CORPORATE ISOLATIONISM VS. GLOBAL IMMUNITY-

MNE INTERNATIONALIZATION AND RESILIENCE TO THE COVID-19 PANDEMIC

Olga Venger
Master Student
Vienna University of Economics and Business (WU)

Harald Puhr
Research Associate & PhD Student of International Business
Vienna University of Economics and Business (WU)
harald.puhr@wu.ac.at

Jakob Müllner
Associate Professor
Vienna University of Economics and Business (WU)
jakob.muellner@wu.ac.at

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globaltrends v.0.0.2
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ABSTRACT

Our study is among the first ones to analyze the relationship between pandemic resilience and firm-level internationalization. The COVID-19 pandemic provides a unique empirical laboratory to study the resilience of MNE's of different degrees of internationalization to large scale global shocks and, therein, can provide valuable contributions to the traditional internationalization and risk literature in IB. We study cumulative abnormal returns of S&P 500 firms during the outbreak and find that internationalization makes MNE's less vulnerable to US pandemic outbreaks. In addition to this empirical contribution, we introduce a novel uniquely versatile measure of firm-level internationalization that is based on the global distribution of Google search queries.

Keywords: Resilience, Internationalization, Google Trends, Measuring Internationalization, COVID-19, globaltrends Package.

INTRODUCTION

Economic effects of COVID-19 Pandemic are material and unprecedented (Caligiuri, De Cieri, Minbaeva, Verbeke, & Zimmermann, 2020, Van Assche & Lundan, 2020). Because of the considerable uncertainty of the COVID-19 pandemic, in early April 2020 the UN Department of Economic and Social Affairs (2020) estimated that the global economy is projected to shrink by approximately 0.9% in 2020, down from the forecast of 2.5% growth. They also warned the pandemic is likely to undermine efforts to achieve the 2030 sustainable development goals, with highly differentiated impacts on lower income countries. Additionally, stock markets as a main transmission channel of this on-going, global, systemic shock, have responded instantly and dramatically (Zhang, Hu, & Ji, 2020) – all major stock market indexes experienced a sharp decline by more than 30% during the one-month period and registered the worst days of trading in their history, according to Bloomberg estimates.

On the one hand, studying COVID-19 resilience has immanent practical value to learn from the global pandemic fallout and be better prepared for future pandemics. For researchers, on the other hand, the global pandemic has created an exogenous shock that can be used as a natural laboratory to test research questions that were previously plagued by empirical identification issues. One such research question in the field of IB regards the relationship of internationalization and firm-risk, which has yielded inconsistent results.

Within the discipline of IB, literature there is a long tradition of research on the relationship between internationalization & systemic risk. On the one hand, it is argued, internationalization provides diversification benefits, lower risk and lower costs of capital (Reeb, Mansi, & Allee, 2001), as a result. On the other hand, *"internationalization may also increase exposure to other pervasive economic factors, and therefore increase"* firms' risk exposure to, for example *"foreign exchange risk and political risk"* (Reeb, Kwok, & Baek, 1998). While much of this literature has focused on systematic risk, there is no study on the effect of exogenous shocks like global pandemics, which, contrary to foreign exchange or political risk are global in magnitude and not diversifiable.

Existing theories provide potentially diverging predictions on the effect of internationalization on firm resilience to global shocks. Network perspectives (Borgatti & Halgin, 2011, Provan, Fish, & Sydow, 2007) would suggest that internationalized MNEs have a higher likelihood of being affected by pandemics and that negative effects of pandemics would spread within the network of subsidiaries impeding the functioning of the network as a whole and making them very vulnerable to interruptions of global value chains. Conversely, real options (Chi, Li, Trigeorgis, & Tsekrekos, 2019, Trigeorgis, 1993) and operational flexibility (Kogut & Kulatilaka, 1994, Tang & Tikoo, 1999) arguments would suggest that internationalized MNEs are more capable of reacting to external shocks because of their global outreach, thus becoming more resilient to pandemics than less internationalized competitors do.

Ours is the first study in IB to and closes this research gap by studying CARs of S&P 500 firms during the US COVID-19 pandemic. Because of the timeliness of the pandemic, there is very little research on economic effects of COVID-19 on firms in general, and only one study on corporate resilience. The study by Harvard Business School authored by Cheema-Fox, LaPerla, Serafeim & Wang, 2020, however, focuses on firms' responses in form of their external communication as a determinant of their negative stock returns and not on firms' a-priori vulnerability as a function of the firms' degree of internationalization (Cheema-Fox, LaPerla, Serafeim, & Wang, 2020). We find that the benefits of diversification and real options (as well as financial benefits) outweigh the negative effects of internationalization in global pandemics. According to our findings, internationalization shields MNE value from global shocks.

Our paper contributes to IB research in two ways. First, we add to the discussion on firm-internationalization and risk (Reeb, Kwok, & Baek, 1998), extending the empirical inquiry to include large, global pandemics. We show that internationalization makes firms more resilient to large-scale exogenous shocks, even if previous research has shown that internationalized firms have higher systematic risk in their day-to-day operations (Kwok & Reeb, 2000, Olibe, Michello, & Thorne, 2008). Second, our results support strategic management narrative that real options and operational flexibility benefits hold even under times of global shocks, making firms less vulnerable and more resilient (Lee & Makhija, 2009).

In addition, our paper makes an equally important methodological contribution to IB literature by introducing a novel and uniquely versatile measure of firm internationalization that has been used in other disciplines like finance (Preis, Moat, & Stanley, 2013), economics (Castelnuovo & Tran, 2017, Vosen & Schmidt, 2011), political science (Stephens-Davidowitz, 2014) and, ironically for this paper, in epidemiology (Carneiro & Mylonakis, 2009, Cervellin, Comelli, & Lippi, 2017)[1]. As part of this paper, we developed the *globaltrends* (Puhr, 2020) package for R, which is available through GitHub. We use this package to download data on Google search queries around the globe and to compute search scores across a set of 66 countries for each firm in our sample. Based on these search scores, we measure each firm's degree of internationalization. This measure can be used to compare firms' degree of internationalization and to describe single firms' internationalization process over time. The measure is based on more detailed data as Google search data is available historically even at a district level. Thus, the measure can also be used to

[1] For an overview see Jun, Yoo, & Choi, 2018.

measure within country footprints of firms, persons or products. Finally and most importantly, the measure is updated daily while traditional, accounting based measures are mostly available on a yearly basis. Such fine-grained data allows IB researchers in the future to apply intra-year methodologies (e.g. event studies) and ask previously unanswerable research questions. While our study shows that our Google-based internationalization measure can be used as a supplement for traditional measures - yielding the identical results in our setting - it is important to stress that the global distribution of search queries captures a different, more consumer recognition based type of firm-level internationalization that may be less suitable in other contexts but, potentially, more suitable for others than traditional accounting measures. As such, our measure has the potential to capture a different type of internationalization because it is not based on the distribution of assets or sales in different countries but the firms' recognition in the eyes of customers/investors.

Our paper is structured as follows. We first provide an overview of the literature on corporate resilience to crises (focusing only on external rather than internal crises), the scarce scientific attempts to link crisis resilience to firm-internationalization. We then provide our theoretical arguments for our hypothesized, positive effect of firm-internationalization on crisis resilience before introducing our empirical setting, the COVID-19 crisis in the US. We then present our empirical study on S&P 500 firms and our novel measure of internationalization. Finally, we discuss findings, limitations and implications of our study.

LITERATURE REVIEW

The concept of crisis describes a range of events that disrupt the operations of any firm, industry, national or global economy and is viewed as something that can be avoided if the organizations know how to handle them in a strategic and proactive way (Johansen, Aggerholm, & Frandsen, 2012). Henderson (2007) suggests the classification of crises by defining certain domains such as economic, political, socio-cultural, environmental, technological and commercial, and by distinguishing internal and external crises threats. While many researchers focus on studying the role of internal crisis management before, during and after a crisis within a firm (Johansen, Aggerholm, & Frandsen, 2012), this paper gives priority to external crises, considering that pandemics fall into the external environmental crisis category.

To understand different responses to exogenous changes and shocks the concept of resilience is used, which addresses the "*capacity for an enterprise to survive, adapt, and grow in the face of turbulent change*" (Fiksel, 2006, Hamel & Valikangas, 2004). The RBV, which suggests that some firm-specific capabilities can serve as a source of competitive advantage and resilience to shocks, additionally encourages researchers to examine which characteristics make firms overcome crisis situations (Lee, Beamish, Lee, & Park, 2009).

First of all, the academic literature draws a strong relation between a firm's size and crisis management. Johansen, Aggerholm, and Frandsen (2012) claim that the larger the organization, the more likely it to have a crisis plan, a crisis team and managers with some education in crisis management. On the contrary, Williams and Vorley (2014) argue that small firms are particularly responsive to exogenous shocks as they are more flexible, adaptable and innovative than large enterprises.

Additionally, a firm's organizational structure can serve as an important determinant of its resilience – the more rigidly organized firms, especially the ones with strong hierarchical system, tend to lose capacities to respond flexibly to a changing environment, overcome exogenous shocks and remain competitive, as such structures can complicate the decision making in crisis situations and hinder the use of the necessary defense mechanisms (Williams & Vorley, 2014). Moreover, the organizational culture can predetermine the communication during the crisis and the employees' mood and perception of the crisis, which, in their turn, influence organizations' ability to handle a crisis (Johansen, Aggerholm, & Frandsen, 2012).

Another firm-specific determinant, which is exceptionally crucial for being resilient to any type of shocks, is a firm's profitability, i.e. its ability to generate earnings. Laczkowski, Mysore, and Brown (2019) suggest that driving margin growth by cutting the operating costs during the downturn period can help to move faster to the recovery stage. Their study on the firm's resilience during the GFC showed that the resilient firms, which were able to grow EBITDA consistently, no matter what the outside conditions were, cut their operating costs by half a dollar for every dollar of revenue change, while non-resilient firms increased their operating costs in the same period.

Researchers also distinguish some other determinants that make a firm resilient to the continuous crisis such as liquidity, industry or sector, presence of social capital, training and education of personnel, adaptability, knowledge, creativity, receptiveness and flexibility in the organization, product diversification, and the degree of internationalization.

Gaining access to foreign markets and increasing the degree of internationalization is often a necessary part of a firm's strategy to obtain strategic competitive advantages and long-term success and reduce risk. Moreover, as the intensity of the downturn may differ across regions, the wide international networks and distribution across a larger number of geographical locations allows firms to have more options to deal with shocks and uncertainties. Such an additional operational flexibility and efficiency under economy-wide shocks usually results in a higher performance and, thus, makes geographic diversification an effective and valuable strategy in economic downturns (Garrido-Prada, Delgado-Rodriguez, & Romero-Jordán, 2019). Myles Shaver (2011) and Jang (2017) in their studies find that firms with operations in foreign markets have also a much higher financial flexibility compared to non-geographically diversified firms, as more stable expected cash flows can increase external capital providers' willingness to fund investments and, thus, mitigate investment liquidity constraints during a crisis.

Additionally, Lee et al. argue that firms with non-location-bound flexible capabilities quickly adapt to the economic shocks and drastic changes in an environment and outperform those that are locked in with location-bound inflexible capabilities. Furthermore, the assumptions about the geographical diversification benefits goes in line with the real options perspective, which suggests that organizational capabilities that provide flexibility in the market serve as a foundation for a firm's competitive advantage during a crisis situation (Bowman & Hurry, 1993, Kogut & Kulatilaka, 1994).

In an economic downturn, under a high level of external uncertainty, managing foreign operations and making the right decisions may further increase coordination costs and undermine efficiency. For this reason, Garrido-Prada et al. (2019) explains the trade-off between the possible costs and benefits from the higher degree of internationalization with the U-shaped relationship between geographic diversification and firm performance, meaning that a firm can gain advantages from geographic diversification, if the firm has enough geographical presence to maintain a flexible strategy and compete in foreign markets, and be more capable to overcome the effects of an economic downturn.

During the COVID-19 pandemic, as during any other economic crisis, investors are looking for evidence that a firm can be resilient. As the coronavirus pandemic is a recent phenomenon, the research on which firm-specific determinants can increase the resilience to this crisis, is still very scarce.

Nevertheless, Cheema-Fox, LaPerla, Serafeim, and Wang (2020) already address this issue by examining whether a firm that invested in its stakeholder relations demonstrates stronger relative stock market performance during the COVID-19 market collapse in March, 2020. Based on their results, firms with more positive public sentiment for the way they respond to the COVID-19 crisis and their effects on employees, suppliers, and customers, are perceived as more resilient and, thereby, earn less negative stock returns and outperform their counterparts during the market collapse.

Although Cheema-Fox, LaPerla, Serafeim, and Wang (2020) contribute a lot to the literature on how firms might develop relational contracts with their stakeholders and on corporate actions during sharp market declines, their study does not include insights on such firms' characteristic as the degree of internationalization, which serves as the main focus of the current paper.

INTERNATIONALIZATION AND PANDEMIC RESILIENCE

From a network theory perspective, one could argue that internationalized firms are more affected by global pandemics because they operate as networks and inefficiencies gridlock or problems proliferate within the MNE network when they occur. Problems in one subsidiary contain other subsidiaries and potentially lead to a collapse of internationally dispersed operations.

Other theories, however, suggest that internationalization reduces vulnerability (i.e. increases resilience): Harry Markowitz with his modern portfolio theory, introduced to academic circles in his article "*Portfolio Selection*", states that investment risk can be reduced by creating a diversified portfolio of unrelated assets. Investing in a single security does not make sense according to Markowitz; thus, diversification underpinned by concepts of risk, return, variance, and covariance lies in the foundation of the modern portfolio theory. In essence, Markowitz's theory shows how diversification, the act of selecting assets that are unequally affected by specific market volatility, can ultimately help to stabilize a portfolio as a whole (Markowitz, 1952).

The Markowitz portfolio diversification theory can be applied from the perspective of geographic diversification as well. When MNEs have their investment (for example, in the form of subsidiaries) in multiple locations and operate in multiple markets, the market (volatility) risk is diversified across several locations. Since global shocks and pandemics commonly do not affect all locations at the same time, multinational or geographically-diversified firms have a-priori lower exposures to pandemics.

Beyond diversification of downside risks, MNEs have subsidiaries in several locations and can actively use these operative flexibilities to actively counter the fallout from a pandemic and reap upside returns (at least vis-a-vis more affected smaller, domestic competitors) (Lee & Makhija, 2009).

In their paper, Kogut and Kulatilaka (1994) see the multinational corporation as a network of activities located in different countries and attribute the value of this network to the operational flexibility to shift factors of production across different countries within the network. When one subsidiary encounters difficulties in one country, its problems may be solved through interaction with sister subsidiaries in its multinational network (Chung, Lee, Beamish, & Isobe, 2010).

Therefore, the operational flexibility can be conceived as owning the option to respond to uncertain events in some parts of the world. Real options confer the firm the right, but not the obligation, to undertake some future specified action, enabling it to reduce downside risk while claiming upside opportunities (Bowman & Hurry, 1993, McGrath, 1997).

In other words, firms with flexible operations in several countries have an ability to exercise the option to coordinate, switch production or sales and transfer resources internationally. A larger global footprint allows a MNE not only to diversify a-priori (i.e. risk diversification), but also to react more efficiently ex-post (i.e. real options). In contrast, SMEs are often forced to reduce essential investments in terms of crises (Flammer & Ioannou, 2018).

From a financial point of view, MNEs are more resilient to global pandemics for two reasons: First, because large, mature firms are commonly blue-chip and low risk investments (Bartik, Bertrand, Cullen, Glaeser, Luca, & Stanto, 2020). In times of crisis and financial market turmoil investors commonly reallocate capital from high risk/high yield investments into low risk alternatives and large shares. An international reputation, therein, makes a firm more visible and a more likely safe haven for fleeing capital. Second, larger and more internationalized firms have more degrees of freedom in internal capital markets. They dispose of a broader variety of capital sources and more opportunities to channel capital to locations most in need. As a result, large internationalized MNEs are less dependent on external capital markets that may also be affected by external shock. Because of these three arguments, we hypothesize:

> *Hypothesis 1: A higher degree of MNE internationalization reduces negative market reactions in the form of cumulative abnormal returns.*

EMPIRICAL SETTING COVID-19

A pneumonia of unknown cause detected in the city of Wuhan, China, was first reported to the World Health Organization (WHO) Country Office in China in December 31st, 2019. In early January 2020, 41 patients with confirmed infections by a novel coronavirus (later named as COVID-19) had been admitted to hospitals in China (Huang, Wang, Li, Ren, Zhao, Hu, Zhang, Fan, Xu, & Gu, 2020). With the first death reported on January 11th, Chinese authorities placed Wuhan, a city of more than 11 million people, under quarantine on January 23rd – and the rest of the Hubei province a few days later.

Despite the rapid spread of the virus within China, many political leaders in other parts of the world were initially largely disregarding the virus outbreak. Therefore, the global air transport had carried the virus to all continents before any measures were taken and, due to such extremely high-speed dissemination, on March 11th, the WHO declared the outbreak a pandemic. Moreover, the limited testing capacities in many countries and the considerable fraction of undocumented but infectious cases, which are unrecognized owing to mild, limited, or lack of symptoms, caused an exposure of a far greater portion of the population to the virus than would otherwise occur (Li, Pei, Chen, Song, Zhang, Yang, & Shaman, 2020). While the total number of real cases remained unknown, the number of confirmed infections continued to rise quickly during March and April, with the US having the most confirmed cases. A striking example is that by mid-April confirmed cases approached 2 million (with over 125,000 deaths) in over 200 countries, while by end-March the virus had been registered only in about 170 countries with over 750,000 confirmed cases (with nearly 40,000 deaths) (Gössling, Scott, & Hall, 2020, WHO, 2020)

The US, now accounting for the biggest share of confirmed cases worldwide, announced the first confirmed coronavirus case on US soil on January 21st, 2020. Already on January 31st, the Trump administration suspended entry into the United States by any foreign nationals who had traveled to China in the past 14 days, excluding the immediate family members of American citizens or permanent residents. On February 29th, a state health official announced that a patient infected with the novel coronavirus in Washington state has died, marking the first death due to the virus in the United States. On the same day, President Donald Trump announced additional travel restrictions involving Iran and increased warnings about travel to Italy and South Korea.

Due to this and further corona-related event, all the US stock market indexes, including the S&P 500, experienced a sharp decline and registered some of the worst days of trading in their history. For the S&P 500 index the worst trading days were 16th March (decline of 12%), ranked the third worst day in the history, 12th March (decline of 9.5%), ranked as the sixth worst decline, and 9th March (decline of 7.6%), the 19th worst. All three days were then called "*Black Monday*", "*Black Thursday*", and "*Black Monday II*". Therefore, the three trading days, prior to the "*black*" trading days, namely March 6th, 11th, and 13th were chosen for the event study to calculate cumulative abnormal return for the S&P 500 firms.

DATA & METHODS

We focus our analysis on the S&P 500 firms, because the index ensures to reflect the US market best. It includes approximately 500 of the top firms in the US with high visibility and represents approximately 80% of the total value of the US stock market. For our study, we obtain data from several sources. We extract daily-adjusted closing stock prices from the Yahoo Finance database to compute abnormal returns. To obtain fundamental firm data such as total assets, number of employees, subsidiaries indicators, we use Orbis Bureau van Dijk. To approximate a firm's degree of internationalization, we apply a variety of measures from different sources. On the one hand, we obtain traditional approximations of internationalization from Orbis Bureau van Dijk. On the other hand, we compute a novel and flexible measure for degree of internationalization based on data from Google Trends. We classify each firm's main industry with the help of classifications from the MSCI database.

Dependent variables

We select a market-based study as a dependent variable because stock prices accurately reflect the markets' expectation of the firm (Tang & Tikoo, 1999) for the future and after the event. In addition, stock prices reflect firm value. Our dependent variable are the cumulative abnormal returns for S&P 500 firms obtained from an event study. Our dependent variables are the cumulative abnormal returns (CARs) for S&P 500 firms obtained from with the use of the event study methodology package provided by Schimmer, Levchenko, and Müller (2019):

$$CAR(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{i,t}.$$

The abnormal return ($AR_{i,t}$) on a distinct day within the event window represents the difference between the actual stock return ($R_{i,t}$) on that day and the normal/'no-event' return, which is predicted based on two inputs; the typical relationship between the firm's stock and its reference index (expressed by the α and β parameters), and the actual reference market's return ($R_{m,t}$):

$$AR_{i,t} = R_{i,t} - (\alpha_i + \beta_i \times R_{m,t}).$$

MacKinlay (1997) states that for those cases where the event date is difficult to identify, as it is in the case of pandemics, event studies may have limitations and, thus, require a more careful determination of the event date or, preferably, choosing several event dates in order to ensure the robustness of the results. Therefore, the cumulative abnormal returns are calculated for three different event dates, March 6th, 11th, and 13th, and in four different periods from $t_1 \in \{0, -10\}$ to $t_2 \in \{1, 5, 10\}$. All twelve types of CARs are used as a dependent variable in the regression models.

Independent variables

Degree of internationalization (DOI):

For the purpose of this paper, we create a tailor-made variable of firm-level internationalization that does not approximate the configuration of the firm's international operations but relies on their global recognition. Our measure is uniquely flexible, reliable and detailed and has the potential to answer questions that IB research cannot address with other measures. We use our measure indistinctively as an alternative measure for traditional IB measures in this paper (e.g. FSTS, FATA, subsidiary count etc.). Yet, we want to stress that our measure captures facets of firm-level internationalization that other measures, based on firms' distribution of activities (Marshall, Brouthers, & Keig, 2020), cannot capture.

Our measure takes advantage of available data on the global distribution of search queries on Google Trends. Numerous studies, especially in the fields of epidemiology, economics and finance successfully use Google Trends in predictive analytics (Dorobantu & Mullner, 2019, Wilcoxson, Follett, & Severe). Google Trends offers daily updated data and availability even at the district level. Therefore, it provides an extremely detailed and fine-grained measure of the global recognition of a search term, person, phenomenon, or, in our case, a firm. We discuss the vast opportunities that result from this novel measurement approach for IB research in the discussion.

To construct our Google Trends measure of degree of internationalization, we use the *globaltrends* package (Puhr, 2020) implemented in R software and available through GitHub to extract country-level time-series between January 2010 and July 2020 for every firm in the S&P 500 index. A download for one firm over this period generates 3,964,940 total data points for those 66 countries that contribute at least 0.1% to global GDP (Fisch, 2012). In sum, we calculate our internationalization measures from 32,360 country-year observations and billions of firm search queries across the globe.

Google Trends organizes its data output as single-country data batches of five search terms. Within these batches, Google Trends normalizes search trends to a score between 0 and 100. We devise a mapping algorithm to transform Google Trends output to a more general data structure. For each country, we download a batch of baseline terms that captures usual search activities in the country. The baseline terms include "*Gmail*", "*Maps*", "*Translate*", "*Wikipedia*", and "*Youtube*". We then download 114 batches of firm names, including synonyms and alternative spellings, for each of the 66 countries. Next, we follow Castelnuovo and Tran (2017) to map firm names to the baseline batches of each country. From these country search trends, we compute seasonally adjusted and trends-only time-series that we use as robustness checks (Bokelmann & Lessmann, 2019). We then use these time-series to compute a search score as the ratio between the search trends for firm *i* in comparison to search trends for the baseline terms *b1* to *b5* in each country c:

$$search\ score_{i,c} = \frac{search\ trend_{i,c}}{\sum_{b=b1}^{b5} search\ trend_{b,c}}$$

In a final step, we apply these search score time-series to create three alternative measures of firm internationalization. We follow extant literature and compute a firm's degree of internationalization as the inverted Gini coefficient (Fisch, 2012) the inverted Herfindahl-Hirschman index (Bühner, 1987), and the inverted entropy measure (Hitt, Hoskisson, & Kim, 1997) of the search score distribution.

Inverted Gini coefficient

$$DOI\ Gini_i = 1 - \frac{\sum_{c=1}^{n}\sum_{d=1}^{n}\left|search\ score_{i,c} - search\ score_{i,d}\right|}{2n\sum_{c}^{n} search\ score_{i,c}},$$

where $search\ score_{i,c}$ and $search\ score_{i,d}$ are the search scores for firm *i* across all country pairs *c* and *d*.

Inverted Herfindahl-Hirschman index

$$DOI\ HHI_i = 1 - \frac{\sum_{c=1}^{n} search\ score_{i,c}^2}{\left(\sum_{c=1}^{n} search\ score_{i,c}\right)^2}$$

where *search score*$_{i,c}$ is equal to the search score for firm *i* in country *c*.

Inverted entropy

$$DOI\ Entropy_i = \frac{1}{\sum_{c=1}^{n}\left[search\ score_{i,c} * ln\left(\frac{1}{search\ score_{i,c}}\right)\right]},$$

where *search score*$_{i,c}$ is equal to the search score for firm *i* in country *c*.

We use average inverted Gini coefficient for 2019 (DOI Gini) as our main measure for degree of internationalization. The other measures serve as robustness checks. First, we compute the average degree of internationalization for 2020 (DOI Gini$_{2020}$). Second, we use seasonally adjusted (DOI Gini$_{SAD}$) and trend-only (DOI Gini$_{TRD}$) time-series specifications rather than original Google Trends scores. Third, we measure degree of internationalization based on the Herfindahl-Hischman Index (DOI HHI) and as inverted entropy (DOI Entropy).

In Figures 1 and 2, we illustrate the Google-based degree of internationalization for three highly internationalized firms in our S&P 500 sample (panel A) and for three counterparts of low degree of internationalization (panel B). Among the most internationalized firms in our sample are Microsoft, Facebook and Coca-Cola with inverted Gini coefficients between 0.55 and 0.65. Boxplots show that the inverted Gini coefficients obtained from yearly data and from monthly data are very consistent between them. The reliability of the measures is supported looking at the range of values for firms over time. For example, the inverted Gini coefficients for Coca-Cola Company ranged from 0.51 to 0.57 between 2010 and 2020. This very tight distribution shows that results are largely unaffected by fads in Google search behavior (for both the firm and the base-line terms). On the lower end of the internationalization scale in S&P 500, we find the firms Alaska Air Group, Illinois Tool Works and J.M. Smucker Company. Alaska Air Group, for example, achieves a degree of internationalization between 0.015 and 0.038. Because we map Google Trends data to the same scale for all observations, the degree of internationalization is comparable across the entire sample. Therefore, we can show that on average, Microsoft is roughly 30 times more international than Alaska Air.

Figure 2 shows the internationalization history of the same six firms between 2010 and 2020. There is no common trend observable, indicating that the base-line search queries selected do not influence time-series systematically. Most strikingly, the internationalization time-line of Alaska Air

Group shows the steep increase (doubling) in internationalization following its acquisition of Virgin America on April 4th, 2016. In sum, the firm comparisons in Figure 1 as well as the internationalization time-lines in Figure 2 underscore the high validity of or degree of internationalization measure. While we intentionally use the measure as a complement to traditional measures in this study, we discuss unique empirical and theoretical characteristics, as well as possible applications of our Google Trends measure in the discussion section.

Insert Figure 1 & Figure 2 about here

Alternative measures of Degree of internationalization (DOI):

To illustrate the validity of our measure and the robustness of our results, we include a number of more traditional measures of degree of internationalization (i.e. count of non-domestic locations, count number of foreign subsidiaries, and share of foreign subsidiaries). Non-domestic geographic locations show the number of countries, apart from the US, a firm operates in, basically reflecting the breadth of a firm's multinational network. Number of foreign subsidiaries, in turn, represents not only the breadth but also the depth of a firm's multinational network by showing how many subsidiaries a firm has abroad. The share of foreign subsidiaries in a total number of subsidiaries aims to further demonstrate the importance of foreign operations in firm's activities.

Control variables

In order to increase the explanatory power of the statistical model, it is essential to include control variables in the regression, since the relationship between the dependent and independent variables could be influenced by them.

A firm size, represented by total assets, is the most common indicator used in similar studies as a control variable. Additionally, we control for total number of employees, following the assumptions in the academic literature that labor-intense firms can lack flexibility and, thus, react negatively to the shocks.

Although the literature does not directly determine profitability as a factor providing advantages or disadvantages for firms in crisis situations, the profitability factor is included in the regression model and represented by two indicators – profit margin and return on equity (ROE).

When controlling for industry, both negative and positive effects are expected depending on the industry and type of the event. For the industry factor we use data on 11 sectors, defined with the use of the Global Industry Classification Standard (GICS), developed by S&P Dow Jones Indices and MSCI, and derived from the MSCI database.

Insert Table 1 and Table 2 about here

Modelling strategy

In order to test the hypothesis, the choice of a research method falls on a cross-sectional regression study. In statistics and econometrics, a cross-sectional regression analysis is a type of regression analysis, in which the dependent and independent variables are associated with the same single time period or time point. Additionally, the cross-sectional study is ideal for the analysis of so-called common shocks, which can happen due to macroeconomic, technological, political, health or sociological reasons and have different effects on population units. In a cross-sectional regression, population units can represent people, households, cities or firms and organizations (Andrews, 2005). The coronavirus pandemic can be assigned to the common shocks, while S&P 500 firms can serve as population units, which further explains the choice of the regression type.

Regression analysis is a statistical method to formulate the relationship between dependent variables and independent variables as a model function. Since there is never an exact relationship between two variables, other factors have to be allowed to affect the dependent variable. However, the idea of a simple linear regression is to find those coefficients of independent variables for which the error term or disturbance in the relationship, which represents other influencing factors, is minimized. That is why the regression analysis is based on the smallest square method, also known as the Ordinary Least Squares (OLS) method. The Ordinary Least Squares allows to produce the best possible coefficient estimates when the model satisfies the OLS assumptions for a linear regression.

Our hypothesis aims to investigate whether a higher degree of firm's internationalization reduces negative market reactions in the form of cumulative abnormal returns. Consequently, the main task of the regression model is to evaluate the relationship between the CARs and the degree of internationalization. The data is analyzed with the use of R software, and the regression equation is formulated as following:

$$CAR_{i,t} = \alpha + \beta_1 \times DOI_{i,t} + \beta_2 \times Control\ variables_{i,t} + \varepsilon_{i,t},$$

where $CAR_{i,t}$ – a dependent variable, which represents cumulative abnormal returns observed for period *t* of a firm *i*, α represents a constant term, $DOI_{i,t}$ – an independent variable, which represents one of the indicators of the degree of internationalization, β_1 represents the coefficient of $DOI_{i,t}$, $Control\ variables_{i,t}$ – control variables, which are not of primary interest for testing the hypothesis, but are taken into account to prevent the results from being distorted, β_2 represents the coefficient of any control variable, and $\varepsilon_{i,t}$ represents a noise term reflecting other factors that influence $CAR_{i,t}$.

Given the hypothesis of this paper, β_1 is the main sought value, as it represents the strength that the degree of internationalization variable affects the cumulative abnormal return variable. Importantly, the dependent variable of cumulative abnormal return is represented in the model in twelve different ways. On the one hand, this enables a robustness check and ensures that the results of the models with CARs from different measurement periods support each other. On the other hand, the observation of different points in time during the pandemic may allow to gain more detailed insights into how the relationship between independent and dependent variables changed with the time. The baseline model for answering the hypothesis is chosen based on the previously obtained CAR results and subsequently is checked for the robustness including different DOI measures and different event windows and event dates.

RESULTS

Table 3 shows our base-line results. Different regression models are used to answer the hypothesis – dependent variable changes due to the different event windows and event dates of the CARs, the explanatory/independent variable changes as well due to different indicators of the degree of internationalization, and control variables stay the same.

Table 3 generalizes the results for abnormal returns within a 21-day window (-10, +10) around March 11th, 2020. Model 1 comprises the control variables only. In models 2 to 5, we use DOI Gini, Foreign Locations, Foreign Subsidiaries, and Share Foreign Subsidiaries as measurements for degree of internationalization, respectively.

The results show that all the indicators of the main sought variable – degree of internationalization – have a positive relationship with the dependent variable of the CARs in the corresponding models. The coefficients of DOI variables are all significant, with level of significance ranging from of 1 to 10%. Importantly, Google measure *DOI Gini* (0.133, p = 0.009) shows the strongest relationship among all the internationalization indicators. Additionally, the ratio of foreign subsidiaries to total subsidiaries *Share Foreign Subsidiaries* (0.116, p = 0.0002) demonstrates stronger relationship than geographic location *Foreign Locations* (0.001, p = 0.006) and foreign subsidiaries *Foreign Subsidiaries* (0.0001, p = 0.106) indicators, meaning that the relative value is more substantial than the absolute ones. Therefore, we can conclude that the more international a firm, the more positive the abnormal returns are, which supports the hypothesis that a higher degree of internationalization reduces negative market reactions in the form of cumulative abnormal returns.

The control variable of employees (*Employees*), a firm size indicator, shows a positive relationship to the dependent variable, with a significance level of less than 10%, but only in models (1), (2) and (5), which contradicts the initial assumptions about a firm size. The control variable of profit margin (*Return on Sales*), a firm profitability indicator, also shows a positive relationship to the dependent variable, with a significance level of less than 1% in all models. These two aspects indicate that the bigger and the more profitable a firm, the more positive the abnormal returns are.

Insert Table 3 about here

ROBUSTNESS CHECKS

We conduct a series of robustness checks to scrutinize our results. In Table 4, we show that our results are robust to different specifications of the Google Trends degree of internationalization measures. Next, in Table 5, we test the robustness of our results to different computations of cumulative abnormal returns in response to COVID-19 measures.

First, we test the robustness of the observed effects for our proposed Google Trends degree of internationalization measure to different specifications. For our base model, we specify *DOI Gini* as the average of monthly internationalization scores for 2019. In model 6, we adapt this measure and use the average score for the first seven months of 2020. The positive effect for $DOI\ Gini_{2020}$ (0.124, p = 0.16) shows that our findings are robust to this change in measurement. In models 7 and 8, we clean the underlying search score time-series to get a measure for internationalization that is less affected by outliers. To this end, we adjust the respective time-series for seasonally effects ($DOI\ Gini_{SAD}$) and extract the time-series' underlying trend ($DOI\ Gini_{TRD}$). Again, we observe positive effects for $DOI\ Gini_{SAD}$ (0.123, p = 0.011) and $DOI\ Gini_{TRD}$ (0.098, p = 0.027), corroborating our findings from the base model. In models 9 and 10, we apply different measures to approximate the firm's degree of internationalization based on the distribution of its search scores. The positive effect for *DOI HHI* (0.076, p = 0.022) in model 9 shows that our findings are robust to a different approach to computation. The marginally negative effect for *DOI Entropy* (-0.00002, p = 0.424) in model 10, however, runs against our expectations. The highly robust findings highlight the validity and reliability of our proposed measure for degree of internationalization.

In addition to robustness checks for the computation of our degree of internationalization measure, we test whether our results hold for different specifications of the cumulative abnormal returns estimation. For the robustness checks, we use abnormal return windows of two days (0, +1), six days (0, +5), eleven days (0, +10), and 21 days (-10, +10). We compute abnormal returns for all four windows around three key dates for the global spread of COVID-19: March 6th, March 11th, and March 13th. The base line models use cumulative abnormal returns estimated for a 21-day window around March 11th. The effects observed in models 11-17 show that the effects for *DOI Gini* observed in the base model holds across a variety of alternative abnormal return specifications. These findings underline that the validity of our findings is not contingent on a particular abnormal return measurement.

Insert Table 4 & Table 5 about here

DISCUSSION

In the paper, we study the effect of internationalization on firms' resilience to large crises and use the impact of the recent COVID-19 pandemic and relevant events in the US on a sample of S&P 500 firms. We show that internationalization reduces the negative effect of the pandemic on stock prices and firm value. Our results lend support to the diversification argument of internationalization that firms are able to reduce their resilience to large-scale exogenous shocks. This risk reducing effect is caused by a higher degree of operational flexibility in internationalized firms that allows them to respond more efficiently to exogenous shocks and reap flexibility rents beyond the reduction of risks.

On a theoretical side, our findings, at first sight, contradict IB research on internationalization and firm-level risk (Kwok & Reeb, 2000, Olibe, Michello, & Thorne, 2008) that has documented an increasing, positive effect of internationalization on systemic risk. These studies use beta as a measure of firms' systematic risk and do not focus on a single event of global magnitude. Our setting focuses not on systematic risk of stocks under regular market activities but at firms' resilience to large-scale, exogenous shocks. Thus, theoretically our results indicate that firms might, under normal circumstances, pay for internationalization through higher systematic risk, betas and cost of capital, but become more resilient to global crises events.

This finding, though based on a single hypothesis, has some strong implications for practice. First, stock investors should account for the degree of internationalization of firms as they rearrange their portfolios prior to looming crises. By shifting capital into more internationalized firms, investors reduce the resilience of their investment portfolio during times of crises. Ironically, this run for internationalized assets, will, in turn increase the resilience of these stocks towards the crisis investors are fleeing from. Second, and from a corporate viewpoint, the higher resilience of internationalized firms indicates that investor relations offices should inform shareholders explicitly of internationalization efforts and the diversification and strategic real options that they create. If firms succeed in educating shareholders of the benefits of their internationalized corporate structure, shareholders become less sensitive to financial market sell-offs.

The context in which we make our contribution to the internationalization-risk literature in IB has some idiosyncrasies that limits the generalization of our findings but also provides interesting theoretical insights and opportunities for future IB research. Arguably, the recent COVID-19 pandemic is a historically unique event of unprecedented global scale. As such, it is uncertain and the task for future researchers to test the effect of internationalization on firm crisis resilience in other crises or political events (e.g. the Brexit vote)[2]. In our operationalization of abnormal returns, we intentionally focused on three event days that were important for the US. As a result, the abnormal returns will reflect investors' assessment of the US pandemic. It is possible and an interesting avenue for future research to test if some of the negative abnormal returns for these S&P firms were already priced into the stock price before the pandemic hit the US, thus creating a spurious effect.

In addition to supporting the positive effect of internationalization on crises resilience, our paper makes an equally important methodological contribution to IB literature by introducing a novel and uniquely flexible measure of firm internationalization. In our study, we show empirically that our measure performs equally well as other, traditional measures of internationalization but does not suffer from the secondary data limitations that these measures are plagued with (reporting accuracy, reporting frequency, reporting coverage, and reporting detail).

As a measure of internationalization, our measure and the proposed *globaltrends* package (Puhr, 2020) offers a wide array of empirical possibilities. It allows researchers to compare firms' degrees of internationalization on a unified scale. In addition, the time-series nature of Google Trends allows for historical analysis of internationalization patterns and speed within firms. The enormous detail of the data opens up additional applications in IB research that are impossible with traditional measures. For instance, using Google Trends DOI on a subnational level allows IB researchers to study proliferation within a country and, for example, to trace a particular market entry. In addition, researchers can apply daily time-series data to methodologies that previously did not lend themselves to internationalization research (e.g. event-study methodology, abnormal internationalization returns). Further, the Google Trends DOI offers applications beyond firms' internationalization and time-series data on products, persons, events, fads or scandals, even academic authors and papers. A product-level analysis of the internationalization of a hyped kids

[2] There is some similar evidence on risk reduction through internationalization in the airline industry in the aftermath of the 9/11 terrorist attacks (Carter & Simkins, 2004; Drakos, 2004) while other research on the same crises event showed a negative relationship for other industries (Czinkota, Knight, Liesch, & Steen, 2010; Czinkota, Knight, Liesch, & Steen, 2005).

gadget, the fidget spinner in Figure A1 (Appendix), for example, shows its internationalization from a Brooklyn basement to the most sold toy worldwide within the short time frame of only two months (Economist, 2017, Rashid, 2017).

While, the possible applications of the Google Trends DOI are vast in the study of internationalization, it is important to concede that Google Trends data captures the global distribution of interest in a firm, or its recognition, and not necessarily the location of its operations. People google firms (and people) for different reasons, they may be customers (market side), suppliers (supply side), investors (capital side) or they may be employees or activists (stakeholders). As such, the Google Trends DOI captures a different facet, or different facets, of firm internationalization that may not be perfect substitutes for traditional measures in all settings. While our study shows that results hold under certain circumstances where firm recognition is of great importance in explaining the hypothesized effect, the measure may not perform equally well in settings where the mechanism studied is more related to physical or operational presence (e.g. transaction cost mechanisms based on specific assets). On the positive side, this conceptual difference provides an opportunity for further theoretical development of the internationalization construct in IB.

Finally, Google Trends allow IB scholars to study completely different firm-level traits. For example, the temporal variation of queries can serve as an indicator of firm-level risk. Using the related queries function that records keywords that appear frequently in connection with the primary search term, scholars could separate positive and negative sentiments on firms, calculate its co-associations of firms with phenomena (e.g. CSR) or even political actors (e.g. Trump).

Despite these strengths, a number of limitations of the proposed Google Trends measure should be discussed and addressed in future research. First, Google Trends search terms can be biased if firm names have a primary meaning. Search terms for Apple Corp., for example, are contaminated by searches for the fruit apple. Second, search term results are systematically biased by language differences, especially if firm names differ across languages (as is often the case in Japan). Finally, the accuracy of country-level timelines may vary depending on the use of Google as the primary search engine in a particular country, or access of the population to the internet more broadly. For example, Chinese time-series may be biased by governmental restrictions and time-series for small, developing nations may be less reliable because Google users in a country with low digitalization rates may be less representative of the population as a whole.

REFERENCES

Andrews, D. W. 2005. Cross-section regression with common shocks. *Econometrica*, 73(5): 1551-85.

Bartik, A. W., Bertrand, M., Cullen, Z. B., Glaeser, E. L., Luca, M., & Stanto, C. T. 2020. How are small businesses adjusting to Covid-19? Early evidence from a survey, *Working Paper* National Bureau of Economic Research.

Bokelmann, B. & Lessmann, S. 2019. Spurious patterns in Google Trends data - An analysis of the effects on tourism demand forecasting in Germany. *Tourism Management*, 75: 1-12.

Borgatti, S. P. & Halgin, D. S. 2011. On Network Theory. *Organization Science*, 22(5): 1168-81.

Bowman, E. H. & Hurry, D. 1993. Strategy through the option lens: An integrated view of resource investments and the incremental-choice process. *Academy of Management Review*, 18(4): 760-82.

Bühner, R. 1987. Assessing international diversification of West German corporations. *Strategic Management Journal*, 8(1): 25-37.

Caligiuri, P., De Cieri, H., Minbaeva, D., Verbeke, A., & Zimmermann, A. 2020. International HRM insights for navigating the COVID-19 pandemic: Implications for future research and practice. *Journal of International Business Studies*, 51(5): 697-713.

Carneiro, H. A. & Mylonakis, E. 2009. Google trends: a web-based tool for real-time surveillance of disease outbreaks. *Clinical Infectious Diseases*, 49(10): 1557-64.

Carter, D. A. & Simkins, B. J. 2004. The market's reaction to unexpected, catastrophic events: the case of airline stock returns and the September 11th attacks. *The Quarterly Review of Economics and Finance*, 44(4): 539-58.

Castelnuovo, E. & Tran, T. D. 2017. Google It Up! A Google Trends-based Uncertainty index for the United States and Australia. *Economics Letters*, 161: 149-53.

Cervellin, G., Comelli, I., & Lippi, G. 2017. Is Google Trends a reliable tool for digital epidemiology? Insights from different clinical settings. *Journal of Epidemiology and Global Health*, 7(3): 185-89.

Cheema-Fox, A., LaPerla, B. R., Serafeim, G., & Wang, H. S. 2020. Corporate Resilience and Response During COVID-19. *Working Paper* SSRN 3578167.

Chi, T. L., Li, J., Trigeorgis, L. G., & Tsekrekos, A. E. 2019. Real options theory in international business. *Journal of International Business Studies*, 50(4): 525-53.

Chung, C. C., Lee, S.-H., Beamish, P. W., & Isobe, T. 2010. Subsidiary expansion/contraction during times of economic crisis. *Journal of International Business Studies*, 41(3): 500-16.

Czinkota, M. R., Knight, G., Liesch, P. W., & Steen, J. 2010. Terrorism and international business: A research agenda. *Journal of International Business Studies*, 41(5): 826-43.

Czinkota, M. R., Knight, G. A., Liesch, P. W., & Steen, J. 2005. Positioning terrorism in management and marketing: research propositions. *Journal of International Management*, 11(4): 581-604.

Dorobantu, S. & Mullner, J. 2019. Debt-side governance and the geography of project finance syndicates. *Journal of Corporate Finance*, 57: 161-79.

Drakos, K. 2004. Terrorism-induced structural shifts in financial risk: airline stocks in the aftermath of the September 11th terror attacks. *European Journal of Political Economy*, 20(2): 435-46.

Economist, T. 2017. The lessons of fidget spinner: Fidget revolution, *The Economist*. London.

Fiksel, J. 2006. Sustainability and resilience: toward a systems approach. *Sustainability: Science, Practice and Policy*, 2(2): 14-21.

Fisch, J. H. 2012. Information Cost and Internationalization Performance. *Global Strategy Journal*, 2(4): 296-312.

Flammer, C. & Ioannou, I. 2018. To save or to invest? Strategic management during the financial crisis. *Strategic Management during the Financial Crisis (October 28, 2018)*.

Garrido-Prada, P., Delgado-Rodriguez, M. J., & Romero-Jordán, D. 2019. Effect of product and geographic diversification on firm performance: Evidence during an economic crisis. *European Management Journal*, 37(3): 269-86.

Gössling, S., Scott, D., & Hall, C. M. 2020. Pandemics, tourism and global change: a rapid assessment of COVID-19. *Journal of Sustainable Tourism*: 1-20.
Hamel, G. & Valikangas, L. 2004. The quest for resilience. *Revista Icade. Revista de las Facultades de Derecho y Ciencias Económicas y Empresariales*(62): 355-58.
Henderson, J. C. 2007. *Tourism crises: causes, consequences and management*: Routledge.
Hitt, M. A., Hoskisson, R. E., & Kim, H. 1997. International Diversification: effects on innovation and firm performance in product-diversified firms. *Academy of Management Journal*, 40(4): 767-98.
Huang, C., Wang, Y., Li, X., Ren, L., Zhao, J., Hu, Y., Zhang, L., Fan, G., Xu, J., & Gu, X. 2020. Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. *The Lancet*, 395(10223): 497-506.
Jang, Y. 2017. International corporate diversification and financial flexibility. *The Review of Financial Studies*, 30(12): 4133-78.
Johansen, W., Aggerholm, H. K., & Frandsen, F. 2012. Entering new territory: A study of internal crisis management and crisis communication in organizations. *Public Relations Review*, 38(2): 270-79.
Jun, S.-P., Yoo, H. S., & Choi, S. 2018. Ten years of research change using Google Trends: From the perspective of big data utilizations and applications. *Technological Forecasting and Social Change*, 130: 69-87.
Kogut, B. & Kulatilaka, N. 1994. Operating Flexibility, Global Manufacturing, and the Option Value of a Multinational Network. *Management Science*, 40(1): 123-39.
Kwok, C. C. Y. & Reeb, D. M. 2000. Internationalization and firm risk: an upstream-downstream hypothesis. *Journal of International Business Studies*, 31(4): 611-29.
Laczkowski, K., Mysore, M., & Brown, S. 2019. Stronger for longer: How top performers thrive through downturns, *McKinsey Quarterly*. London.
Lee, S.-H., Beamish, P. W., Lee, H.-U., & Park, J.-H. 2009. Strategic choice during economic crisis: Domestic market position, organizational capabilities and export flexibility. *Journal of World Business*, 44(1): 1-15.
Lee, S.-H. & Makhija, M. 2009. Flexibility in internationalization: is it valuable during an economic crisis? *Strategic Management Journal*, 30(5): 537-55.
Li, R., Pei, S., Chen, B., Song, Y., Zhang, T., Yang, W., & Shaman, J. 2020. Substantial undocumented infection facilitates the rapid dissemination of novel coronavirus (SARS-CoV-2). *Science*, 368(6490): 489-93.
MacKinlay, A. C. 1997. Event studies in economics and finance. *Journal of Economic Literature*, 35(1): 13-39.
Markowitz, H. 1952. Portfolio selection. *The Journal of Finance*, 7(1): 77-91.
Marshall, V. B., Brouthers, L. E., & Keig, D. L. 2020. RIMS: A new approach to measuring firm internationalization. *Journal of International Business Studies*, 51(7): 1133-41.
McGrath, R. G. 1997. A real options logic for initiating technology positioning investments. *Academy of Management Review*, 22(4): 974-96.
Myles Shaver, J. 2011. The benefits of geographic sales diversification: How exporting facilitates capital investment. *Strategic Management Journal*, 32(10): 1046-60.
Olibe, K. O., Michello, F. A., & Thorne, J. 2008. Systematic risk and international diversification: An empirical perspective. *International Review of Financial Analysis*, 17(4): 681-98.
Preis, T., Moat, H. S., & Stanley, H. E. 2013. Quantifying trading behavior in financial markets using Google Trends. *Nature*, 3: 1684.
Provan, K. G., Fish, A., & Sydow, J. 2007. Interorganizational networks at the network level: A review of the empirical literature on whole networks. *Journal of Management*, 33(3): 479-516.
Puhr, H. 2020. globaltrends: Download and Measure Global Trends through Google Searches. Version 0.0.2., *R Package*. Available at https://github.com/ha-pu/globaltrends.
Rashid, B. 2017. How these two 17-year-olds are cashing in on the fidget spinners everyone is talking about, *Forbes Magazine*. New York.

Reeb, D. M., Kwok, C. C. Y., & Baek, H. Y. 1998. Systematic risk of the multinational corporation. *Journal of International Business Studies*, 29(2): 263-79.

Reeb, D. M., Mansi, S. A., & Allee, J. M. 2001. Firm internationalization and the cost of debt financing: evidence from non-provisional publicly traded debt. *Journal of Financial & Quantitative Analysis*, 36(3): 395-414.

Schimmer, M., Levchenko, A., & Müller, S. 2019. EventStudyTools: Event Study Anaylsis. Version 0.36. , *R Package*. Available at https://CRAN.R-project.org/package=EventStudy.

Stephens-Davidowitz, S. 2014. The cost of racial animus on a black candidate: Evidence using Google search data. *Journal of Public Economics*, 118: 26-40.

Tang, C. Y. & Tikoo, S. 1999. Operational flexibility and market valuation of earnings. *Strategic Management Journal*, 20(8): 749-61.

Trigeorgis, L. 1993. Real Options and Interactions with Financial Flexibility. *Financial Management*, 22(3): 202-24.

Van Assche, A. & Lundan, S. 2020. From the editor: COVID-19 and international business policy. *Journal of International Business Policy*, 3(3): 273-79.

Vosen, S. & Schmidt, T. 2011. Forecasting private consumption: survey-based indicators vs. Google trends. *Journal of Forecasting*, 30(6): 565-78.

WHO. 2020. Research on Corona Virus: World Health Organization.

Wilcoxson, J., Follett, L., & Severe, S. Forecasting Foreign Exchange Markets Using Google Trends: Prediction Performance of Competing Models. *Journal of Behavioral Finance*.

Williams, N. & Vorley, T. 2014. Economic resilience and entrepreneurship: lessons from the Sheffield City Region. *Entrepreneurship & Regional Development*, 26(3-4): 257-81.

Zhang, D., Hu, M., & Ji, Q. 2020. Financial markets under the global pandemic of COVID-19. *Finance Research Letters*: 101528.

Table 1: Summary statistics

Variable	Obs.	SD	Mean	Median	Min.	Max.
CAR (-10/+10)	439	0.203	-0.072	-0.047	-1.028	0.530
Employees	439	128,299	51,773	19,100	97	2,200,000
Total Assets	439	238,704,864	77,686,362	21,284,905	954,930	2,687,380,000
Return on Equity	439	55.385	29.344	17.969	-109.258	611.691
Return on Sales	439	14.568	15.642	13.458	-76.212	57.410
DOI Foreign Locations	439	23.739	26.847	23	1	98
DOI Foreign Subsidiaries	439	223.624	146.715	61	0	1,826
DOI ShareForeign Subsidiaries	439	0.278	0.362	0.379	0	0.998
DOI Gini	439	0.159	0.198	0.145	0.004	0.707
DOI $Gini_{2020}$	439	0.159	0.205	0.157	0.015	0.718
DOI $Gini_{SAD}$	439	0.165	0.235	0.208	0.015	0.702
DOI $Gini_{TRD}$	439	0.180	0.269	0.247	0.015	0.745
DOI HHI	439	0.258	0.717	0.800	0	0.981
DOI Entropy	439	319.218	24.833	1.479	0	6,303.182

Table 2: Correlations

	Variable	14	13	12	11	10	9	8	7	6	5	4	3	2	1
1	*CAR (-10/+10)*	-0.07	0.27***	0.22***	0.23***	0.24***	0.25***	0.38***	0.10	0.29***	0.18**	0.19**	-0.02	0.10	1
2	*Employees*	-0.02	0.12	0.04	0.06	0.08	0.10	0.05	0.22***	0.20**	-0.12	0.06	0.20***	1	
3	*Total Assets*	-0.01	0.06	0.03	0.03	0.05	0.05	-0.08	0.29***	0.15	0.16*	-0.06	1		
4	*Return on Equity*	-0.02	0.07	0.06	0.06	0.07	0.07	0.04	-0.06	0.03	0.27***	1			
5	*Return on Sales*	-0.01	-0.16	-0.01	0.00	0.01	0.00	-0.06	-0.12	-0.19**	1				
6	*DOI Foreign Locations*	-0.05	0.46***	0.44***	0.44***	0.44***	0.45***	0.66***	0.73***	1					
7	*DOI Foreign Subsidiaries*	-0.04	0.30***	0.27***	0.27***	0.28***	0.29***	0.48***	1						
8	*DOI Share Foreign Subsidiaries*	-0.07	0.42***	0.36***	0.35***	0.34***	0.33***	1							
9	*DOI Gini*	-0.05	0.67***	0.91***	0.96***	0.99***	1								
10	*DOI* $Gini_{2020}$	-0.05	0.65***	0.92***	0.96***	1									
11	*DOI* $Gini_{SAD}$	-0.06	0.66***	0.98***	1										
12	*DOI* $Gini_{TRD}$	-0.06	0.64***	1											
13	*DOI HHI*	-0.08	1												
14	*DOI Entropy*	1													

Significance levels: * $p < 0.10$, ** $p < 0.05$; *** $p < 0.01$.

Table 3: Baseline models

	CAR(-10/+10) 2020-03-11				
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
	-0.068	-0.108	-0.103	-0.080	-0.108
Constant	(0.035)	(0.038)	(0.037)	(0.036)	(0.036)
	p = 0.053	p = 0.005	p = 0.006	p = 0.026	p = 0.003
	0.000	0.000	0.000	0.000	0.000
Employees	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	p = 0.059	p = 0.071	p = 0.118	p = 0.104	p = 0.075
	-0.000	-0.000	-0.000	-0.000	0.000
Total Assets	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	p = 0.855	p = 0.649	p = 0.479	p = 0.571	p = 0.986
	0.0002	0.0002	0.0002	0.0002	0.0002
Return on Equity	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
	p = 0.119	p = 0.135	p = 0.157	p = 0.109	p = 0.106
	0.002	0.002	0.003	0.003	0.003
Return on Sales	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	p = 0.0002	p = 0.0003	p = 0.00002	p = 0.0001	p = 0.0001
		0.133			
DOIGini		**(0.051)**			
		p = 0.009			
			0.001		
DOI Foreign Locations			**(0.0004)**		
			p = 0.006		
				0.0001	
DOI Foreign Subsidiaries				**(0.00004)**	
				p = 0.106	
					0.116
DOI Share Foreign Subsidiaries					**(0.031)**
					p = 0.0002
Industry FE	Incl.	Incl.	Incl.	Incl.	Incl.
# Industries	11	11	11	11	11
Obs.	439	439	439	439	439
R^2	0.421	0.430	0.432	0.425	0.440
Adj. R^2	0.402	0.410	0.411	0.404	0.420

Note: Exact p-values, standard errors in parentheses

.

Table 4: Robustness checks Google Trends measure

	CAR(-10/+10)				
	2020-03-11				
	(6)	*(7)*	*(8)*	*(9)*	*(10)*
	-0.107	-0.109	-0.103	-0.133	-0.067
Constant	(0.038)	(0.038)	(0.038)	(0.045)	(0.035)
	p = 0.006	p = 0.005	p = 0.008	p = 0.004	p = 0.055
	0.000	0.000	0.000	0.000	0.000
Employees	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	p = 0.065	p = 0.060	p = 0.054	p = 0.066	p = 0.059
	-0.000	-0.000	-0.000	-0.000	-0.000
Total Assets	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	p = 0.656	p = 0.686	p = 0.693	p = 0.618	p = 0.814
	0.0002	0.0002	0.0002	0.0002	0.0002
Return on Equity	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
	p = 0.131	p = 0.133	p = 0.136	p = 0.149	p = 0.120
	0.002	0.002	0.002	0.003	0.002
Return on Sales	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	p = 0.0003	p = 0.0003	p = 0.0002	p = 0.0001	p = 0.0002
	0.124				
DOI Gini$_{2020}$	**(0.051)**				
	p = 0.016				
		0.123			
DOI Gini$_{SAD}$		**(0.048)**			
		p = 0.011			
			0.098		
DOI Gini$_{TRD}$			**(0.044)**		
			p = 0.027		
				0.076	
DOI HHI				**(0.033)**	
				p = 0.022	
					-0.00002
DOI Entropy					**(0.00002)**
					p = 0.424
Industry FE	Incl.	Incl.	Incl.	Incl.	Incl.
# Industries	11	11	11	11	11
Obs.	439	439	439	439	439
R^2	0.429	0.430	0.428	0.428	0.422
Adj. R^2	0.409	0.410	0.407	0.408	0.401

Note: Exact p-values, standard errors in parentheses

Table 4: Robustness checks event window and event date

	CAR (0/+5) 2020-03-06	*CAR (0/+10) 2020-03-06*	*CAR (-10/+10) 2020-03-06*	*CAR (0/+1) 2020-03-11*	*CAR (0/+10) 2020-03-11*	*CAR (0/+1) 2020-03-13*	*CAR (-10/+10) 2020-03-13*
	(11)	*(12)*	*(13)*	*(14)*	*(15)*	*(16)*	*(17)*
	-0.059	-0.087	-0.130	-0.028	-0.050	-0.010	-0.130
Constant	(0.027)	(0.045)	(0.053)	(0.019)	(0.028)	(0.018)	(0.038)
	p = 0.028	p = 0.052	p = 0.015	p = 0.141	p = 0.073	p = 0.571	p = 0.001
	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Employees	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	p = 0.033	p = 0.008	p = 0.012	p = 0.715	p = 0.375	p = 0.460	p = 0.034
	0.000	-0.000	-0.000	-0.000	0.000	0.000	-0.000
Total Assets	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	p = 0.913	p = 0.800	p = 0.394	p = 0.839	p = 0.408	p = 0.297	p = 0.476
	0.0002	0.0001	0.0001	0.00004	0.00001	0.0001	0.0003
Return on Equity	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
	p = 0.038	p = 0.674	p = 0.546	p = 0.553	p = 0.959	p = 0.187	p = 0.034
	0.001	0.002	0.003	0.0004	0.001	0.0002	0.003
Return on Sales	(0.0004)	(0.001)	(0.001)	(0.0003)	(0.0005)	(0.0003)	(0.001)
	p = 0.004	p = 0.013	p = 0.005	p = 0.230	p = 0.114	p = 0.474	p = 0.00003
	0.065	**0.113**	**0.160**	**0.045**	**0.076**	**0.042**	**0.089**
DOI Gini	**(0.035)**	**(0.059)**	**(0.071)**	**(0.025)**	**(0.037)**	**(0.024)**	**(0.050)**
	p = 0.066	**p = 0.059**	**p = 0.025**	**p = 0.077**	**p = 0.043**	**p = 0.076**	**p = 0.075**
Industry FE	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.
# Industries	11	11	11	11	11	11	11
Obs.	439	439	439	439	439	439	439
R^2	0.391	0.374	0.373	0.297	0.367	0.238	0.397
Adj. R^2	0.370	0.352	0.350	0.272	0.345	0.211	0.375

Note: Exact p-values, standard errors in parentheses

Figure 1: Box-plot examples of DOI using Google Trends measure (monthly & yearly)

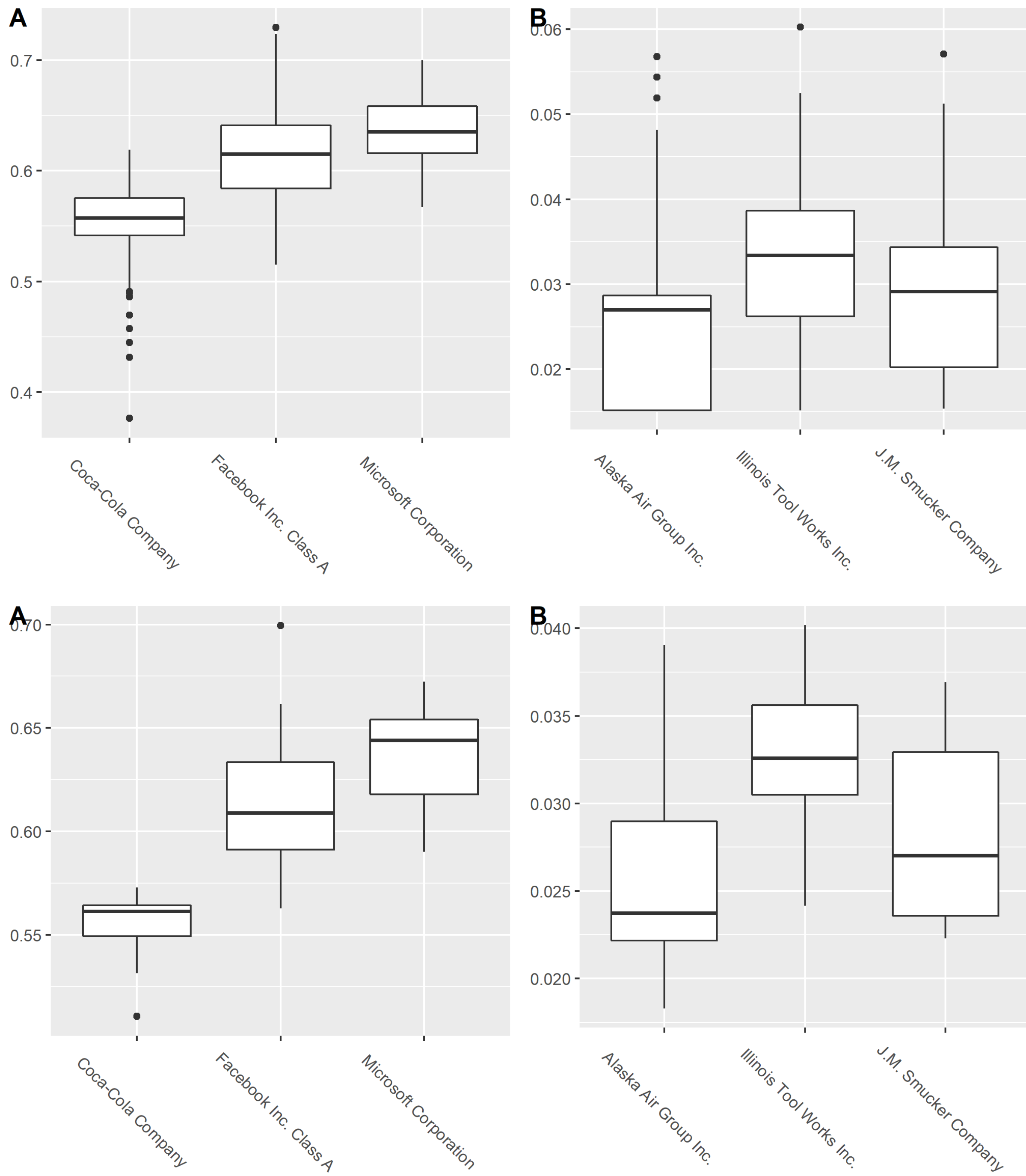
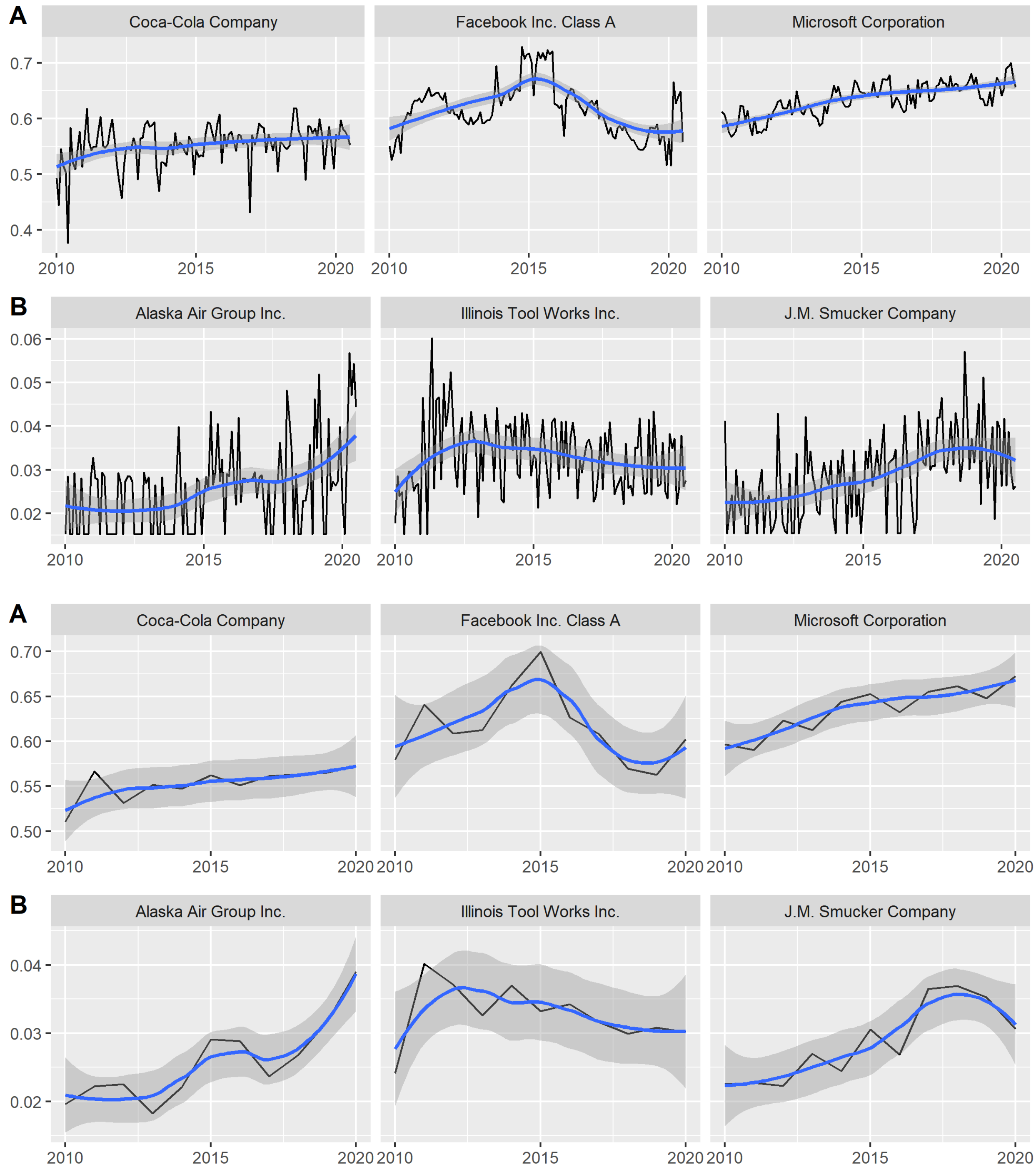


Figure 2: Time-series examples of DOI using Google Trends measure (monthly & yearly)



Appendix

Figure A1: Proliferation of the fidget spinner within the US and across the Atlantic