liquidity ratios (quick ratio) and industry effects, seem to significantly impact returns during the coronavirus crisis. The main examples of this are Health Care performing well, and Real Estate among the worst during all three periods.

1 Introduction

The sudden outbreak of a new virus took most of humanity by surprise. Stock market returns were remarkably high in 2019, and early 2020 was characterized by substantial optimism after the announcement of a 'phase one' trade deal between the US and China. Expectations were quickly shattered however, as a looming 'lockdown' of the economy would greatly impact the operational stability of companies. With many firms unable to survive prolonged closure and uncertainty surrounding government aid, the expectations of the market quickly became uncertain, ultimately leading to the worst day in trading history since the 1987 crash. This paper aims to assess the effect of various events related to the outbreak of the coronavirus (Covid-19) on the S&P 500 composite index and how return differences in the cross-section can be explained by company-specific variables. The event periods considered are based on important events tied to market expectations (especially early on) and government policies.

This paper will also attempt to integrate supply chain analysis for each company to determine its dependence on China, which was commonly seen as a 'weakness' during the early days of the crisis. In fact, there is evidence that supply chain glitches (delays) can greatly deteriorate shareholder value (Hendricks & Singhal, 2003). Given the magnitude of this effect (about 10% negative abnormal return), the expectation of it happening to US companies on a large scale could well mean that a substantial portion of negative returns is due to this expectation. Of course, traditional financial ratios and accounting variables are included as controls, with a particular role for leverage.

The aim is to provide an answer to the question, "how can supply chain dependence, leverage ratios, cash holdings, and industry-effects explain cross-sectional return differences during the recent coronavirus crisis?"

This will be done in various parts focusing on the following issues:

1. Does supply chain dependence on foreign parties, and China in particular, lead to significantly more negative returns?
2. Do companies with a better liquidity position (in particular cash reserves) show significantly less negative returns due to lower risk of bankruptcy?
3. Does a company with less leverage (market and/or book), and therefore less equity risk, show significantly less negative returns?

4. What industries are hit hardest by the crisis, and which ones are affected the least?

Providing answers to these questions and subsequently the main research question can have a large impact on government policy, as instead of relying on 'real signals' from the ground, it can determine which (public) companies need help based on proper statistical analysis based on international supply chains and industry classifications. There is a possibility that this can be done ahead of time, before measures are put into place, allowing policymakers to 'dampen' equity market responses by putting stimuli in place for companies hardest hit by the measures. Furthermore, supply chain analysis is a relatively new part of event studies, which has seen the widespread use of custom or proprietary datasets. This paper will use a readily available supply chain dataset, however, meaning that it can more easily be replicated and that, if an effect is found, that means supply chain analysis can be more widely used in future academic research related to event studies.

2 Literature

As this paper is by and large an event study augmented with supply chain analysis, current literature regarding the topic is both vast (event studies) and very limited at the same time. When ignoring the novel variables, this problem is mostly similar to that of the 2016 Presidential Elections (Wagner, Zeckhauser, & Ziegler, 2018). Unlike the elections, however, this is an event that seemed to be set in stone from before the event periods. As investors came to realize that the US would follow Europe and China, the effect of the epidemic could have also been known by and large. Therefore, there was no "new" information per se, other than when policy measures would be implemented. Similar research into the Space Shuttle Challenger crash of 1986, can examine the efficiency of markets because information regarding the probability of such a disaster was largely private (Maloney & Mulherin, 2003). In this case, the information will be a mix of already public information that is slow to be digested by the market, and private information held by companies in the form of survivability prospects. The lack of clear-cut information disclosure can pose a threat to the significance of the statistics.

On the topic of survivability prospects, Chen showed that market leverage is a good predictor of survivability in banks during the Japanese Great Recession in the 1990s (2013). He showed that in those cases, market leverage is superior to book leverage, mainly because book leverage reflects the historical cost rather than the current value of the firm. It might, therefore, result in a distorted leverage ratio that does not reflect the truth (Berk & DeMarzo, 2014). Market and book leverage are defined as the inverse of the ones used by Fama and French (1992), as suggested by Chen (2013). This means that book leverage concerns the book value of equity (shareholder capital) over the total assets, and that market leverage is defined as the market value of equity ($\textit{share price} * \textit{shares outstanding}$) over total assets. An important note here is that 'less' leverage in this case, means a higher number.

Financial ratios have been shown to be a relatively good predictor of bankruptcy, providing a good basis as a proxy for equity risk (Ohlson, 1980). It must be noted, however, that Ohlson found that other variables should be considered to improve upon the ratios. In this case, those are leverage, supply chain dependence, and an industry effect.

Wagner, Zeckhauser & Ziegler use raw returns for each of their event periods, as well as Capital Asset Pricing Model (CAPM) and Fama French adjusted abnormal returns. In most cases, the significance of the effect does not differ between the three returns (Wagner, Zeckhauser, & Ziegler, 2018). Given the small differences between CAPM and Fama French, this paper will use raw returns and CAPM adjusted abnormal returns.

Much like their research, this paper will define event periods and calculate their returns, after which Ordinary Least Squares is used to determine the cross-sectional effect of multiple explanatory variables. Another notable inclusion from this paper is the logarithm of the market value of equity, which will also be included here to compensate for company size.

There are no published papers that incorporate supply chain analysis into event studies. This means that there is no precedent to follow, and variables considering the supply chain will be largely based on intuition. Luckily there are some recent papers covering the subject of operationalizing the supply chain variables. These will be discussed in the Data & Methods section.

Next, I will develop the hypotheses to the sub-questions. After this, the process of determining the event dates is described, followed by a look at the data and the methodology, leading to the eventual results.

3 Hypotheses

Earlier, I identified four sub-questions. Understanding these questions and developing their hypotheses based on the literature discussed earlier is an important step towards answering them. This will be done one-by-one, starting with the question, the reason the sub-question was chosen, and then the theoretical basis for the hypothesis to that question.

3.1 Supply Chain Dependence

The first sub-question is "*Does supply chain dependence on foreign parties, and China in particular, lead to significantly more negative returns?*". At the end of February and early March, reports surfaced that many US firms would soon face supply chain problems (Brown R. , 2020). Given that, as explained earlier, supply chain disruptions can greatly impact company performance, the uncertainty would lead to a significant decrease in the share price (up to 10%) (Hendricks & Singhal, 2003). Looking at the large problems that a pandemic could create for globally integrated supply chains, a significant negative return for companies that are more likely to experience such a setback would seem the logical outcome. Therefore, the supply chain dependence is an essential part of quantifying the entire effect and is thus included in the regression. Given the above, the hypothesis will be that:

(H1) *Companies more dependent on China or other foreign countries have, on average, a more negative abnormal return.*

3.2 Liquidity

The second sub-question is related to liquidity indicators. "*Do companies with liquidity (in particular cash reserves) show significantly less negative returns due to lower risk of bankruptcy?*". When companies have to close their doors to prevent the spread of a virus (in a sense a negative externality), they can quickly become illiquid as revenues dry up but salaries, rent, and other liabilities still have to be paid. When this happens, bankruptcy looms. Given that during liquidation of a company, shareholders come after debtholders, bankruptcy is especially dangerous to the interest of shareholders (Berk & DeMarzo, 2014). This means that when illiquidity is expected, shareholders will try to sell their shares, driving prices down. This is a documented and substantial effect and should, therefore, be included in the analysis. Given this substantial effect, these indicator(s) are included in the regression. The hypothesis naturally follows from the above in that:

(H2) *Companies that have a worse liquidity position show more negative abnormal returns, due to increased risk of bankruptcy.*

3.3 Leverage

As we saw in the previous hypothesis ("liquidity"), bankruptcy risk can lead to negative abnormal returns. However, liquidity is not the only indicator of the equity risks tied to bankruptcy. Take the quick ratio, for example:[1]

$$QR = \frac{CE+MS+AR}{CL} \tag{1}$$

Liquidity refers to the numerator of the fraction, more liquidity results in a higher (better) quick ratio. However, when we look at the denominator instead (current liabilities), higher liabilities result in a lower (worse) quick ratio. What constitutes these liabilities? On the one hand, there are day to day payables, e.g. salaries, suppliers, etc. On the other hand, interest payable also falls under current liabilities. This means that a more heavily debt-financed ("leveraged") company inherently has more current liabilities than its unleveraged counterpart.

The above was just an illustration of how bankruptcy between leverage and liquidity is related. However, the more

[1] *QR:* Quick Ratio *CE:* Cash & Cash Equivalents *MS:* Marketable Securities *AR:* Account Receivable *CL:* Current Liabilities

appropriate indicator of leverage is a *solvency* rather than a *liquidity* indicator, i.e. the *leverage ratio*:

$$Leverage\ Ratio = \frac{Debt}{Equity} \tag{2}$$

As outlined in the literature section, book and market leverage are calculated in a different way. As outlined before, market leverage will be used for the main statistical results. The fact that leverage is also an indicator of shareholder risk leads us to the third sub-question: "*Does a company with less leverage (market or book), and therefore less equity risk, show significantly less negative returns?*"

Given that liquidity ratios (i.e. the quick ratio) do not necessarily capture the solvency of a company, the addition of a leverage ratio is necessary to reflect this fully in the regression.

Everything considered, the hypothesis to this question resembles that of *liquidity*:

(H3) *Companies with less leverage show less negative abnormal returns.*

3.4 Industries

Finally, different industries could well have different effects.

As an example, USA Today reports that the food industry actually benefits from a positive supply shock because of the pandemic. Demand greatly increased as a consequence of hoarding behavior (Snider, 2020). Whereas clearly, some are hit very hard, such as airlines due to widespread travel restrictions.

This hypothesized effect results in the following sub-question:

"*What industries are hit hardest by the crisis, and which ones are affected the least?*"

Clearly, these effects can be substantial, as companies can show positive returns in some industries, while others are substantially negative. This leads to the following hypothesis:

(H4) *There are large significant differences in abnormal returns between industries, and clear worst and best-performing industries can be identified.*

4 Event dates, Data & Methods

4.1 Event Dates

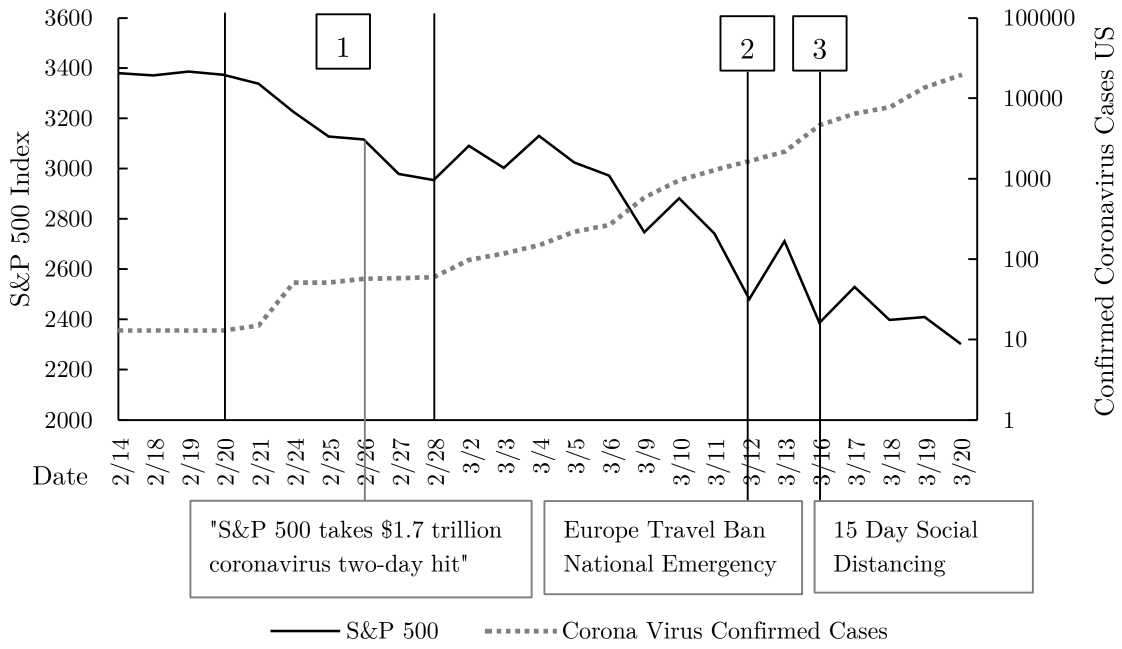

Figure 1: Events surrounding coronavirus and the S&P 500 index

Initially, three interesting events were identified; these periods are identified in Figure 1, along with their main news 'headlines.' These will be referred to as Period 1, Period 2, Period 3. All periods were identified based on research into key events, usually based on newspaper headlines or official government publications, along with tracking the biggest dips in the market as a starting point for the search. For Period 1 it is interesting to look at the development of confirmed cases in the US. While we see little to no increase in the confirmed number of cases in the US in Period 1 (in fact only 3 new cases), the fear for a situation similar to that of China and Europe is mentioned as the main motivation behind the very negative returns in Period 1 (O'Halloran, 2020). This is reasoning is followed by multiple sources, and throughout the period (Times, 2020). Making a slow realization by the market seem the most likely scenario. This period is especially interesting because of the low tangible domestic impact on the US so far.

On March 11, The White House decided to suspend all air travel from and to European countries (excluding the UK), in an attempt to fight the coronavirus (Frost, 2020). This was done after trading, and its results would show on Marth 12th. Furthermore, there was an anticipation of a National Emergency on March 12, and it was announced the day after (BBC, 2020). Both these news items seem to have led to a negative return on March 12, making it a good candidate for Period 2.

Finally, Period 3 is closely tied to what many had feared during Period 1. On March 16, the White House announced 15 days of social distancing, forcing large parts of the economy to shut down. This led to significantly negative returns on March 16, some even referring to the day as 'another black Monday' (Valetkevitch, 2020).

The three periods above can be described as follows: Period 1 is about fear and adjustment of expectations, but no tangible impact on the economy. Period 2 is the continuing of expectation adjustments because of government measures (national emergency and Europe travel ban). Period 3 is the start of social distancing amidst the high growth of confirmed cases, resulting in material economic impact.

The dates belonging to the periods are as follows:

- Period 1: February 21 to February 28
- Period 2: March 12 (closing 11 to closing 12)
- Period 3: March 16 (closing *13* [Fri] to closing 16)

Raw returns are calculated by taking the closing prices of the above periods and calculating the percentual return between them. This means that for Period 1 there is a 7-day return period because the event is not clear cut, and for the other two periods, there is an event window from 0 to +1. For CAPM abnormal returns, more intricate estimation is used, which will be explained in the methods section.

4.2 Data

The paper is based on S&P 500 companies. First, the index constituents were retrieved from Compustat through Wharton Research Data Services (WRDS), after which daily stock price data on all companies were acquired from the same source. This also included Global Industry Classification Standard codes (GICS codes), which can be used to determine the return differences by industry. Financial fundamental variables and financial ratios were retrieved for each of the companies for the last available quarter before the first event (February 20, 2020) from the same source. Supply chain data was retrieved from Factset, the only readily available source of granular (company level) supply chain data. Excel sheets, as provided by Factset, were retrieved using an automated script, given the large number of companies[2]. Given the relative unusualness of this dataset in the world of event studies, it is further explained in Section 4.2.2 below.

The resulting datasets were incompatible, as they used different indexes. Therefore, a conversion was necessary to match the right data to the right company. For some companies, there was no data available on the supply chain; upon further inspection, these were determined to be real estate companies, and therefore given "zero" Chinese/Foreign suppliers (instead of leaving them out). Merging the data was done programmatically with a custom-built Python script[3] that made it significantly easier to match the indices of the different datasets, and greatly improved the speed at which the many supply chain Excel sheets could be processed.

4.2.1 GICS

The GICS codes that were retrieved from WRDS came in various granularity levels. For example, the code *451020* (IT Services) belongs to *Sector* 45 (IT) of which *Industry Group* 10 (Software and Services) within which *Industry* 20 stands for IT Services. This multilayered approach to codes means that different granularities can be used. Given the relatively small amount of observations (companies), there is too little variety within the two most granular levels (Industry Group &

[2] Made available here: https://link.tkon.nl/oathesis as "gather.js"
[3] See (2), the Python script is referred to as "dataset.py"

Industry) to allow for proper differentiation between the Industry effect and other effects. E.g., it could be that only one company belongs to the 451020 Industry, which could lead to part of the effect being wrongly attributed to that specific industry, rather than other characteristics of that company. Given that the focus of the research is on the supply chain effect, the uppermost granularity was chosen, i.e. the *Sector*.

Other industry codes do exist and often employ a similar layered system; examples of these are the *North American Industry Classification System* (NAICS) or the *Statistical Classification of Economic Activities in the European Community* (NACE). These were considered but showed little to no benefit over GICS, as NACE codes are not applicable to all US companies, and NAICS is mostly based on *establishments* rather than entire businesses.

Non-layered codes are, for example, the *Standard Industrial Classification* (SIC) and the *International Standard Industrial Classification of All Economic Activities* (ISIC). These are ruled out by default as they are convoluted to work with (due to letter-based codes, or many top-level codes).

4.2.2 Deep dive into the origins of the data

As mentioned before, FactSet is one of the key sources in this paper. Given that granular supply chain data on the stock-level is unconventional and innovative, it warrants a deep dive into its origins and meaning.

Normally, for macroeconomic purposes, industry level supply dependencies are sufficient. These are more widely available. However, when it comes to the granular level of individual stocks, necessary for an event study, only FactSet and Bloomberg offer this data. Due to the impact of the measures put in place by the Dutch government and the university to contain the spread of the coronavirus, I was unable to access a Bloomberg terminal on campus. This resulted in FactSet being the only viable option. The dataset used is called “FactSet Supply Chain Relationships” and is published by “Data Feed by FactSet.” They have released this feed in its current form in 2014 and have been updating it since. The North American data has been published since 2003, after which more regions were added (most relevant is Asia in 2013). It includes data on

10,400 North American ‘entities’ and 12,400 Asian ones. Both numbers are important because of how FactSet gathers this data, which they describe as follows:

“FactSet Revere Supply Chain Relationships data is built to expose business relationship interconnections among companies globally. This feed provides access to the complex networks of companies' key customers, suppliers, competitors, and strategic partners, collected from annual filings, investor presentations, and press releases.” (FactSet, 2020)

This means that the complex network includes reverse relationships, e.g. company A does not disclose its relationship with company B, but B does disclose its relationship with A. FactSet then takes the disclosure of B’s relationship with A and infers that the two are related. This means that many undisclosed suppliers (or customers/partners) are included in the dataset (for company A in the example). This is especially helpful if we consider that for big companies (such as those in the S&P 500) a sizable number of suppliers is identified from these ‘reverse’ relationships. This process is shown in Figure 2 below.

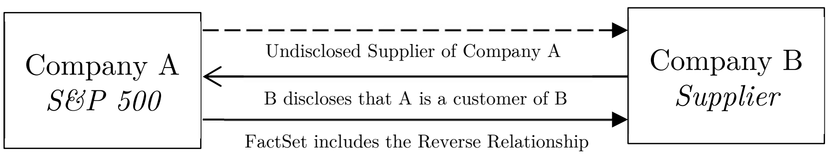

Figure 2: Illustration of FactSet Reverse Relationships

Furthermore, FactSet assigns each relationship that a company has a “Rel Rank” (Relationship Rank), signifying the relative importance of each relationship. The algorithm used to do this is unknown to me at the time of writing, since it is only disclosed to business customers of FactSet. However, it is likely based on a version of a “network importance” algorithm, such as Google’s PageRank (Wu, 2015). There are examples of papers that utilize this Relationship Rank and, although not transparent, its use should be comprehensive and risk-free. This means that, when the Rank is combined with the country of the supplier, it is possible to construct weighted country-dependence variables, which will be created in the Methods section.

Having acquired the relevant datasets, returns were then generated for each of the event periods. For now, these are raw returns. Abnormal returns could be considered for Period 1, given its duration. These were then merged with basic company info, such as Ticker and GICS codes, and financial fundamentals & ratios. The complete list of available variables is given in Appendix A.1.

4.3 Methods

Operationalization of the supply chain dependence is the biggest problem faced when handling this particular dataset. Ideally, there is data in the form of a network, with each of the nodes as a company and the edges indicating the dependence of one company on the other. However, in this case, there is no such data. Each of the companies has one Excel sheet that lists its relationships, which can be thought of as an abstraction of the network itself. These relationships can be characterized as a Supplier, Customer, or Partner. These are non-exclusive, a single company can be more than one. Each relationship item has a rank, company name, and country. These variables are consistent and present for most of the relationships. For public companies, there is a 3 Month Price Correlation variable, market capitalization (market cap), and for a very limited amount of companies, there is a 'relationship value.' Given the lack of availability of the correlation, market cap, and 'relationship value' variables, these will not be used.

While writing this thesis, FactSet published an article detailing methods to quantify country exposures in light of the coronavirus pandemic (Bushnell, 2020). Their method of quantifying the Relationship Ranks closely resembles my initial intuition. However, the focus of the article is mostly on customer relationships, whereas I am more interested in the supply chain.

The main takeaway from the article that will be used here is the relative importance formula used, where for each company *i*, we define the following for one of its relationships *j*:

- $Rels_i$: number of relationships that company *i* has
- $Rank_j$: the relationship rank as determined by FactSet
- $IsChina_j$: 1 if the company of the relationship is in China
- $IsForeign_j$: 1 if the company of the relationship is outside the US
- $IsSupplier_j$: 1 if relationship company *j* is a supplier

Furthermore, $Weight_j$ is defined as the inverse rank (i.e. an importance weight). For example, the relationship with Rank 1, is given the value of the lowest (numerically highest) rank to reflect its importance rather than position. I.e.:

$$Weight_j = (Rels_i + 1) - Rank_j \tag{3}$$

This essentially means that a company more dependent on (for example) China will have a *higher* value for the RankChinaRel variable.

This results in the following formula for the Rank China Relationship variable (*rankchinarel*):

$$WeightChinaRel_i = \frac{\sum_{j=0}^{Rels_i}(Weigh\ _j * IsChina_j)}{\sum_{j=0}^{Rels_i}(Weight_j)} \tag{4}$$

Similarly, for the Rank Foreign Relationship variable (*rankforeignrel*) the formula is:

$$WeightForeignRel_i = \frac{\sum_{j=0}^{Rels_i}(Weight_j * IsForeign_j)}{\sum_{j=0}^{Rels_i}(Weight_j)} \tag{5}$$

In a sense, both formulas (4) and (5) measure the rank-weighted proportion of relationships that are Chinese or Foreign, respectively. Adding the $IsSupplier_j$ variable restricts this to suppliers only in the following way:

$$WeightChinaSup_i = \frac{\sum_{j=0}^{Rels_i}(Weigh\ _j * IsChina_j * IsSupplie\ _j)}{\sum_{j=0}^{Rels_i}(Weight_j * IsSupplier_j)} \tag{6}$$

$$WeightForeignSup_i = \frac{\sum_{j=0}^{Rels_i}(Weight_j * IsForeign_j * IsSupplier_j)}{\sum_{j=0}^{Rels_i}(Weight_j * IsSupplier_j)} \tag{7}$$

Lastly, a dummy variable indicating whether a company has any number of Chinese suppliers was created (*dchinasup*).

Now that all supply chain variables have been considered. We move on to the financial variables. As noted before, Wagner, Zeckhauser & Ziegler use the logarithm of the market value of equity (LMVE) to compensate for the size of the company. This is done here as well, using the following formula:

$$LMVE = \log\left(Stock\ Price\ First\ Period * Shares\ Oustanding\right) \tag{8}$$

Note that the Stock Price used here is defined as the opening price of the first day of the first period. This should, therefore, exclude any of the effects that are studied, but still be as close as possible to the event period. For future reference, MVE is the non-logarithmic version of LMVE.

As for the liquidity variable, there are multiple that can be considered. In Kennedy (1975) four common financial ratios are studies in a behavioral setting. The most commonly used liquidity ratio is the Quick Ratio, and although this research is old, it is still among the fundamental ratios looked at when assessing the liquidity of a company today. Given its widespread use, it is interesting to see how it performs as an indicator of firm performance in times of crisis. The Quick Ratio was supplied by Compustat and did not have to be calculated manually.

As an additional financial control variable, the gross profit margin is used to reflect financial performance. It was chosen because it is quite hard to manipulate and should, therefore, reflect the true state of a company well enough.

Then, leverage is operationalized. As noted, Chen (2013) shows that market leverage can be considered superior to book leverage when it comes to reflecting true leverage. Market Leverage (ML) is calculated in the following way:

$$ML = \frac{MVE}{Total\ Assets} \tag{9}$$

Similarly, Book Leverage (BL) is calculated based on the Compustat variable TEQQ, which is the Total Stockholders Equity. Both leverage ratios are used to run all regressions, but the main results section only includes those ran with ML.

4.3.1 CAPM Abnormal Returns

For the determination of CAPM abnormal returns, an estimation window of two months is used. Typically, a three-month period is used (Brown & Warner, 1985). However, given the US-China trade war in late 2019, a shorter period was chosen in which this was less of a driving force behind returns. Concretely this means that the betas for each of the companies are calculated from December 15 2019 to February 15 2020. Leaving a five-day margin between the end of the estimation period and the beginning of the events. The CAPM betas were calculated using Python's Scikit library and written to a STATA compatible CSV for each company.

Given that the first event is quite broad (not a clear-cut event) this period picks up a lot of noise. In event study terminology, it has a window of 0 to +7, which would be considered *very* broad for a clearly determined event. For Period 2 and Period 3 an event window of 0 to +1 is used, which falls into the normal range for the use of Cumulative Abnormal Returns (CAR).

Using the previously estimated CAPM betas, each stock's expected return is calculated based on the market performance during each day of each period. Taking the difference between this expected return and the actual return results in the Abnormal Returns (AR) that we are looking for. In formula format this becomes:

$$AR_{it} = R_{it} - E(R_{it}) \tag{10}$$

Where $E(R_{it})$ is determined as follows:

$$E(R_{it}) = r_f + \beta_i * (R_{Mt} - r_f) \tag{11}$$

In formulas (10) and (11) R_{it} is the raw return of stock i on a particular day t, R_{Mt} is the market return on that day, and r_f is the risk-free rate. For the risk-free rate, the daily FED 10 Year Treasury rate is used.

If the event spans multiple days (i.e. Period 1), CAR is used to aggregate the returns. This results in the final variables, allowing for the construction of descriptive statistics, as shown in Table 1 below.

Having operationalized all the variables necessary, the event study is then performed using Ordinary Least Squared regression. Each of the Periods' raw returns is regressed on financial ratios (quick ratio, LMVE, gross profit margin), GICS industry codes, the leverage ratio, and on one of the supply chain variables. This is then repeated for each of the supply chain variables, isolating their effects. The above is repeated for CAPM adjusted abnormal returns.

Table 1: Descriptive Statistics

Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Period 1	489	-0.129	0.044	-0.332	0.114
Period 2	489	-0.105	0.045	-0.358	0.008
Period 3	489	-0.127	0.062	-0.336	0.113
GPM (Gross Profit Margin)	489	0.464	0.226	0.028	1.000
Quick Ratio	422	1.237	1.008	0.092	7.493
ML (Market Leverage)	489	2.194	5.575	0.036	114.568
BL (Book Leverage)	489	0.378	0.664	-1.532	13.038
LMVE	489	24.089	1.033	21.860	27.983
WeightChinaRel	489	0.017	0.040	0.000	0.400
WeightChineSup	489	0.018	0.053	0.000	0.500
WeightForeignRel	489	0.310	0.208	0.000	0.905
WeightForeignSup	489	0.314	0.228	0.000	1.000
Dummy China Supplier	489	0.364	0.482	0.000	1.000
GICS Sector Code					
10 (Energy)	489	0.055	0.229	0.000	1.000
15 (Materials)	489	0.055	0.229	0.000	1.000
20 (Industrials)	489	0.143	0.351	0.000	1.000
25 (Consumer)	489	0.127	0.333	0.000	1.000
30 (Food & Household)	489	0.067	0.251	0.000	1.000
35 (Health Care)	489	0.121	0.326	0.000	1.000
40 (Financials)	489	0.133	0.340	0.000	1.000
45 (IT)	489	0.143	0.351	0.000	1.000
50 (Communication)	489	0.039	0.193	0.000	1.000
55 (Utilities)	489	0.057	0.233	0.000	1.000
60 (Real Estate)	489	0.059	0.236	0.000	1.000

5 Results

The regressions for raw returns, as shown below in Table 2 were repeated for Book Leverage (BL) as well; these are included in Appendix A.2.

Table 3 below shows the results for the CAPM Abnormal Returns for Market Leverage (ML); their BL counterpart can be found in Appendix A.2.

Having run the regressions, it is now time to reflect on the hypotheses and determine whether the results support them.

5.1 Hypothesis 1: Supply Chain Dependence

(H1) *Companies more dependent on China or other 'foreign' countries, have, on average, a more negative abnormal return.*

Under raw returns (Table 2) we observe significant negative coefficients in both Period 1 and Period 2 for the foreign relationship variable. Ceteris paribus, a company with 10%-point more foreign relationships, has, on average, a 0.261%-point more negative return in Period 1 and 0.225%-point more negative return in Period 2. For CAPM AR (Table 3) this becomes insignificant for the first two periods and significant for Period 3. And instead, Chinese Relationships are tied to a significantly positive return in all three periods.

There seems to be evidence to support the hypothesis that foreign relationships are tied to more negative returns during the coronavirus crisis. The economic rationale to support a causal relationship would be the increased chance of supply chain disruption that comes with reliance on a more complex global network, rather than a more domestic-focused one. However, given the CAPM AR evidence of a significantly positive coefficient, such a causal relationship should still be considered unsupported. Important and interesting to note, however, is that Relationships with suppliers only (i.e. WeightForeignSup) are not significant on their own. There seems to be an important contribution of the foreign Customers and Partners of a company.

5.2 Hypothesis 2: Liquidity

(H2) *Companies that have a worse liquidity position, as indicated by the quick ratio, show more negative abnormal returns, due to increased risk of bankruptcy.*

Evidence from the raw returns regressions (Table 2) suggests that there is no significant effect of the Quick Ratio on returns in any of the three periods. However, when looking at the CAPM AR (Table 3) the Quick Ratio does become significantly positive even at the 1% confidence level. This suggests that an increase in the Quick Ratio (better) corresponds to an average 1.28%-point higher return during the three periods considered. It supports the economic rationale that liquidity is a strong indicator of bankruptcy risk (a reason for negative returns).

5.3 Hypothesis 3: Leverage

(H3) *Companies with less leverage show less negative abnormal returns.*

First, it has to be noted once again that this paper uses the inverse leverage (relative to Fama French). This means that it concerns Equity over Total Assets. A 'higher' leverage, as referred to in the hypothesis, would be the inverse of this. Therefore, we expect that more equity relative to total assets leads to less negative returns, i.e. a positive coefficient. For the market leverage (ML) results shown in Table 2 there does not seem to be a sizable effect large enough to support this hypothesis. All ML coefficients, in all periods, and for all supply chain variables, are insignificantly different from zero. When looking at the book leverage (BL) regressions in Appendix A.2 this finding does not change. However, when looking at the CAPM AR regressions (Table 3) significant negative coefficients are observed in Period 1; this could be because of an anomaly relating to CARs over longer periods of time (more than a few days) (Brown & Warner, 1985). It seems very unlikely, based on an economic explanation, that more debt would lead to higher returns. Essentially, leverage cannot be shown to be of significance for returns during the coronavirus crisis.

Table 2: Regression Results per Period and per Supply Chain Rank Variable (Market Leverage)

	Period 1				**Period 2**				**Period 3**			
	China Rel	*China Sup*	*Frgn Rel*	*Frgn Sup*	*China Rel*	*China Sup*	*Frgn Rel*	*Frgn Sup*	*China Rel*	*China Sup*	*Frgn Rel*	*Frgn Sup*
Market Leverage	-0.0002	-0.0003	-0.0002	-0.0002	0.0004	0.0003	0.0004	0.0003	0.0006	0.0005	0.0005	0.0005
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
LMVE	0.0044 **	0.0044 **	0.0049 **	0.0045 **	0.003	0.0032	0.0035	0.0032	-0.0026	-0.0025	-0.0026	-0.0027
	(0.002)	(0.0021)	(0.002)	(0.0021)	(0.0021)	(0.0022)	(0.0021)	(0.0022)	(0.0027)	(0.0028)	(0.0027)	(0.0028)
Gross Profit Margin	0.0299 ***	0.0294 ***	0.0326 ***	0.0296 ***	0.0265 **	0.0255 **	0.0288 **	0.0258 **	0.0336 **	0.0332 **	0.0331 **	0.0324 **
	(0.0107)	(0.0109)	(0.0107)	(0.0109)	(0.0112)	(0.0114)	(0.0112)	(0.0114)	(0.0143)	(0.0146)	(0.0144)	(0.0146)
Quick Ratio	0.0008	0.0023	0.0021	0.0024	0	0.001	0.0011	0.0012	-0.0011	0.0003	-0.0001	-0.0002
	(0.0024)	(0.0024)	(0.0023)	(0.0024)	(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0032)	(0.0032)	(0.0031)	(0.0032)
WeightChinaRel	0.0624	-	-	-	0.0536	-	-	-	0.0999	-	-	-
	(0.0569)	-	-	-	(0.0596)	-	-	-	(0.076)	-	-	-
WeightChinaSup	-	-0.0274	-	-	-	0.0173	-	-	-	0.0102	-	-
	-	(0.0442)	-	-	-	(0.0462)	-	-	-	(0.0592)	-	-
WeightForeignRel	-	-	-0.0261 **	-	-	-	-0.0225 **	-	-	-	0.0077	-
	-	-	(0.0109)	-	-	-	(0.0115)	-	-	-	(0.0147)	-
WeightForeignSup	-	-	-	-0.0063	-	-	-	-0.0041	-	-	-	0.0145
	-	-	-	(0.0095)	-	-	-	(0.01)	-	-	-	(0.0128)
10 (Energy)	0 ***	0 ***	0 ***	0 ***	0 ***	0 ***	0 ***	0 ***	0 ***	0 ***	0 ***	0 ***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
15 (Materials)	0.052 ***	0.0526 ***	0.0572 ***	0.0535 ***	0.0318 ***	0.032 ***	0.0362 ***	0.0328 ***	0.0239	0.0244	0.0232	0.0221
	(0.0112)	(0.0113)	(0.0113)	(0.0114)	(0.0117)	(0.0118)	(0.0119)	(0.0119)	(0.015)	(0.0151)	(0.0152)	(0.0153)
20 (Industrials)	0.0479 ***	0.0491 ***	0.0497 ***	0.0491 ***	0.0265 ***	0.0263 ***	0.028 ***	0.0273 ***	0.0408 ***	0.0419 ***	0.0418 ***	0.0403 ***
	(0.0093)	(0.0095)	(0.0093)	(0.0095)	(0.0098)	(0.01)	(0.0097)	(0.0099)	(0.0125)	(0.0128)	(0.0125)	(0.0127)
25 (Consumer)	0.0382 ***	0.0392 ***	0.0416 ***	0.04 ***	0.0062	0.0067	0.0091	0.0075	-0.0041	-0.0031	-0.0039	-0.0054
	(0.0096)	(0.0096)	(0.0096)	(0.0097)	(0.01)	(0.0101)	(0.01)	(0.0102)	(0.0128)	(0.0129)	(0.0128)	(0.013)
30 (Food & Household)	0.0694 ***	0.0702 ***	0.072 ***	0.0708 ***	0.0352 ***	0.0356 ***	0.0374 ***	0.0361 ***	0.0855 ***	0.0862 ***	0.0855 ***	0.0847 ***
	(0.0107)	(0.0108)	(0.0106)	(0.0108)	(0.0112)	(0.0112)	(0.0112)	(0.0113)	(0.0142)	(0.0144)	(0.0143)	(0.0145)
35 (Health Care)	0.0608 ***	0.0606 ***	0.061 ***	0.0612 ***	0.0457 ***	0.0459 ***	0.0459 ***	0.046 ***	0.0435 ***	0.0436 ***	0.0436 ***	0.0426 ***
	(0.0097)	(0.0098)	(0.0097)	(0.0098)	(0.0102)	(0.0103)	(0.0101)	(0.0103)	(0.013)	(0.0131)	(0.013)	(0.0132)
40 (Financials)	0.0658 ***	0.063 ***	0.069 ***	0.0646 ***	0.0308 **	0.0248 *	0.0336 **	0.0253 *	0.0157	0.0154	0.0131	0.0125
	(0.0138)	(0.0143)	(0.0138)	(0.0144)	(0.0145)	(0.0149)	(0.0145)	(0.015)	(0.0184)	(0.0191)	(0.0186)	(0.0192)
45 (IT)	0.0386 ***	0.0388 ***	0.0405 ***	0.0391 ***	0.0227 **	0.0231 **	0.0243 **	0.0232 **	0.009	0.0095	0.0091	0.0088
	(0.0097)	(0.0098)	(0.0096)	(0.0098)	(0.0101)	(0.0102)	(0.0101)	(0.0102)	(0.0129)	(0.0131)	(0.013)	(0.0131)
50 (Communication)	0.0554 ***	0.0547 ***	0.0554 ***	0.0552 ***	0.0278 **	0.0275 **	0.0277 **	0.0276 **	0.0449 ***	0.0444 ***	0.0444 ***	0.0435 ***
	(0.0124)	(0.0125)	(0.0123)	(0.0125)	(0.013)	(0.0131)	(0.0129)	(0.0131)	(0.0165)	(0.0167)	(0.0166)	(0.0167)
55 (Utilities)	0.0535 ***	0.0533 ***	0.0495 ***	0.0529 ***	0.0338 ***	0.0337 ***	0.0304 ***	0.0333 ***	0.0273 *	0.027 *	0.0279 *	0.0282 *
	(0.011)	(0.0111)	(0.0111)	(0.0112)	(0.0116)	(0.0116)	(0.0116)	(0.0117)	(0.0148)	(0.0149)	(0.0149)	(0.0149)
60 (Real Estate)	0.0552 ***	0.0562 ***	0.0506 ***	0.0567 ***	0.0325 ***	0.0295 **	0.0285 **	0.0293 **	-0.0334 **	-0.0288 *	-0.0333 **	-0.0292 *
	(0.0112)	(0.0123)	(0.0112)	(0.0123)	(0.0117)	(0.0129)	(0.0118)	(0.0129)	(0.015)	(0.0165)	(0.0151)	(0.0165)
Constant	-0.2936 ***	-0.2945 ***	-0.3012 ***	-0.2951 ***	-0.2158 ***	-0.2195 ***	-0.2223 ***	-0.2202 ***	-0.1014	-0.104	-0.1023	-0.1021
	(0.0492)	(0.0497)	(0.049)	(0.0497)	(0.0516)	(0.052)	(0.0514)	(0.052)	(0.0657)	(0.0666)	(0.0659)	(0.0665)

*: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$

Table 3: Regression Results for CAPM Abnormal Returns per Period and per Supply Chain Rank Variable (Market Leverage)

	Period 1				**Period 2**				**Period 3**			
	China Rel	*China Sup*	*Frgn Rel*	*Frgn Sup*	*China Rel*	*China Sup*	*Frgn Rel*	*Frgn Sup*	*China Rel*	*China Sup*	*Frgn Rel*	*Frgn Sup*
Market Leverage	-0.0009 *	-0.0011 **	-0.001 *	-0.0011 **	-0.0002	-0.0003	-0.0003	-0.0003	-0.0001	-0.0003	-0.0003	-0.0003
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0007)	(0.0007)	(0.0006)	(0.0007)
LMVE	0.002	0.0022	0.0019	0.0021	0.0012	0.0015	0.0012	0.0014	-0.0048	-0.0046	-0.0055	-0.0049
	(0.003)	(0.003)	(0.003)	(0.003)	(0.0028)	(0.0028)	(0.0028)	(0.0028)	(0.0036)	(0.0037)	(0.0037)	(0.0037)
	0	0	0	0	0	0	0	0	0	0	0	0
Gross Profit Margin	-0.0023	-0.0055	-0.004	-0.0059	0.0019	-0.0011	0.0009	-0.0013	0.0026	-0.0004	-0.0021	-0.0017
	(0.0157)	(0.016)	(0.0159)	(0.0161)	(0.0146)	(0.0148)	(0.0147)	(0.0148)	(0.0191)	(0.0196)	(0.0192)	(0.0195)
Quick Ratio	0.0127 ***	0.0165 ***	0.0151 ***	0.0162 ***	0.0091 ***	0.0118 ***	0.011 ***	0.0117 ***	0.0104 **	0.014 ***	0.0124 ***	0.0131 ***
	(0.0036)	(0.0035)	(0.0035)	(0.0036)	(0.0033)	(0.0033)	(0.0032)	(0.0033)	(0.0043)	(0.0043)	(0.0042)	(0.0043)
WeightChinaRel	0.2408 ***	-	-	-	0.1898 **	-	-	-	0.2716 ***	-	-	-
	(0.0835)	-	-	-	(0.0773)	-	-	-	(0.1016)	-	-	-
WeightChinaSup	-	0.044	-	-	-	0.0719	-	-	-	0.0789	-	-
	-	(0.0649)	-	-	-	(0.0599)	-	-	-	(0.0791)	-	-
WeightForeignRel	-	-	0.0225	-	-	-	0.0146	-	-	-	0.0546 ***	-
	-	-	(0.0162)	-	-	-	(0.015)	-	-	-	(0.0196)	-
WeightForeignSup	-	-	-	0.0112	-	-	-	0.0093	-	-	-	0.0314 *
	-	-	-	(0.014)	-	-	-	(0.0129)	-	-	-	(0.017)
10 (Energy)	0 ***	0 ***	0 ***	0 ***	0 ***	0 ***	0 ***	0 ***	0 ***	0 ***	0 ***	0 ***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
15 (Materials)	0.0573 ***	0.0584 ***	0.0549 ***	0.0569 ***	0.0358 **	0.0365 **	0.0345 **	0.0354 **	0.0289	0.0301	0.021	0.0253
	(0.0164)	(0.0166)	(0.0168)	(0.0167)	(0.0152)	(0.0153)	(0.0155)	(0.0155)	(0.02)	(0.0202)	(0.0203)	(0.0204)
20 (Industrials)	0.0391 ***	0.0423 ***	0.0415 ***	0.0422 ***	0.0197	0.0211	0.0217 *	0.0221 *	0.0323 *	0.0354 **	0.0339 **	0.0338 **
	(0.0137)	(0.014)	(0.0138)	(0.0139)	(0.0127)	(0.0129)	(0.0127)	(0.0129)	(0.0167)	(0.017)	(0.0166)	(0.017)
25 (Consumer)	0.0317 **	0.0341 **	0.0317 **	0.0326 **	0.0012	0.0029	0.0016	0.0018	-0.0103	-0.0079	-0.0134	-0.0125
	(0.014)	(0.0141)	(0.0142)	(0.0143)	(0.013)	(0.013)	(0.0131)	(0.0132)	(0.017)	(0.0172)	(0.0171)	(0.0174)
30 (Food & Household)	-0.0163	-0.0144	-0.0168	-0.0155	-0.0303 **	-0.0291 **	-0.0304 **	-0.0298 **	0.003	0.0047	0	0.0016
	(0.0156)	(0.0158)	(0.0158)	(0.0158)	(0.0145)	(0.0146)	(0.0146)	(0.0146)	(0.019)	(0.0192)	(0.0191)	(0.0193)
35 (Health Care)	0.0315 **	0.0321 **	0.0319 **	0.0312 **	0.0234 *	0.0241 *	0.0237 *	0.0231 *	0.0153	0.0162	0.0156	0.0137
	(0.0143)	(0.0144)	(0.0144)	(0.0144)	(0.0132)	(0.0133)	(0.0133)	(0.0133)	(0.0174)	(0.0176)	(0.0173)	(0.0175)
40 (Financials)	-0.0031	-0.016	-0.01	-0.0188	-0.0218	-0.0354 *	-0.0267	-0.0383 *	-0.0506 **	-0.0606 **	-0.063 **	-0.0678 ***
	(0.0203)	(0.021)	(0.0205)	(0.0211)	(0.0188)	(0.0193)	(0.019)	(0.0195)	(0.0246)	(0.0256)	(0.0248)	(0.0257)
45 (IT)	0.0577 ***	0.0593 ***	0.0578 ***	0.0586 ***	0.0373 ***	0.0388 ***	0.0375 ***	0.0381 ***	0.0273	0.0292 *	0.0258	0.0275
	(0.0142)	(0.0143)	(0.0143)	(0.0143)	(0.0131)	(0.0132)	(0.0132)	(0.0132)	(0.0173)	(0.0175)	(0.0173)	(0.0174)
50 (Communication)	0.024	0.023	0.0227	0.0221	0.0038	0.0032	0.0028	0.0023	0.0147	0.0138	0.0129	0.0116
	(0.0181)	(0.0183)	(0.0183)	(0.0183)	(0.0168)	(0.0169)	(0.0169)	(0.0169)	(0.0221)	(0.0223)	(0.0221)	(0.0223)
55 (Utilities)	-0.0744 ***	-0.0751 ***	-0.0725 ***	-0.0743 ***	-0.0639 ***	-0.0643 ***	-0.0628 ***	-0.0638 ***	-0.0958 ***	-0.0967 ***	-0.0896 ***	-0.0942 ***
	(0.0162)	(0.0163)	(0.0165)	(0.0164)	(0.015)	(0.0151)	(0.0152)	(0.0151)	(0.0197)	(0.0199)	(0.0199)	(0.0199)
60 (Real Estate)	-0.0412 **	-0.0344 *	-0.0405 **	-0.0351 *	-0.0411 ***	-0.0397 **	-0.0411 ***	-0.0408 **	-0.1262 ***	-0.1161 ***	-0.121 ***	-0.1176 ***
	(0.0164)	(0.0181)	(0.0167)	(0.018)	(0.0152)	(0.0167)	(0.0155)	(0.0167)	(0.02)	(0.022)	(0.0202)	(0.0219)
Constant	-0.092	-0.096	-0.0933	-0.095	-0.0615	-0.0676	-0.0633	-0.0671	0.093	0.0874	0.0981	0.0908
	(0.0722)	(0.0729)	(0.0728)	(0.0729)	(0.0668)	(0.0673)	(0.0673)	(0.0674)	(0.0878)	(0.0889)	(0.0878)	(0.0886)

*: p < 0.1 **: p < 0.05 ***: p < 0.01

5.4 Hypothesis 4: Industry Effect

(H4) *There are large significant differences in abnormal returns between industries and clear worst and best performing industries can be identified.*

First and foremost, in the regression, the base category chosen for the GICS Sectors is Energy. Any of the other coefficients for the categories are, therefore, relative to this 'baseline.'

For raw returns, there are indeed significant differences in returns between sectors (based on standard errors, one can look at whether the coefficients are significantly different from each other). For example, Health Care and Food seem to be performing significantly better than Consumer goods, perhaps because Consumer goods are often luxury goods or goods of which consumption can more easily be postponed (unlike Health Care and Food). This economic rationale seems to line up with articles published during the crisis (see 5.1 Event Dates). Looking at the CAPM AR regressions, a similar image can be seen with less significant abnormal returns across the board. Interesting here is that across all periods, utilities and real estate remain significantly negative, meaning that they are underperforming compared to their expectations.

In general, there seems to be strong support for the hypothesis that certain sectors can be identified that perform significantly better/worse than others.

6 Conclusion

In short, there are large discrepancies between raw returns and the CAPM AR. However, both seem to largely support the same side of the hypotheses. Looking back at the main question:

> "*How can supply chain dependence, leverage ratios, cash holdings, and industry-effects explain cross-sectional return differences during the recent coronavirus crisis?*"

Supply chain dependence has been shown to correlate significantly with returns in at least the first two periods, especially when looking at Foreign Relationships. It supports the idea that global supply chains are fragile and increase shareholder risk because of their complexity in times of crisis. Leverage ratios remained insignificant for the most part, and where they were significant, they did not show the appropriate sign to support an economic explanation. Cash holdings, in the form of the Quick Ratio, were shown to be significantly positive in all periods when looking at CAPM AR regressions. Industry effects were indeed significant across all regressions, with some showing more significance than others in especially the CAPM AR results. The key takeaway then becomes that there is indeed some explanatory value in the financial variables and – most noteworthy – in Supply Chain Dependence on Foreign Relationships. This means that, when viewed as a causal relationship, companies looking to sail steadily through a crisis should limit their global supply chain dependence (of suppliers, customers, *and* partners). Of course, this does not consider the great benefits that a global supply chain can bring outside of crises (i.e. higher profit margins due to lower production costs).

7 Limitations & Suggestions

The main limitation of this paper is the number of firms considered. Using a larger dataset can very well lead to more significant outcomes, as Supply Chain effects could well be very intricate, requiring more data to show their true potential. The initial results are there, but future research should strive to incorporate Supply Chain analysis into event studies, given these initial results. Furthermore, the difference between including consumers and partners and only including suppliers, means that it could be interesting to look at each of these effects as separate variables. Given enough data to be able to distinguish these effects from random, there could well be a more serious dependence on customers, for instance.

Using a buy-and-hold return rather than Cumulative Abnormal Returns for longer periods (Period 1) could also improve the results. As currently, the Chinese Relationship variable seems to be unexpectedly very positive.

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A Appendix

A.1 Variable List

Financial Ratios	
bm	Book/Market
pe_exi	P/E (Diluted, Excl. EI)
pe_inc	P/E (Diluted, Incl. EI)
npm	Net Profit Margin
gpm	Gross Profit Margin
roa	Return on Assets
roe	Return on Equity
roce	Return on Capital Employed
GProf	Gross Profit/Total Assets
equity_invcap	Common Equity/Invested Capital
debt_invcap	Long-term Debt/Invested Capital
totdebt_invcap	Total Debt/Invested Capital
capital_ratio	Capitalization Ratio
cash_ratio	Cash Ratio
quick_ratio	Quick Ratio (Acid Test)
curr_ratio	Current Ratio
divyield	Dividend Yield
Financial Fundamentals	
acoq	Current Assets - Other - Total
actq	Current Assets - Total
altoq	Other Long-term Assets
ancq	Non-Current Assets - Total
atq	Assets - Total
cheq	Cash and Short-Term Investments
chq	Cash
dlttq	Long-Term Debt - Total
lctq	Current Liabilities - Total
lltq	Long-Term Liabilities (Total)
ltq	Liabilities - Total
rectq	Receivables - Total
req	Retained Earnings
cik	CIK Number
Supply Chain Dependence	
Weighgtchinasup	Rank-weighted Chinese Suppliers
Weightchinarel	Rank-weighted Chinese Relationships
WeightForeignSup	Rank-weighted Foreign Suppliers
WeightForeignRel	Rank-weighted Foreign Relationships
Industry Classification	
gind	GICS Industry
gsector	GICS Sector
gsubind	GICS Sub-Industry
ggroup	GICS Industry Group
Leverage	
ML	Market leverage
BL	Book leverage

A.2 Regression Results Book Leverage

Raw Returns	Period 1				Period 2				Period 3			
	China Rel	*China Sup*	*Frgn Rel*	*Frgn Sup*	*China Rel*	*China Sup*	*Frgn Rel*	*Frgn Sup*	*China Rel*	*China Sup*	*Frgn Rel*	*Frgn Sup*
Book Leverage	-0.0024	-0.0028	-0.0026	-0.0027	-0.0007	-0.0009	-0.0009	-0.0009	0.0035	0.003	0.003	0.0029
	(0.003)	(0.003)	(0.003)	(0.003)	(0.0031)	(0.0032)	(0.0031)	(0.0032)	(0.004)	(0.004)	(0.004)	(0.004)
LMVE	0.0043 **	0.0043 **	0.0048 **	0.0043 **	0.0034	0.0035	0.0038 *	0.0035 *	-0.0022	-0.0021	-0.0023	-0.0023
	(0.002)	(0.002)	(0.002)	(0.002)	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0027)	(0.0027)	(0.0027)	(0.0027)
	0	0	0	0	0	0	0	0	0	0	0	0
Gross Profit Margin	0.0295 ***	0.0289 ***	0.0321 ***	0.0291 ***	0.0274 **	0.0263 **	0.0297 ***	0.0266 **	0.0349 **	0.0343 **	0.0343 **	0.0335 **
	(0.0107)	(0.0109)	(0.0107)	(0.0109)	(0.0112)	(0.0114)	(0.0112)	(0.0114)	(0.0143)	(0.0146)	(0.0144)	(0.0146)
Quick Ratio	0.0011	0.0025	0.0022	0.0026	0.0009	0.0017	0.0018	0.0019	-0.0009	0.0006	0.0001	0.0001
	(0.0024)	(0.0024)	(0.0023)	(0.0024)	(0.0026)	(0.0025)	(0.0025)	(0.0026)	(0.0033)	(0.0032)	(0.0032)	(0.0033)
WeightChinaRel	0.0607	-	-	-	0.0476	-	-	-	0.0985	-	-	-
	(0.057)	-	-	-	(0.0597)	-	-	-	(0.0761)	-	-	-
WeightChinaSup	-	-0.0281	-	-	-	0.0165	-	-	-	0.0104	-	-
	-	(0.0442)	-	-	-	(0.0463)	-	-	-	(0.0593)	-	-
WeightForeignRel	-	-	-0.026 **	-	-	-	-0.0226 **	-	-	-	0.0075	-
	-	-	(0.0109)	-	-	-	(0.0115)	-	-	-	(0.0147)	-
WeightForeignSup	-	-	-	-0.0062	-	-	-	-0.0038	-	-	-	0.0145
	-	-	-	(0.0095)	-	-	-	(0.01)	-	-	-	(0.0128)
10 (Energy)	0 ***	0 ***	0 ***	0 ***	0 ***	0 ***	0 ***	0 ***	0 ***	0 ***	0 ***	0 ***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
15 (Materials)	0.0517 ***	0.0521 ***	0.0567 ***	0.053 ***	0.0321 ***	0.0322 ***	0.0364 ***	0.0329 ***	0.0247	0.0251 *	0.0239	0.0227
	(0.0112)	(0.0113)	(0.0113)	(0.0114)	(0.0118)	(0.0118)	(0.0119)	(0.0119)	(0.015)	(0.0152)	(0.0152)	(0.0153)
20 (Industrials)	0.0475 ***	0.0486 ***	0.0492 ***	0.0486 ***	0.0271 ***	0.0267 ***	0.0285 ***	0.0277 ***	0.0418 ***	0.0428 ***	0.0428 ***	0.0412 ***
	(0.0093)	(0.0095)	(0.0093)	(0.0095)	(0.0098)	(0.01)	(0.0097)	(0.0099)	(0.0125)	(0.0128)	(0.0125)	(0.0127)
25 (Consumer)	0.0374 ***	0.0382 ***	0.0406 ***	0.039 ***	0.0067	0.007	0.0094	0.0078	-0.0024	-0.0016	-0.0024	-0.004
	(0.0095)	(0.0096)	(0.0096)	(0.0097)	(0.01)	(0.0101)	(0.01)	(0.0102)	(0.0128)	(0.0129)	(0.0129)	(0.0131)
30 (Food & Household)	0.0688 ***	0.0695 ***	0.0713 ***	0.0701 ***	0.0356 ***	0.0359 ***	0.0377 ***	0.0364 ***	0.0869 ***	0.0874 ***	0.0867 ***	0.0858 ***
	(0.0107)	(0.0107)	(0.0106)	(0.0108)	(0.0112)	(0.0113)	(0.0112)	(0.0113)	(0.0143)	(0.0144)	(0.0143)	(0.0145)
35 (Health Care)	0.0602 ***	0.0599 ***	0.0603 ***	0.0604 ***	0.0457 ***	0.0457 ***	0.0457 ***	0.0459 ***	0.0444 ***	0.0444 ***	0.0444 ***	0.0434 ***
	(0.0097)	(0.0098)	(0.0097)	(0.0099)	(0.0102)	(0.0103)	(0.0102)	(0.0103)	(0.013)	(0.0132)	(0.0131)	(0.0132)
40 (Financials)	0.0649 ***	0.0621 ***	0.0681 ***	0.0638 ***	0.0307 **	0.0246	0.0335 **	0.0251 *	0.017	0.0163	0.0143	0.0133
	(0.0138)	(0.0143)	(0.0138)	(0.0144)	(0.0145)	(0.015)	(0.0145)	(0.0151)	(0.0185)	(0.0192)	(0.0186)	(0.0193)
45 (IT)	0.038 ***	0.0379 ***	0.0397 ***	0.0383 ***	0.0236 **	0.0237 **	0.025 **	0.0239 **	0.0107	0.011	0.0106	0.0102
	(0.0096)	(0.0097)	(0.0096)	(0.0097)	(0.0101)	(0.0102)	(0.0101)	(0.0102)	(0.0129)	(0.013)	(0.0129)	(0.013)
50 (Communication)	0.055 ***	0.0543 ***	0.055 ***	0.0548 ***	0.0271 **	0.0269 **	0.0271 **	0.027 **	0.0451 ***	0.0445 ***	0.0445 ***	0.0436 ***
	(0.0124)	(0.0125)	(0.0123)	(0.0125)	(0.013)	(0.0131)	(0.0129)	(0.0131)	(0.0166)	(0.0168)	(0.0166)	(0.0167)
55 (Utilities)	0.0531 ***	0.0528 ***	0.0491 ***	0.0524 ***	0.034 ***	0.0339 ***	0.0306 ***	0.0334 ***	0.0281 *	0.0277 *	0.0285 *	0.0289 *
	(0.011)	(0.0111)	(0.0111)	(0.0112)	(0.0116)	(0.0117)	(0.0116)	(0.0117)	(0.0148)	(0.0149)	(0.0149)	(0.015)
60 (Real Estate)	0.0549 ***	0.0557 ***	0.0502 ***	0.0562 ***	0.0327 ***	0.0297 **	0.0287 **	0.0295 **	-0.0326 **	-0.0281 *	-0.0327 **	-0.0284 *
	(0.0112)	(0.0123)	(0.0112)	(0.0123)	(0.0118)	(0.0129)	(0.0118)	(0.0129)	(0.015)	(0.0165)	(0.0151)	(0.0165)
Constant	-0.2911 ***	-0.2908 ***	-0.2978 ***	-0.2914 ***	-0.2249 ***	-0.2272 ***	-0.2307 ***	-0.2279 ***	-0.1123 *	-0.1138 *	-0.1124 *	-0.1118 *
	(0.0486)	(0.049)	(0.0483)	(0.049)	(0.0509)	(0.0513)	(0.0508)	(0.0513)	(0.0649)	(0.0657)	(0.0651)	(0.0657)

*: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$

CAPM	**Period 1**				**Period 2**				**Period 3**			
	China Rel	*China Sup*	*Frgn Rel*	*Frgn Sup*	*China Rel*	*China Sup*	*Frgn Rel*	*Frgn Sup*	*China Rel*	*China Sup*	*Frgn Rel*	*Frgn Sup*
Book Leverage	-0.0078 *	-0.0088 **	-0.009 **	-0.009 **	-0.0049	-0.0055	-0.0058	-0.0057	-0.0018	-0.0028	-0.0032	-0.0032
	(0.0044)	(0.0044)	(0.0044)	(0.0044)	(0.0041)	(0.0041)	(0.0041)	(0.0041)	(0.0053)	(0.0054)	(0.0053)	(0.0054)
LMVE	0.0015	0.0016	0.0013	0.0015	0.0013	0.0014	0.0012	0.0014	-0.0049	-0.0047	-0.0056	-0.0051
	(0.003)	(0.003)	(0.003)	(0.003)	(0.0027)	(0.0028)	(0.0028)	(0.0028)	(0.0036)	(0.0036)	(0.0036)	(0.0036)
	0	0	0	0	0	0	0	0	0	0	0	0
Gross Profit Margin	-0.0043	-0.0076	-0.0062	-0.008	0.0016	-0.0016	0.0004	-0.0018	0.0024	-0.0009	-0.0026	-0.0023
	(0.0157)	(0.016)	(0.0159)	(0.016)	(0.0145)	(0.0147)	(0.0146)	(0.0148)	(0.0191)	(0.0195)	(0.0192)	(0.0195)
Quick Ratio	0.0129 ***	0.0166 ***	0.0153 ***	0.0164 ***	0.0099 ***	0.0125 ***	0.0118 ***	0.0124 ***	0.0106 **	0.0141 ***	0.0127 ***	0.0133 ***
	(0.0036)	(0.0036)	(0.0035)	(0.0036)	(0.0033)	(0.0033)	(0.0032)	(0.0033)	(0.0044)	(0.0043)	(0.0042)	(0.0043)
WeightChinaRel	0.239 ***	-	-	-	0.1838 **	-	-	-	0.2701 ***	-	-	-
	(0.0835)	-	-	-	(0.0772)	-	-	-	(0.1017)	-	-	-
WeightChinaSup	-	0.0425	-	-	-	0.0704	-	-	-	0.0784	-	-
	-	(0.0649)	-	-	-	(0.0598)	-	-	-	(0.0791)	-	-
WeightForeignRel	-	-	0.023	-	-	-	0.0148	-	-	-	0.0547 ***	-
	-	-	(0.0162)	-	-	-	(0.015)	-	-	-	(0.0196)	-
WeightForeignSup	-	-	-	0.0114	-	-	-	0.0097	-	-	-	0.0315 *
	-	-	-	(0.014)	-	-	-	(0.0129)	-	-	-	(0.017)
10 (Energy)	0 ***	0 ***	0 ***	0 ***	0 ***	0 ***	0 ***	0 ***	0 ***	0 ***	0 ***	0 ***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
15 (Materials)	0.0558 ***	0.0568 ***	0.0531 ***	0.0551 ***	0.0352 **	0.0357 **	0.0337 **	0.0345 **	0.0286	0.0296	0.0204	0.0247
	(0.0164)	(0.0166)	(0.0168)	(0.0167)	(0.0152)	(0.0153)	(0.0155)	(0.0154)	(0.02)	(0.0202)	(0.0203)	(0.0204)
20 (Industrials)	0.0373 ***	0.0404 ***	0.0395 ***	0.0402 ***	0.0193	0.0204	0.021 *	0.0213 *	0.032 *	0.0349 **	0.0333 **	0.0331 *
	(0.0137)	(0.014)	(0.0137)	(0.0139)	(0.0126)	(0.0129)	(0.0127)	(0.0129)	(0.0166)	(0.017)	(0.0166)	(0.0169)
25 (Consumer)	0.0287 **	0.0306 **	0.0282 **	0.029 **	0	0.0012	-0.0001	0.0001	-0.0109	-0.0089	-0.0145	-0.0137
	(0.014)	(0.0141)	(0.0142)	(0.0143)	(0.0129)	(0.013)	(0.0131)	(0.0132)	(0.017)	(0.0172)	(0.0171)	(0.0174)
30 (Food & Household)	-0.0188	-0.0173	-0.0196	-0.0184	-0.0313 **	-0.0304 **	-0.0317 **	-0.0312 **	0.0025	0.0039	-0.0009	0.0007
	(0.0156)	(0.0158)	(0.0158)	(0.0158)	(0.0145)	(0.0145)	(0.0146)	(0.0146)	(0.019)	(0.0192)	(0.0191)	(0.0193)
35 (Health Care)	0.0295 **	0.0298 **	0.0295 **	0.0287 **	0.0222 *	0.0227 *	0.0222 *	0.0216	0.0148	0.0154	0.0148	0.0128
	(0.0143)	(0.0144)	(0.0144)	(0.0145)	(0.0132)	(0.0133)	(0.0133)	(0.0133)	(0.0174)	(0.0176)	(0.0174)	(0.0176)
40 (Financials)	-0.0059	-0.0186	-0.0133	-0.0215	-0.0234	-0.037 *	-0.0286	-0.0401 **	-0.0512 **	-0.0614 **	-0.0641 **	-0.0688 ***
	(0.0203)	(0.021)	(0.0206)	(0.0211)	(0.0188)	(0.0194)	(0.019)	(0.0195)	(0.0247)	(0.0256)	(0.0248)	(0.0257)
45 (IT)	0.0548 ***	0.0559 ***	0.0545 ***	0.0552 ***	0.0364 ***	0.0375 ***	0.0363 ***	0.0368 ***	0.0269	0.0283	0.0249	0.0265
	(0.0141)	(0.0143)	(0.0143)	(0.0143)	(0.0131)	(0.0132)	(0.0132)	(0.0132)	(0.0172)	(0.0174)	(0.0172)	(0.0174)
50 (Communication)	0.0231	0.022	0.0216	0.021	0.0028	0.0022	0.0017	0.0012	0.0144	0.0134	0.0124	0.0111
	(0.0182)	(0.0183)	(0.0183)	(0.0183)	(0.0168)	(0.0169)	(0.0169)	(0.0169)	(0.0221)	(0.0224)	(0.0221)	(0.0223)
55 (Utilities)	-0.0759 ***	-0.0768 ***	-0.0742 ***	-0.076 ***	-0.0646 ***	-0.0652 ***	-0.0636 ***	-0.0647 ***	-0.0961 ***	-0.0971 ***	-0.0901 ***	-0.0948 ***
	(0.0162)	(0.0163)	(0.0165)	(0.0164)	(0.015)	(0.0151)	(0.0152)	(0.0151)	(0.0197)	(0.0199)	(0.0199)	(0.0199)
60 (Real Estate)	-0.0425 ***	-0.0362 **	-0.0419 **	-0.037 **	-0.0417 ***	-0.0406 **	-0.0417 ***	-0.0417 **	-0.1265 ***	-0.1166 ***	-0.1214 ***	-0.1181 ***
	(0.0164)	(0.0181)	(0.0167)	(0.018)	(0.0152)	(0.0166)	(0.0154)	(0.0166)	(0.02)	(0.022)	(0.0202)	(0.0219)
Constant	-0.0765	-0.0775	-0.0758	-0.0763	-0.0608	-0.064	-0.0609	-0.0633	0.0946	0.0917	0.1016	0.0956
	(0.0712)	(0.0719)	(0.0718)	(0.0719)	(0.0658)	(0.0663)	(0.0663)	(0.0664)	(0.0867)	(0.0877)	(0.0867)	(0.0875)

*: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$