IMPACT OF DISASTERS ON FIRMS IN DIFFERENT SECTORS: IMPLICATIONS FOR SUPPLY CHAINS

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Disasters keep damaging infrastructure, disrupting supply chains and affecting firm profitability. There is an urgent need for better understanding of disaster impact on supply chains but very few publications address this issue. This exploratory study takes an indirect approach and investigates disaster impact on firms in various industry sectors. This approach allows us to take full advantage of large secondary data bases of firm and disaster data in order to analyze the impact of over 3,500 disasters on more than 100,000 firm-year observations over 15 years. Our results indicate that disasters impact all sectors within a supply chain. We found that damage by windstorms and floods seem to be dramatically different from that of an earthquake, providing evidence against the all-hazards approach. We also show that the impact of floods on total asset turnover of a firm is dependent on the firm's position in the supply chain. We found that while upstream partners enjoy a positive impact, downstream partners have to plan for the opposite. Supply chain managers can use our results to better understand disaster impact on their business. Our study suggests a supply chain–wide mitigation strategy rather than a company-specific one.

Keywords: *risk; supply chain management; archival research; regression analysis*

INTRODUCTION

During the last decade the attention of supply chain researchers and practitioners alike has focused on risk and disruption management (Martha and Subbakrishna 2002; Mitroff and Alpaslan 2003; Craighead, Blackhurst, Rungtusanatham and Handfield 2007). In spite of this interest, there has been relatively little research on the system-wide or global impact of supply chain disruptions both upstream, downstream and laterally in the supply chain (Blackhurst, Craighead, Elkins and Handfield 2005). Natural disasters such as earthquakes, floods and fires, can create such disruptions because they impair business functions and decrease the productive capacity of firms operating in the affected region (Miller 1991). Very few publications address the effects of catastrophic events on supply chains.

We believe there is an urgent need for better understanding the impact of disasters on global supply chains for the following reasons. First, there is compelling evidence that the frequency and intensity of natural disasters are increasing (Schönwiese, Grieser and Trömel 2003; Emanuel 2005; Altay 2008). Other studies such as Ibarrarán, Matthias, Sanjana and London (2009) have linked an increase in natural disaster occurrence to climate change. Anderson and Bausch (2006) show that for Europe, heat waves are becoming more likely and at the same time precipitation events are becoming more severe. Second, there is evidence that disasters are becoming more economically costly (Horwich 2000). Finally, the costs of such disruptive events tend to amplify as the density and complexity of supply networks grow.

A supply chain is defined as "a set of three or more entities (organizations or individuals) directly involved in the upstream and downstream flows of products, services/finances and/or information from a source to a customer" (Mentzer, DeWitt, Keebler, Min, Nix, Smith and Zacharia 2001, p. 4). This definition implies a direct link between

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the companies in a supply chain. Hence, success depends on the understanding that a supply chain is a collection of interdependent organizations and coordination should be a strategic response to the issues arising from these dependencies within the chain (Xu and Beamon 2006). It is the integration of business processes, not individual functions, that creates value for customers and these processes reach beyond the boundaries of the firm (Vickery, Jayaram, Droge and Calantone 2003). Consequently, to properly study the impact of major disruptions on supply chains, one needs to know the specific linkages in a given chain. However, even with the proper knowledge, because of the global nature of the markets and supply networks, local catastrophes increasingly result in indirect global consequences (Gassebner, Keck and Teh 2006; Wagner and Bode 2008). For example, the March 2010 earthquake in Chile disrupted lumber shipments leaving the country and halted the operations of a construction firm in Chicago, which buys their lumber directly from their Chilean supplier. Even though the supplier's facilities were unharmed from the effects of the earthquake, the closing of ports caused major supply delays. As evident from this example, unless the complexities of all linkages within a supply chain are understood and mapped it is difficult to measure the impact of a disruption in one firm's operations on another in the same supply chain (Gardner and Cooper 2003).

In this paper, we take an indirect approach to the problem of understanding the impact of disasters on supply chains and investigate the impact of disasters on firms within business sectors. We operate under the assumption that if we understand the effect of major disruptions on manufacturing firms, for example, this will help us to better understand how a supply chain would react if the manufacturer in the chain was hit by a disaster. In other words, we are assuming that firm behavior within a business sector (e.g., manufacturing, wholesale, retail, etc.) is representative of that echelon in a supply chain. To date, there has been no research that investigates the impact of natural disasters on different echelons of the supply chain. For example, the question of whether disasters affect upstream and downstream partners of a supply chain differently remains unanswered. This paper aims to stimulate a stream of research on the impact of disasters on supply chains by providing initial results.

The objectives of this paper are twofold. First, this study offers, to the best of our knowledge, the first published investigation of the impact of catastrophic disruptions on firms within specific business sectors. It takes a first step toward understanding the effects of disasters on supply chains — although piecemeal — by exploring the impact of disasters on firms in different links in the chain. Analyzing the effects of such major disruptions on firms in the extraction (raw material supply), manufacturing, wholesale and retail sectors may provide clues about how disasters could affect different echelons of a supply chain.

Second, our analysis and results contribute to the ongoing all-hazard versus specific-hazard mitigation debate in the literature. The FEMA accepted all-hazard approach, assumes that disasters have similar impacts on humankind and frameworks for their analysis and mitigation (Scawthorn, Schneider and Schauer 2006). There is also literature that suggests that different kinds of events have different impacts on societies and economies and certain disaster-specific mitigation approaches may prove more effective (Heger, Julca and Paddison 2008). This paper tests whether natural disasters have a similar impact on firms in different sectors by first analyzing the impact of all disasters combined and then comparing those results with the outcomes of specific events.

Our analysis is built upon secondary data sources. Firm-level data are clustered into the four echelons of a typical supply chain (raw material supply, manufacturing, wholesale and finally retail) to cover the whole spectrum of material flow. We examine whether a firm's position in the supply chain makes a difference in disruption impact using fixed-effect regression.

The rest of the paper is organized as follows. The next section reviews relevant supply chain literature on risk, security and resilience. That is followed by a discussion of disaster impact on macro- and microeconomies from which hypotheses were derived. The ensuing two sections describe the study's methodology and the data sets utilized. The results are then discussed and the paper concludes with a discussion of the limitations of the study and future research directions.

SUPPLY CHAIN RISK, SECURITY AND RESILIENCE

Research on disaster impact crosses multiple focus areas within the supply chain literature: supply chain risk management, supply chain security, disruption management, vulnerability and resilience. Major disruptions paralyze the operations of one or more nodes of a supply chain significantly and for extended periods. As a firm's dependence on its customers and suppliers increases and as inventory in the system diminishes in tightly coupled supply chains, the severity of such an event will be amplified (Swaminathan 2003; Wagner and Bode 2006; Craighead et al. 2007). Traditional risk buffering approaches are no longer sufficient to deal with this new environment (Giunipero and Eltantawy 2004). For example, Ericsson lost €400 million in 2000 after a supplier's semiconductor plant caught fire. In 1998, Dole suffered large losses of revenue and market share after Hurricane Mitch destroyed their banana plantations in South America (Sheffi 2005).

Such low-frequency incidents are hard to predict and manage, thus making it difficult to justify why resources should be devoted to proactively manage such risks. If a risk never materializes the expenses incurred on risk assessment and management activities are hard to justify to top management (Zsidisin, Panelli and Upton 2000). Consequently, firms give disaster preparedness a low priority (Helferich and Cook 2002). It has been previously reported that despite the risks, 95 percent of Fortune 500 companies are not equipped to manage a disruption that the company has not experienced before (Mitroff and Alpaslan 2003).

There is evidence, on the other hand, that failure to manage supply chain risks effectively can have a significant negative impact on organizations. Such impacts include not only financial losses but also reduction in product quality, damage to assets and loss of reputation (Khan and Burnes 2007). Within the supply chain literature, significant attention has been given to routine operational risks like equipment malfunctions and transportation delays and to human-centered risks such as strikes or negligence (Kleindorfer and Saad 2005). In their empirical study across a wide range of industries, Hendricks and Singhal (2005b) found that what they referred to as supply chain glitches have a negative impact on a firm's operating performance. The good news is that firms may seem to finally realize the need to develop effective emergency response strategies within their supply chain to react and recover from inevitable supply chain disruptions (Hale and Moberg 2005).

Effective emergency response strategies require a good understanding of risks in the supply chain. Risk can be defined as "the probability of loss and the significance of that loss to the organization or individual" (Mitchell 1995, p. 116). Therefore, risk management begins with assessing the likelihood of specific events occurring and understanding their consequences should the events actually occur (Harland, Brenchley and Walker 2003; Khan and Burnes 2007; Wagner and Bode 2008).

Risk and supply chain disruption work has been studied and categorized in various ways in the supply chain literature (Chopra and Sodhi 2004; Peck 2006; Rao and Goldsby 2009). Zsidisin et al. (2000) wrote one of the early papers identifying natural catastrophes as a source for supply risk and emphasized the importance of risk assessment. Ritchie and Marshall (1993) listed sources of business and organizational risk as environmental factors, industry factors, organizational factors, problem-specific factors and decision maker-related factors. Environmental risk variables are those that affect the overall business context across industries. Jüttner, Peck and Christopher (2003) point out that supply chain risk includes disruptions affecting flow of information, materials and products across organizational boundaries. When a major disruption occurs, while the magnitude of impact across different sectors may be different, the underlying premise is that everyone in the supply chain will be affected to some extent (Kouvelis, Chambers and Wang 2006). Grounded on contingency theory, Trkman and McCormack (2009) proposed a new approach to assess supplier risk based on firm strategy, structure and performance. They suggested modifying firm attributes depending on the level of "turbulence" in the firm's specific environment. Alternatively, inspired by a methodology from the insurance industry, Knemeyer, Zinn and Eroglu (2009) developed a process to quantify the risk of different catastrophic events on key supply chain locations.

To the best of our knowledge, outside the works of Hendricks and Singhal (2003, 2005a, b) and Wagner and Bode (2008) there has not been an empirical attempt to understand the impact of disruptions on supply chain performance. The Hendricks and Singhal papers focus on the relationship between frequent operational disruptions (a mismatch between demand and supply) as announced in the newspapers and operational and equity performance. They report that all three performance measures tested, namely, operating income, return on sales and return on assets, experienced a sharp decline upon the announcement of a supply chain problem. More importantly, they show that firms do not quickly recover from the negative economic consequences of supply chain glitches.

They did not differentiate among different disruptions and did not necessarily consider the probability of various events. However, it has been argued that high-impact extreme events should not be treated in the same manner as low-impact "business-as-usual" events (Klibi, Martel and Guitouni 2010).

Wagner and Bode (2008), on the other hand, recognize that supply chain disruptions can be highly diverse with completely different attributes and therefore different effects on supply chain performance. They considered five different classes of risks, namely demand side, supply side, regulatory, infrastructure and catastrophic risks. For catastrophic risks they identified a four-item scale that captures risks originating from terrorism, sociopolitical crises, natural disasters and epidemics. Their hypothesis was that the higher the risks from catastrophes the lower the supply chain performance. However, their cross-industry survey data showed no support for this hypothesis. As Wagner and Bode (2008) also agree, these results seem to be counter to the recent direction of research and practice in supply chain risk management. It is hard to argue that catastrophic events do not affect supply chain performance when Sheffi's (2005) book *The Resilient Enterprise* is full of anecdotal evidence claiming the opposite. We believe, as Wagner and Bode (2008) also pointed out in their paper, the culprit in their counterintuitive finding may lie within respondent bias. Human beings cannot properly make judgments on things they have not previously experienced. Therefore, their results are dependent on the judgment of executives surveyed in the study. This result begs for a "double-check" based on objective statistical data and that is exactly what our study intends to do.

Another area of supply chain research that interfaces with disaster impact is supply chain security. Supply chain security has been defined as "the application of policies, procedures and technology to protect supply chain assets (product, facilities, equipment, information and personnel) from theft, damage, or terrorism and to prevent the introduction of unauthorized contraband, people, or weapons of mass destruction in the supply chain" (Closs and McGarrell 2004, p. 8). Although disaster damage is implied in this definition (e.g., with damage to assets) we found that supply chain security research has been more concerned with intentional acts to breach and disrupt a supply chain than disasters (Autry and Bobbitt 2008; Williams, Lueg and LeMay 2008).

HYPOTHESES

Because the impact of major disasters on firms in different industry sectors has not been previously investigated through the use of secondary data sources, our research takes an exploratory approach. Using three financial performance measures we try to understand how firms in a given sector would be generally affected by a disaster. We focus our attention on leverage, total asset turnover (TAT) and operational cash flow (OCF). Our hypotheses on firm performance are derived from existing literature. We test whether firms in certain sectors behave differently than expected.

Although there has been plenty of case study research focusing on specific disaster events and their costs and consequences (e.g., Tierney 1997; Horwich 2000; Selcuk and Yeldan 2001; Narayan 2003; Benson and Clay 2004; Worthington and Valadkhani 2004; Halliday 2006), empirical research on the macroeconomic impact of natural disasters has been limited. This may be because disasters are unique in the way they affect a certain location. Real long-term damages are difficult to measure and economic measures usually follow while impact is mostly on capital and labor (Tol and Leek 1999).

Dacy and Kunreuther (1969) probably established the groundwork for a theory on the economics of natural disasters. Their work suggests that the Gross Domestic Product (GDP) is generally found to increase in the periods immediately following a natural disaster. This phenomenon is later confirmed by others (Albala-Bertrand 1993; Charvériat 2000). One simple explanation for the post-event increase in GDP is simply the fact that most of the damage caused by disasters is reflected in the loss of capital and durable goods. Because stocks of capital are not measured in GDP but replacing them is, GDP increases in periods immediately following a natural disaster (Skidmore and Toya 2002). If indeed that is the case, the loss of capital and durable goods should lead firms to borrow capital in order to replace lost assets. Consequently, the financial leverage of firms should increase shortly after the catastrophic event. Because firms at all levels of the supply chain are exposed to the risk of losing equipment, infrastructure and inventory, the impact of a natural disaster on leverage should be the same across all echelons of the supply chain.

H1: A firm's financial leverage increases in response to a disaster.

Along the same lines, the impact of an external shock could be measured with TAT. TAT is a measure of efficiency, showing how many dollars of sales are generated by each dollar unit of assets. If a natural disaster damages equipment and other assets, all replacements and repairs will be added to its value, thus pushing the TAT lower. Alternatively, if there is an increase in demand, sales will also go up pressuring the TAT higher. TAT is also sensitive to changes in inventory levels. If firms increase inventory levels (assets) in response to external disturbances such as disasters, that should drive TAT down.

H2: A firm's TAT will decrease in response to a disaster.

There is pervasive evidence that disasters are becoming more economically costly (Horwich 2000). Past research also suggests that in the long term, the GDP of a country improves with natural disasters (Albala-Bertrand 1993). Using data from the EM-DAT database[1] Skidmore and Toya (2002) studied the long-term effects of natural disasters on economic growth. They found that "higher frequencies of climatic disasters are correlated with higher rates of human capital accumulation, increases in total factor productivity and economic growth" (p. 664). This increased economic activity comes from reconstruction as well as replacement of damaged equipment and property. Tomsho (1999) explains the postevent growth in economic activity with the "Jacuzzi effect." The Jacuzzi effect occurs specifically when homeowners add new or improved features to their dwellings during disaster recovery. Furthermore, federal and state emergency grant and low-interest loans act as economic stimuli. Horwich (2000) posits that the "destruction of physical assets is a form of accelerated depreciation that hastens the adoption of new technologies and varieties of investment."

Our proxy for measuring this increased economic activity is the OCF. Widely used in the finance literature, OCF concentrates on a firm's core line of business. It eliminates any nonoperational activity and accounting entries such as write-offs. Additionally, it allows us to separate any financing activities. If reconstruction efforts indeed increase local economic activity, it is reasonable to expect disaster damage to be positively correlated with OCF.

H3: A firm's OCF will increase in response to a disaster.

Research on the impact of external shocks on an individual firm's performance has been limited to mitigation strategies and contingency planning for operational glitches and supply chain disruptions such as spikes in demand, supply problems, or transportation delays (Tol and

[1]We provide detailed information on EM-DAT in the next section.

Leek 1999; Svensson 2004; Blackhurst et al. 2005; Kleindorfer and Saad 2005; Tang 2006; Craighead et al. 2007). Only recently, researchers have turned their attention to whether natural external shocks impact firm performance and the nature of their effect. Worthington and Valadkhani (2004) show that large natural disasters have an influence on market returns. The results of Ramirez and Altay (2008) support this finding.

METHODOLOGY

To test our hypotheses, fixed-effect regression is utilized. In fixed-effect estimation each firm is considered as a nonrandom or fixed parameter. The estimation procedure allows us to control for all stable characteristics (known and unknown) of the firm that could otherwise be driving our results.

Disaster Damage Measures

The key issue is the measure used to evaluate disaster damage. The number of events at a location does not necessarily translate into actual damage experienced. Frequent events striking a sparsely populated area may not cause significant damage to the local economy. For this reason we also consider the number of people affected as a proxy for potential disruptions. If a disaster affects a considerably large portion of the population in a country, it has the potential of disturbing the availability and productivity of the labor force even when little physical damage is created.

It can be argued that the number of people affected is also an imperfect measure since it does not consider physical damage to infrastructure, which may be critical to business sectors. Consequently, we consider a measure of the monetary damage a disaster causes. It can be seen that developed countries exhibit some of the greater economic losses. For example, only 6 percent of the earthquakes in our sample occurred in Japan but those events account for 58 percent of the economic losses.

The measures discussed so far render cross-country comparisons meaningless because raw figures are not normalized. For example, countries with higher populations will be more likely to exhibit a higher number of people affected. At the same time, developed countries (with more valuable assets and infrastructure) will be more likely to exhibit higher monetary damages. A better way to compare the relative impact of a disaster is to normalize the variables. We define *aff/pop* as the ratio of the total people affected by disasters by year over the population of the country. We define *dam/gdp* as the ratio of yearly monetary damage over the total GDP of the country. Higher values of these variables indicate that the disaster had a bigger impact on the country. While these measures are normalized they still have several potential problems that must be dealt with.

First, while the two variables described above are both proxies for damage and are positively correlated with each other, we believe they are hardly equivalent. For example, in our sample period Morocco had only one earthquake that reported no affected people, but US$400 million in damages. On the other extreme we see that countries such as Argentina and Australia experienced earthquakes that affected people but created no monetary damage. A second problem is that under the "affected" umbrella, a wide variety of cases could occur. Some of the affected people may need only food or clean water for a few days while others may require hospital treatment. People who need temporary shelter or food supplies are given the same weight as those who suffer severe physical injuries. Third, we lose the informational content of the frequency count of disasters. Lacking a theoretical framework one can only assume that a yearly aggregation of damages or number of people affected is the correct methodology. We have no way to know if the impact on firm performance of three small floods in 1 year is the same as one large one. Fourth, the selection of a single measure could be misleading. For example, if we only look at the number of affected people, the 2010 earthquake in Haiti affected 3,000,000 people (roughly 33 percent of the population) while the 2010 earthquake in Chile affected about 2,000,000 (roughly 15 percent of the population). A casual observer could conclude that the impact of the Haiti quake was twice as big. A look at the death toll provides a different conclusion. Almost 230,000 have been confirmed dead in Haiti (an astounding 2.56 percent of the population) while <500 in Chile (0.003 percent of the population). Under this measure, the impact of the Haiti earthquake was 800 times stronger.

The extant literature provides no theoretical framework that indicates which proxy should be the most relevant for use in a business setting. Webb, Tierney and Dahlhamer (2002) suggest that number of deaths is not a good indicator of disaster impact, while Heger et al. (2008) found that simple disaster count was most explanatory. Others proposed composite measures based on a weighted average of disaster count, death toll and monetary loss (Mao, Gu and Wu 2007). To capture the explanatory power of each parameter in our analysis, we follow Mao et al. (2007) and create a simple composite measure of disaster damage based on all available information. We define composite as follows:

$$\begin{aligned}\text{composite} = [&(0.25 \times \text{aff/pop}) + (0.25 \times k/\text{pop}) \\ &+ (0.25 \times \text{count}) + (0.25 \times \text{dam/gdp})]\end{aligned} \tag{1}$$

where aff/pop is the ratio of number of people affected over population of the country, k/pop is the number of people killed over the population of the country, count is the frequency of events and dam/gdp is the ratio of disaster damage over GDP.

Regression Model

To test if natural disasters affect the different business sectors we estimate the three firm-level indicators that we identified in previous sections: Financial Leverage, OCF and TAT. As per our hypotheses, if natural disasters affect the firm, their impact should be observed in these indicators. To test our hypotheses we run OLS fixed-effect regressions with White (1980) robust errors of the following form:

$$\begin{aligned} OP\_\text{Cashflow}_{ict} &= \alpha + \beta_1 \text{Extract}_{ct} \\ &+ \beta_2 \text{Manufacturing}_{ct} + \beta_3 \text{Whole}_{ct} \\ &+ \beta_4 \text{Retail}_{ct} + \Gamma \text{Firm}_{ict} + \Phi \text{Country}_{ct} + e_{ict} \end{aligned} \tag{2}$$

$$\begin{aligned} \text{Leverage}_{ict} &= \alpha + \beta_1 \text{Extract}_{ct} \\ &+ \beta_2 \text{Manufacturing}_{ct} + \beta_3 \text{Whole}_{ct} \\ &+ \beta_4 \text{Retail}_{ct} + \Gamma \text{Firm}_{ict} + \Phi \text{Country}_{ct} + e_{ict} \end{aligned} \tag{3}$$

$$\begin{aligned} \text{TAT}_{ict} = \alpha + \beta_1 \text{Extract}_{ct} &+ \beta_2 \text{Manufacturing}_{ct} \\ &+ \beta_3 \text{WHOLE}_{ct} + \beta_4 \text{Retail}_{ct} + \Gamma \text{Firm}_{ict} \\ &+ \Phi \text{Country}_{ct} + e_{ict} \end{aligned} \tag{4}$$

where the subscript *ict* refers to firm *i*, in country *c*, in year *t*. Extract (representing raw material supply), Manufacturing, Whole (representing wholesale) and Retail are our main explanatory variables. Each one represents the product of a disaster damage proxy (dam/gdp, aff/pop or our composite measure) times a dummy variable that takes the value of 1 for those firm-year observations belonging to the specific sector. For example, Extract takes the value of 0 if a firm is within the sector and no disaster damage was suffered in the firm's country that year. Extract will also take the value of 0 if the firm belongs to another sector. Finally extract takes the value of the damage proxy only if the firm belongs to the sector and there was damage reported in that country that year. Thus we compare firm performance in country-years where a disaster struck against all other firm-year observations in every country. Included in every regression but not shown in tables are Firm and Country that represent firm- and country-level controls, respectively. Firm-specific controls include growth opportunities, size, nondebt tax shields, business risk, cash holdings and tangibility of assets. Country-level controls include, GDP per capita, relative size of the banking sector, country risk and corruption. See the Appendix for variable definitions and sources. Additionally we include but do not report dummy variables for every year and for every two-digit SIC code.

We note that there could be a delay between the time a disaster strikes and the time its impact is reflected in the performance of the firm. For example, a firm could take many months to negotiate new loans or change existing ones. For this reason we create 1-year lagged values of our main variables and estimate our models using them.

Does Disaster Type Matter?

With the establishment of FEMA in 1977 the United States implemented an all-hazards approach to comprehensive emergency management, generalizing policies and plans for all types of emergencies (Altay and Green 2006). The logic behind this generic approach is that most human, organizational and societal aspects of mitigation planning are generic rather than specific for a disaster type. An all-hazards approach saves time and resources by avoiding duplication of efforts, increasing efficiency and avoiding political overlaps (Quarantelli 1999). Because the all-hazards approach is the standard in emergency management we begin our analysis with aggregating various catastrophic events. We pool information from the following disasters: droughts, earthquakes, epidemics, extreme temperature, floods, insect infestation, slides, volcano, wave/surge, wild fires and windstorms.

The all-hazards approach clearly has advantages for the practice of emergency management. From a research point of view, however, aggregating disaster information may hide details that may be important for our understanding of disaster impact on supply chains. Different disaster types will probably produce different kinds of damage across sectors. Earthquakes for example are more likely to destroy the infrastructure of a country — roads, bridges and power lines. An earthquake may also destroy the buildings that host factories or service providers creating long-term problems for supply chains. Alternatively, flood damage can have a shorter duration. A road may be inaccessible for days, or even weeks, but is less likely to be completely destroyed as in the case of earthquakes. The infrastructure of a country may suffer short-term stoppages but is less likely to be wiped out. A similar situation can arise from windstorms when a storm could down power lines and affect many people but the recovery and reconstruction period would be significantly shorter compared with an earthquake. Heger et al. (2008) agree and show with a Chow breakpoint test that there are distinctive differences among the impact of different disasters. We tend to agree with this point of view and estimate our models separately using information for the three different types of disasters we selected (earthquakes, floods and windstorms) to investigate whether the impact of these events are characteristically different.

Robustness Tests

It can be argued that disasters in large countries like China, Canada or the United States are going to impact only those firms close to the location of the disaster. We believe that all companies in a country can be affected by disasters regardless of physical proximity. This impact can be direct or indirect. For example, a windstorm in South Carolina can completely destroy the facilities (direct impact) of a company located there. The same storm is likely to have no physical impact on companies in Oregon, Kentucky or even Mexico. However, if the South Carolina firm had suppliers or customers in those locations they would be affected (indirect impact) nonetheless. Our firm-based analysis allows us to account for possible cross-border effects even if we cannot distinguish them. When we estimate our equations in Tables I–IV, we are comparing disaster firm-year observations (regardless of the country where the disaster took place) against those that are disaster free (regardless of the country). Despite the above analysis and for robustness, we estimate our equations excluding the largest countries in our sample — the United States, Brazil, China, Canada, Russia and India.

Firms in our sample are in general the largest public companies in each country. Based on this we could assume that have a reasonable disaster insurance coverage. If this assumption is wrong, our results could be biased. In order to control for this possibility we include in our regressions the yearly nonlife insurance consumption for each country.

Rich countries have a disproportionate number of firms in our sample. In order to ensure that our results are not determined by this, we estimate our equations excluding firms from countries belonging to the G8. Finally, to examine if potential multicollinearity between the variables could be influencing the results presented so far, we perform a Variance Inflation Factor test (Marquardt 1970).

DATA

Disaster Data

Disaster data are compiled from EM-DAT (http://www.emdat.be/), a database maintained by the Center for Research on the Epidemiology of Disasters (CRED) at the Catholic University of Louvain (Belgium) and the Disaster Data Base Project maintained by the University of Richmond (USA). The EM-DAT data are compiled from different sources such as the United Nations, the U.S. Office of Foreign Disaster Assistance, reinsurance firms, humanitarian organizations and news agencies. The database lists individual events in chronological order and includes date, type of disaster, several measures of affected population, damage estimates and notes about the main sources of data for any particular event.

In the EM-DAT database, disasters are placed in three categories (natural, technological and conflict) each with several subcategories. In this research, we focus on natural disasters, i.e., events that are clearly exogenous to the firm and country which happened between 1990 and 2004. Moreover, we consider only those natural disasters that have rapid onset, rather than those that develop through an extended period of time, such as droughts and famines. This leaves us with earthquakes, floods, wild fires, windstorms, waves and surges, extreme temperatures, volcano episodes and mud slides. From these events, we believe the most important ones are floods and windstorms because they are the most common occurrences and earthquakes since they create the highest damage.

Firm-Level Data

Firm-level data for this study were obtained from Worldscope for the period 1990–2004. It includes firm-year observations for 53 countries. We exclude firms in the financial sector (SIC codes 6000–6999) because many of their decisions could be the result of government regulation or arise for reasons different from those discussed in earlier. We also exclude other regulated industries for similar reasons; these industries include utilities (SIC codes 4300–4399) and postal services (SIC codes 4900–4999). Finally, firm-years with errors such as negative values for sales, total assets, total liabilities, current liabilities, long-term debt and total debt are also excluded. The final sample is comprised of over 150,000 firm-year observations.

In order to study different business sectors, we break our sample into four groups by SIC code: extraction, manufacturing, wholesale and retail (the Appendix provides detailed explanations of the industries). It can be seen that most firms (over 70 percent of firm-year observations) in our sample belong to the manufacturing sector. We note that our sample includes most publicly traded firms in each country and therefore it should be representative of the large firms and not necessarily of the whole economy. For this reason, in some countries such as Turkey and Taiwan, the firms seem to be concentrated in one or two sectors. In others like the United States and the United Kingdom, firms are more diversified.

RESULTS AND DISCUSSION

All-Disasters Approach

Table I shows the results of estimating OCF, financial leverage and TAT using all disasters combined. The first two columns include our monetary proxy for disaster impact; columns 3 and 4 include the number of affected people and columns 5 and 6 include our composite measure. It can be seen that when we use our monetary damage proxy, the coefficients for every sector are negative and significant. All sectors of our sample suffer a decrease in OCF after a disaster. Additionally, the coefficients for our lagged variables are also negative and significant, indicating that this decrease in cash flow is persistent over time. If we analyze results using our people affected proxy we see that for most sectors there is no correlation between disaster damage and cash flow. Only the coefficient for manufacturing is significant but positive, contradicting the results obtained with the monetary proxy. This highlights the importance of a theoretically relevant and empirically sound damage proxy. When we turn to our composite measure, we see support for the negative impact of disasters on firm cash flows.

Table I's panel B shows the results of estimating the impact of natural disasters on financial leverage. Results using our monetary proxy suggest a positive and time-persistent correlation between financial leverage and disaster damage for all sectors with the exception of extractive industries. Firms in manufacturing, wholesale and retail see an

TABLE I

Disaster Damage (All Disasters Combined)

	DAM US$/GDP (Event Year)	DAM US$/GDP (1 Year Lagged)	AFF/POP (Event Year)	AFF/POP (1 Year Lagged)	Composite Measure (Event Year)	Composite Measure (1 Year Lagged)
Panel A — Operational Cash Flow						
Intercept	− 0.44255***	− 0.36084***	− 0.52471***	− 0.50906***	− 0.52379***	− 0.50849***
	(− 8.72)	(− 7.08)	(− 10.32)	(− 9.97)	(− 10.31)	(− 9.97)
Extraction	− 36.87669***	− 34.15513***	− 0.01271	− 0.00614	− 0.00919***	− 0.00915***
	(− 3.35)	(− 3.1)	(− 1.2)	(− 0.57)	(− 4.52)	(− 4)
Lag extraction		− 39.59689***		− 0.03671***		− 0.00023597
		(− 3.61)		(− 3.4)		(− 0.11)
Manufacturing	− 45.29575***	− 39.06554***	0.01813***	0.01901***	− 0.0021***	− 0.00281***
	(− 19.24)	(− 16.44)	(2.76)	(2.85)	(− 3.69)	(− 4.68)
Lag manufacturing		− 42.50994***		− 0.00516		0.00239***
		(− 17.99)		(− 0.77)		(4.07)
Wholesale	− 52.2117***	− 47.97032***	0.02091	0.02083	− 0.00182	− 0.00233*
	(− 8.72)	(− 8)	(1.36)	(1.34)	(− 1.5)	(− 1.87)
Lag wholesale		− 52.54704***		− 0.00185		0.00238**
		(− 8.79)		(− 0.12)		(1.97)
Retail	− 53.36954***	− 51.90418***	0.01782	0.01844	0.00148	− 0.00040486
	(− 7.57)	(− 7.37)	(1.21)	(1.24)	(1.06)	(− 0.27)
Lag retail		− 55.93254***		− 0.00741		0.00463***
		(− 7.97)		(− 0.5)		(3.16)
	107,068	107,027	107,068	107,027	107,068	107,027
	0.165	0.1685	0.1612	0.1613	0.1614	0.1615
Panel B — Financial Leverage						
Intercept	0.50662***	0.50291***	0.50977***	0.50912***	0.50788***	0.50714***
	(51.96)	(51.26)	(52.32)	(51.98)	(52.15)	(51.85)
Extraction	− 0.66713	− 0.49975	0.00118	0.00128	− 0.00065146*	− 0.00028732
	(− 0.31)	(− 0.23)	(0.57)	(0.61)	(− 1.65)	(− 0.65)
Lag extraction		− 1.99161		− 0.00050837		− 0.00071413*
		(− 0.93)		(− 0.24)		(− 1.77)
Manufacturing	2.04174***	1.77395***	0.00004266	− 0.00012255	− 0.00033717***	− 0.0002012*
	(4.45)	(3.83)	(0.03)	(− 0.09)	(− 3.06)	(− 1.73)
Lag manufacturing		1.90756***		0.00103		− 0.00042321***
		(4.14)		(0.8)		(− 3.72)
Wholesale	2.11656*	1.88286	− 0.0017	− 0.0015	− 0.00106***	− 0.00088965***
	(1.82)	(1.61)	(− 0.57)	(− 0.5)	(− 4.49)	(− 3.68)

TABLE I Continued

	DAM US$/GDP (Event Year)	DAM US$/GDP (1 Year Lagged)	AFF/POP (Event Year)	AFF/POP (1 Year Lagged)	Composite Measure (Event Year)	Composite Measure (1 Year Lagged)
Lag wholesale		2.90916**		– 0.00158		– 0.00080545***
		(2.5)		(– 0.53)		(– 3.44)
Retail	2.71368**	2.59367*	0.00333	0.00339	0.00024019	0.00027936
	(1.98)	(1.89)	(1.16)	(1.18)	(0.88)	(0.95)
Lag retail		4.64468***		– 0.00056059		– 0.00009712
		(3.39)		(– 0.2)		(– 0.34)
	107,068	107,027	107,068	107,027	107,068	107,027
	0.2311	0.2314	0.2309	0.231	0.2312	0.2314
Panel C — Total Asset Turnover						
Intercept	1.12863***	1.13506***	1.10969***	1.10582***	1.09064***	1.07917***
	(14.52)	(14.53)	(14.27)	(14.14)	(14)	(13.79)
Extraction	– 3.91512	– 13.50804	0.00879	0.00616	– 0.00037959	– 0.00069937
	(– 0.18)	(– 0.61)	(0.56)	(0.38)	(– 0.12)	(– 0.2)
Lag extraction		102.68911***		0.01457		0.00073921
		(4.05)		(0.91)		(0.24)
Manufacturing	– 9.8387	– 9.20166′	0.02455**	0.02283**	– 0.00227***	– 0.0016*
	(– 1.42)	(– 1.32)	(2.46)	(2.25)	(– 2.62)	(– 1.77)
Lag manufacturing		– 6.72105		0.01049		– 0.00246***
		(– 1.18)		(1.06)		(– 2.78)
Wholesale	– 52.68656***	– 49.7616***	– 0.02247	– 0.02073	– 0.00826***	– 0.0071***
	(– 2.83)	(– 2.67)	(– 0.97)	(– 0.89)	(– 4.48)	(– 3.78)
Lag wholesale		– 36.95646***		– 0.01254		– 0.00635***
		(– 2.62)		(– 0.55)		(– 3.48)
Retail	– 109.91956***	– 105.61389***	0.00021192	– 0.0009201	– 0.0049**	– 0.00372*
	(– 3.91)	(– 3.75)	(0.01)	(– 0.04)	(– 2.33)	(– 1.64)
Lag retail		– 61.03971***		0.01036		– 0.00312
		(– 3.39)		(0.48)		(– 1.42)
	107,068	107,027	107,068	107,027	107,068	107,027
	0.0829	0.0832	0.0828	0.0828	0.083	0.0832

Numbers in parentheses are *t* values. Stars indicate significance level:
*10%, **5%, ***1%.

increase in their total liabilities as an aftermath of a disaster. This increase in debt use continues even 1 year after the disaster. Using our people affected proxy we do not observe any significant correlation, however, our composite proxy for damage identifies a decrease in leverage for all sectors. These conflicting results are hard to reconcile and confirm the importance of using all available information when creating a proxy for damage. Additionally, these results could be a pitfall of aggregating different disasters.

Panel C of Table I shows the impact of disaster damage on TAT. Results from using our monetary and composite proxies show that the coefficients for wholesale and retail are negative and statistically significant. Results using our people proxy are not significant. In general, firms become less efficient in managing their assets (lower sales as a percentage of assets) after a disaster. If we consider the reported decrease in operating cash flows for all sectors, the loss in asset management efficiency could arise from a drop in sales. We explore this possibility by comparing (sector by sector) the sales and asset levels of firm-years that experienced a disaster against those firm-years without a disaster. We find that sales in disaster years are generally higher than sales of disaster-free years. This means that the decrease in asset turnover must be due to an increase in the asset side. One explanation is that besides investing in repairs, firms in the wholesale and retail sector also invest in building inventories. We find that inventories of disaster years are significantly higher than those of years with no disasters.

Disaster-Specific Impact

Given our analysis in the previous sections and the results reported using pooled disaster damage we test whether different disasters have different impacts on firms. Consequently, we proceed to split our disaster data by type. Tables II–IV analyze how different types of catastrophes affect firm OCF, financial leverage and TAT, respectively. We divide our tables in three panels. Panel A shows the impact of earthquakes on our firm performance proxies. Panels B and C are concerned with the impact of windstorms and floods, respectively.

Impact on OCFs. Results of estimating the impact of disaster damage on OCFs are presented in Table II. It can be seen in the first column of panel A that earthquake monetary damage is negatively correlated with the OCF of the firm. With the exception of extractive industries, all links of the supply chain exhibit negative and statistically significant coefficients. The second column shows that even after 1 year of the occurrence of the earthquake, firm OCF continues to be negatively affected. We interpret these results as an indicator that earthquakes disrupt the normal operations of all business sectors. Columns 3 and 4 show the results using affected people as the proxy for earthquake damage. OCFs are generally negatively correlated to earthquake damage. We note, however, that the coefficient for extractive industries is positive. Given the nature of the proxies for damage we turn to our composite measure, which is shown in columns 5 and 6. Using all information available our equally weighted measure shows that cash flows for all sectors is negatively correlated with earthquake damage. These results underscore the importance of the choice of damage proxy.

Panel B in Table II shows regression results of estimating the impact of windstorms on OCF. It can be seen that in general, the coefficients for most sectors in our sample are positive and statistically significant, regardless of the damage proxy used. The main exceptions are the coefficients for the extraction industry, which are not significantly different from zero using both people affected and our composite measure. This marks an interesting contrast with the results obtained for earthquakes, which were all negative except for extractive industries. We propose the following two-part explanation for this result. First, windstorms are more predictable than earthquakes (many windstorms are due to hurricanes and tornadoes that are seasonal) and thus allow for more preparation compared with earthquakes, which occur without any warning. If this assumption is correct, then we should observe similar results with floods because they are similar to windstorms, being relatively seasonal and predictable. Second, the aftermath of a disaster creates an increase in demand for certain goods and services. If the disaster is relatively predictable such as climatic events, then goods can be stocked as the event approaches and after it hits. Earthquakes not only do not allow time for any prestocking but commonly ruin national and business infrastructure so that postevent demand cannot be met. Assuming the infrastructure of the country and firm remains relatively intact after a flood or windstorm, this higher demand will be translated into higher operations cash flows. We note that the after-windstorm OCF increase does not last past the year of the event.

Results based on floods are presented in panel C of Table II. The coefficients for our every damage proxy for damage strongly support a postwindstorm OCF increase in every sector in our sample. This is in line with our explanation that windstorms, similar to floods, are somewhat predictable and thus allow firms to stock goods and supplies before and after the arrival of the disaster. The impact of a flood is an increase in firm OCFs in most sectors of our sample. Additionally, this positive effect tends to last for more than 1 year for wholesale and retail sectors.

Impact on Financial Leverage. Results of estimating the impact of disaster damage on financial leverage are presented in Table III that follows the same format as Table II. Panel A shows a positive correlation between leverage and lagged values of earthquake damage using our monetary proxy. This result is consistent with leverage being a variable that firms cannot alter very quickly. Using people affected and our composite measure, we can see that firms in the extractive sector tend to decrease their leverage after an earthquake; there is some evidence that this deleveraging could last more than 1 year.

TABLE II

Operational Cash Flows

	DAM US$/GDP (Event Year)	DAM US$/GDP (1 Year Lagged)	AFF/POP (Event Year)	AFF/POP (1 Year Lagged)	Composite Measure (Event Year)	Composite Measure (1 Year Lagged)
Panel A — Earthquakes						
Intercept	– 0.49153***	– 0.42964***	– 0.50344***	– 0.47387***	– 0.51466***	– 0.50126***
	(– 9.69)	(– 8.47)	(– 9.93)	(– 9.32)	(– 10.16)	(– 9.89)
Extraction	– 6.15364	– 5.95604	0.22587**	0.20055*	– 0.00012033***	– 0.00010461***
	(– 0.64)	(– 0.62)	(2.16)	(1.85)	(– 3.25)	(– 2.81)
Lag extraction		– 35.28678***		0.07013		– 0.00015205***
		(– 3.69)		(0.65)		(– 4.09)
Manufacturing	– 16.75844***	– 14.78023***	– 0.49468***	– 0.39422***	– 0.00007479***	– 0.00007014***
	(– 12.25)	(– 10.83)	(– 11.34)	(– 8.95)	(– 18.18)	(– 17.07)
Lag manufacturing		– 35.96852***		– 0.68678***		– 0.00008468***
		(– 26.64)		(– 15.68)		(– 20.82)
Wholesale	– 26.01764***	– 26.86139***	– 0.77572***	– 0.69253***	– 0.00012099***	– 0.00012379***
	(– 6.49)	(– 6.74)	(– 5.84)	(– 5.2)	(– 9.61)	(– 9.87)
Lag wholesale		– 54.8124***		– 1.02792***		– 0.00013966***
		(– 13.82)		(– 7.74)		(– 11.15)
Retail	– 18.07042***	– 20.28644***	– 0.58106***	– 0.57003***	– 0.00011152***	– 0.00011459***
	(– 4.41)	(– 4.98)	(– 4.5)	(– 4.42)	(– 8.79)	(– 9.05)
Lag retail		– 51.97998***		– 0.87637***		– 0.00013894***
		(– 12.82)		(– 6.81)		(– 11)
	107,068	107,027	107,068	107,027	107,068	107,027
	0.1627	0.1706	0.163	0.1651	0.1653	0.1703
Panel B — Windstorms						
Intercept	– 0.63408***	– 0.67505***	– 0.52297***	– 0.51222***	– 0.56912***	– 0.56148***
	(– 12.42)	(– 13.11)	(– 10.3)	(– 10.04)	(– 11.19)	(– 10.97)
Extraction	57.61286***	47.14515***	– 0.0115	– 0.01193	– 0.00002813	– 0.00004482
	(5.59)	(4.48)	(– 1.4)	(– 1.34)	(– 1.31)	(– 1.29)
Lag extraction		50.20197***		0.01352		0.00003798*
		(4.97)		(1.57)		(1.64)
Manufacturing	49.40264***	43.88445***	0.01447***	0.01375***	0.00020655***	0.00019511***
	(16.28)	(14.18)	(3.11)	(2.95)	(11.45)	(10.45)
Lag manufacturing		27.99603***		0.00752*		0.0000429**
		(9.29)		(1.63)		(2.31)
Wholesale	30.11217***	29.67408***	0.01121	0.01011	0.00025452***	0.00025982***
	(3.93)	(3.8)	(0.91)	(0.81)	(4.59)	(4.58)

TABLE II Continued

	DAM US$/GDP (Event Year)	DAM US$/GDP (1 Year Lagged)	AFF/POP (Event Year)	AFF/POP (1 Year Lagged)	Composite Measure (Event Year)	Composite Measure (1 Year Lagged)
Lag wholesale		6.15257′		0.0077		− 0.00002913
		(0.81)		(0.62)		(− 0.53)
Retail	90.31484***	86.3202***	0.02065*	0.01999*	0.00030232***	0.00030165***
	(10.33)	(9.77)	(1.67)	(1.63)	(5.17)	(5.11)
Lag retail		32.24489***		0.00572		− 0.00001584
		(3.84)		(0.47)		(− 0.27)
	107,068	107,027	107,068	107,027	107,068	107,027
	0.1641	0.1649	0.1612	0.1615	0.1625	0.1631
Panel C — Flood						
Intercept	− 0.55064***	− 0.53958***	− 0.60455***	− 0.61034***	− 0.52225***	− 0.51245***
	(− 10.84)	(− 10.57)	(− 11.81)	(− 11.83)	(− 10.29)	(− 10.05)
Extraction	59.11932***	53.65831***	0.06743***	0.0542***	0.00000363	0.0000028
	(4.99)	(4.43)	(3.76)	(2.59)	(1.15)	(0.77)
Lag extraction		26.91977**		0.02829		0.00000174
		(2.24)		(1.35)		(0.48)
Manufacturing	31.9843***	31.8857***	0.05127***	0.04349***	0.00000337**	0.00000298**
	(10.34)	(10.18)	(10.79)	(8.26)	(2.38)	(2.07)
Lag manufacturing		0.69447		0.01912***		0.00000207
		(0.22)		(3.65)		(1.43)
Wholesale	49.39301***	45.10268***	0.08965***	0.06973***	0.00029304***	0.00026274***
	(4.25)	(3.77)	(5.16)	(3.23)	(5.26)	(4.66)
Lag wholesale		17.28803		0.03618*		0.00020533***
		(1.45)		(1.68)		(3.66)
Retail	114.45522***	108.18604***	0.08505***	0.05451*	0.00028471***	0.00024231***
	(7.72)	(7.26)	(3.59)	(1.93)	(4.23)	(3.51)
Lag retail		60.06815***		0.05899**		0.00019157***
		(4.06)		(2.09)		(2.78)
	107,068	107,027	107,068	107,027	107,068	107,027
	0.1627	0.1627	0.1623	0.1624	0.1615	0.1616

Numbers in parentheses are *t* values. Stars indicate significance level:
*10%, **5%, ***1%.

TABLE III

Financial Leverage

	DAM US$/GDP (Event Year)	DAM US$/GDP (1 Year Lagged)	AFF/POP (Event Year)	AFF/POP (1 Year Lagged)	Composite Measure (Event Year)	Composite Measure (1 Year Lagged)
Panel A — Earthquakes						
Intercept	0.50961***	0.50753***	0.50976***	0.50894***	0.50993***	0.50962***
	(52.35)	(51.89)	(52.39)	(52.07)	(52.42)	(52.16)
Extraction	– 0.91683	– 0.91333	– 0.09642***	– 0.08181***	– 0.00001722**	– 0.00001605**
	(– 0.49)	(– 0.49)	(– 4.74)	(– 3.89)	(– 2.39)	(– 2.21)
Lag extraction		0.55831		– 0.05645***		– 0.00001006
		(0.3)		(– 2.69)		(– 1.39)
Manufacturing	0.0651	0.00706	0.00191	– 0.00108	0.00000226***	0.00000213***
	(0.24)	(0.03)	(0.22)	(– 0.13)	(2.82)	(2.66)
Lag manufacturing		1.16268***		0.01781**		0.00000252***
		(4.4)		(2.09)		(3.17)
Wholesale	1.09642	1.12666	– 0.00622	– 0.00777	0.0000078***	0.00000795***
	(1.41)	(1.45)	(– 0.24)	(– 0.3)	(3.19)	(3.25)
Lag wholesale		2.53602***		0.01641		0.00000855***
		(3.27)		(0.63)		(3.5)
Retail	0.16023	0.23983	– 0.01865	– 0.01914	0.00000176	0.00000186
	(0.2)	(0.3)	(– 0.74)	(– 0.76)	(0.71)	(0.75)
Lag retail		1.80011**		0.02067		0.0000031
		(2.27)		(0.83)		(1.26)
	107,068	107,027	107,068	107,027	107,068	107,027
	0.2309	0.2312	0.2311	0.2317	0.2315	0.2331
Panel B — Windstorms						
Intercept	0.51531***	0.51394***	0.51133***	0.51092***	0.51551***	0.51681***
	(52.57)	(51.91)	(52.53)	(52.23)	(52.84)	(52.65)
Extraction	2.03233	1.90294	– 0.00328**	– 0.0027	– 0.00001997***	– 0.00001462***
	(1.01)	(0.93)	(– 2.06)	(– 1.61)	(– 4.78)	(– 3.2)
Lag extraction		0.59902		– 0.0018′		– 0.0000126***
		(0.31)		(– 1.08)		(– 2.76)
Manufacturing	– 2.67803***	– 2.69664***	– 0.00276***	– 0.00275***	– 0.00001936***	– 0.00001726***
	(– 4.53)	(– 4.48)	(– 3.07)	(– 3.04)	(– 5.52)	(– 4.76)
Lag manufacturing		0.13977		– 0.00011579		– 0.00000787**
		(0.24)		(– 0.13)		(– 2.18)

TABLE III Continued

	DAM US$/GDP (Event Year)	DAM US$/GDP (1 Year Lagged)	AFF/POP (Event Year)	AFF/POP (1 Year Lagged)	Composite Measure (Event Year)	Composite Measure (1 Year Lagged)
Wholesale	– 1.23524	– 1.65338	– 0.00774***	– 0.00754***	– 0.00004633***	– 0.00004069***
	(– 0.83)	(– 1.09)	(– 3.22)	(– 3.12)	(– 4.3)	(– 3.69)
Lag wholesale		2.08961		– 0.00179		– 0.000026**
		(1.42)		(– 0.75)		(– 2.42)
Retail	– 3.69227**	– 3.90997**	– 0.00072381	– 0.00111	– 0.00002574**	– 0.00002425**
	(– 2.17)	(– 2.27)	(– 0.3)	(– 0.46)	(– 2.26)	(– 2.11)
Lag retail		1.70221		0.00414*		– 0.00000446
		(1.04)		(1.74)		(– 0.39)
	107,068	107,027	107,068	107,027	107,068	107,027
	0.2311	0.2312	0.2313	0.2313	0.2316	0.2317
Panel C — Flood						
Intercept	0.50614***	0.50389***	0.5055***	0.5023***	0.50999***	0.5097***
	(51.93)	(51.42)	(51.42)	(50.68)	(52.41)	(52.15)
Extraction	– 3.37645	– 3.51346	– 0.00386	– 0.0057	0.0000008907164	0.0000004290252
	(– 1.47)	(– 1.49)	(– 1.11)	(– 1.4)	(1.45)	(0.61)
Lag extraction		0.66326		0.00393		0.000000920488
		(0.28)		(0.97)		(1.3)
Manufacturing	3.64205***	3.31321***	0.00295***	0.0017*	– 0.00000118***	– 0.000000998296***
	(6.06)	(5.44)	(3.19)	(1.66)	(– 4.31)	(– 3.56)
Lag manufacturing		2.1919***		0.00297***		– 0.000000951452***
		(3.64)		(2.91)		(– 3.4)
Wholesale	2.81616	2.16943	0.00199	– 0.00001026	– 0.00001647	– 0.00001447
	(1.25)	(0.93)	(0.59)	(0)	(– 1.52)	(– 1.32)
Lag wholesale		2.74062		0.00376		– 0.00001472
		(1.19)		(0.9)		(– 1.35)
Retail	5.53333*	5.05357*	0.00505	0.00177	– 0.00001935	– 0.0000164
	(1.92)	(1.75)	(1.1)	(0.32)	(– 1.48)	(– 1.22)
Lag retail		4.72569*		0.00646		– 0.00001388
		(1.64)		(1.18)		(– 1.04)
	107,068	107,027	107,068	107,027	107,068	107,027
	0.2312	0.2314	0.231	0.2311	0.2311	0.2313

Numbers in parentheses are *t* values. Stars indicate significance level: *10%, **5%, ***1%.

TABLE IV

Total Asset Turnover

	DAM US$/GDP (Event Year)	DAM US$/GDP (1 Year Lagged)	AFF/POP (Event Year)	AFF/POP (1 Year Lagged)	Composite Measure (Event Year)	Composite Measure (1 Year Lagged)
Panel A — Earthquakes						
Intercept	1.12204***	1.12292***	1.11861***	1.11749***	1.11848***	1.11623***
	(14.45)	(14.4)	(14.41)	(14.33)	(14.4)	(14.32)
Extraction	9.89274	9.52742	– 0.05278	– 0.04114	0.00008589	0.00007895
	(0.51)	(0.5)	(– 0.34)	(– 0.25)	(1.32)	(1.2)
Lag extraction		10.85255		– 0.05156		0.00004178
		(0.55)		(– 0.31)		(0.74)
Manufacturing	– 5.82047*	– 6.04288*	– 0.06834	– 0.05748	– 0.00001407*	– 0.00001441*
	(– 1.84)	(– 1.91)	(– 0.82)	(– 0.68)	(– 1.62)	(– 1.66)
Lag manufacturing		– 4.68321*		– 0.09296		– 0.00001442**
		(– 1.79)		(– 1.21)		(– 2.06)
Wholesale	12.67742	12.26463	– 0.42996	– 0.35907	– 0.00000725	– 0.00000805
	(1.02)	(0.98)	(– 1.51)	(– 1.25)	(– 0.18)	(– 0.2)
Lag wholesale		– 4.45096		– 0.4849*		– 0.00002982
		(– 0.51)		(– 1.95)		(– 1.23)
Retail	– 20.55363**	– 20.99441**	– 0.69544***	– 0.67095***	– 0.00008338***	– 0.00008443***
	(– 2.04)	(– 2.08)	(– 2.85)	(– 2.75)	(– 2.74)	(– 2.77)
Lag retail		– 17.35809*		– 0.67758***		– 0.00008569***
		(– 1.93)		(– 2.96)		(– 3.25)
	99,379	107,027	99,379	107,027	99,379	107,027
	0.0831	0.0832	0.0828	0.083	0.0834	0.0841
Panel B — Windstorms						
Intercept	1.08543***	1.053***	1.12194***	1.12284***	1.11014***	1.10504***
	(13.86)	(13.31)	(14.43)	(14.38)	(14.24)	(14.08)
Extraction	– 19.72772	– 17.28716	– 0.00801	– 0.00592	– 0.00002054	– 0.00001323
	(– 1.28)	(– 1.1)	(– 0.66)	(– 0.46)	(– 0.65)	(– 0.38)
Lag extraction		– 10.19703		– 0.0062		– 0.00001946
		(– 0.68)		(– 0.49)		(– 0.56)
Manufacturing	7.75284*	4.64915	– 0.00953	– 0.0097	0.00003135	0.00002387
	(1.69)	(0.99)	(– 1.35)	(– 1.37)	(1.17)	(0.86)
Lag manufacturing		15.48658***		0.00253		0.00002812
		(3.35)		(0.37)		(1.01)
Wholesale	33.94516***	34.09663***	– 0.01971	– 0.01562	0.00000395	0.00001658
	(2.9)	(2.85)	(– 1.07)	(– 0.84)	(0.05)	(0.2)

TABLE IV Continued

	DAM US$/GDP (Event Year)	DAM US$/GDP (1 Year Lagged)	AFF/POP (Event Year)	AFF/POP (1 Year Lagged)	Composite Measure (Event Year)	Composite Measure (1 Year Lagged)
Lag wholesale		2.22576′		−0.03524*		−0.00005884
		(0.19)		(−1.93)		(−0.69)
Retail	57.84712***	51.56915***	0.05684***	0.05685***	0.00011861	0.00010147
	(4.36)	(3.84)	(3.1)	(3.09)	(1.37)	(1.16)
Lag retail		40.92346***		0.00114		0.00011652
		(3.11)		(0.06)		(1.3)
	107,068	107,027	107,068	107,027	107,068	107,027
	0.08	0.0831	0.0828	0.0829	0.0832	0.0832
Panel C — Flood						
Intercept	1.11694***	1.11685***	1.09895***	1.09067***	1.12531***	1.12766***
	(14.36)	(14.28)	(13.99)	(13.76)	(14.49)	(14.46)
Extraction	4.66312	5.63941	0.03758	0.02945	0.0000002	0.0000002829246
	(0.26)	(0.31)	(1.43)	(0.96)	(0.05)	(0.05)
Lag extraction		−5.19377		0.01632		−0.000000161404
		(−0.29)		(0.53)		(−0.03)
Manufacturing	3.96352	3.97727	0.02272***	0.01677**	0.0000002	0.0000001123934
	(0.84)	(0.83)	(3.17)	(2.12)	(0.08)	(0.05)
Lag manufacturing		0.2157		0.01337*		0.0000002357939
		(0.05)		(1.71)		(0.1)
Wholesale	−16.03554	−14.19962	−0.07149***	−0.0426	−0.0001552*	−0.00014107*
	(−0.93)	(−0.79)	(−2.73)	(−1.32)	(−1.89)	(−1.7)
Lag wholesale		−7.61478		−0.04798		−0.00010567
		(−0.43)		(−1.5)		(−1.25)
Retail	−23.40196	−21.87638	−0.15799***	−0.11809***	−0.00034604***	−0.00029913***
	(−1.06)	(−0.98)	(−4.53)	(−2.84)	(−3.49)	(−2.93)
Lag retail		−14.18947		−0.07115*		−0.00020715**
		(−0.64)		(−1.71)		(−2.04)
	107,068	107,027	107,068	107,027	107,068	107,027
	0.0827	0.0827	0.0831	0.0833	0.0829	0.0835

Numbers in parentheses are *t* values. Stars indicate significance level:
*10%, **5%, ***1%.

Panel B shows the effects of windstorms on firm financial leverage. It can be seen that in general windstorms tend to reduce the leverage of firms, regardless of the proxy we use. Additionally, we see that our composite measure provides the best results. Panel C shows the effects of floods on firm leverage. Using our monetary and people proxies, we see a positive correlation between damage and leverage. This result seems to contradict our explanation of similarities between floods and windstorms described above. However, if we look at results using our composite measure we can see that the coefficients are negative. We conclude that damages from floods and windstorms are negatively correlated with leverage while damage from earthquakes tends to increase it.

Impact on TAT. To conclude the analysis of the impacts of disasters on business sectors, we consider the proxy for asset management — TAT. Results are presented in Table IV. Panel A shows that TAT of firms in extractive and wholesale sectors do not seem to be correlated with earthquake damage. However, the manufacturing and retail sectors exhibit coefficients that are negative and significant, regardless of the damage proxy. These results are similar to those obtained when all disasters where combined.

Panel B shows the results of estimating asset turnover after a windstorm. Here our monetary proxy shows an increase in asset turnover for manufacturing, wholesale and retail. Our people proxy shows a positive correlation only for the retail sector. Our composite measure, however, fails to identify any significant correlation. Given the results of our composite measure it is hard to draw conclusions from these results. Finally, panel C of Table III shows the impact of floods on TAT. Looking at the results for people affected, there is evidence that after a flood, firms in the manufacturing sector exhibit an increase in their TAT, while those firms in wholesale and retail show a decline. Interestingly, the coefficients using the monetary damage proxy are not significantly different from zero. Our composite measure confirms the negative correlation for wholesalers and retailers but fails to identify a significant correlation for firms in the manufacturing and extractive sector. These results are also consistent with those obtained from combining disasters.

Robustness Results

As we indicated earlier, we perform a series of robustness tests to make sure our results are not the product of spurious relationships. We first proceed to exclude from our sample those countries that are geographically large. Results presented in this section are not altered by this exclusion. The same can be said for the exclusion of firms from the G8, which represent a large proportion of the firms in our sample. Their exclusion does not alter our findings. We then control for insurance consumption at the country level because this could be a factor that affects the relationship between disasters and firm performance. Our results indicate that insurance consumption does not alter the findings presented so far. Finally, the VIF test indicates that multicollinearity between our variables is not a problem.

CONCLUSIONS, LIMITATIONS AND RESEARCH DIRECTIONS

Disaster preparedness has been traditionally given a low priority among most supply chain managers. This is due to competing business initiatives, a lack of recognition of the true level of disaster vulnerability and the difficulty in justifying allocating resources for events that are hard to predict and manage (Helferich and Cook 2002). However, in the last decade a plethora of anecdotal evidence of disasters disrupting business around the world leaves no question about whether natural disasters affect business activity and impact firm performance. Therefore, the impact of disasters on different echelons of supply chains needs to be investigated. This paper makes three important contributions to the literature. First, the study provides a first step in understanding this issue. We approach the problem indirectly by investigating the impact of natural disasters on firms in different industry sectors, which provides us with information about how supply chain echelons can be affected. This approach allows us to take full advantage of large secondary databases of firm and disaster data in order to analyze the impact of over 3,500 disasters on more than 100,000 firm-year observations. Using fixed-effect regressions we explain how natural disasters impact firms in different industry sectors. Our results indicate that disasters impact the performance of firms — as measured with cash flow, leverage and TAT — in different sectors but not necessarily in the same way.

The second important contribution to the literature consists of providing empirical evidence to advance the all-disasters-combined versus disaster-specific mitigation debate. While emergency management practitioners and researchers prefer an all-hazard approach to mitigation planning, there is compelling evidence (Heger et al. 2008) that suggests different disaster types impact businesses in different ways. We present the case for separation of disasters at the very least for research purposes. Our results support Heger, Julca and Paddison's view indicating that different disasters impact firms differently. The impact of damage from windstorms and floods seem to be dramatically different from that of an earthquake. While the latter decreases OCF the former two increase it. We attribute this to the predictability of climatic events (windstorms and floods) and firms' ability to prepare ahead of time. Earthquakes do not allow for any preparation time and can also destroy national and firm infrastructure making recovery very slow. We also show that the impact of floods on TAT of a firm is dependent on the firm's position in the supply chain. We found that while upstream partners enjoy a positive impact, downstream partners have to plan for the opposite. These results are consistent with the study of Stecke and Kumar (2009), which suggests that the threat posed by a disaster depends on firm-specific factors such as industry, location, culture, political environment and preparedness level.

The third important contribution relates to the measurement of disaster damage. We show how measuring disasters using a single measure, frequency count, monetary damage or people affected could be misleading. We create a simple composite measure and find that results using this measure are more stable.

These results hold important managerial implications. The fact that disasters affect all sectors implies that mitigation for catastrophic disruptions should be a supply chain–wide practice. A firm that is not prepared will disrupt the operations of the rest of the supply chain. Although catastrophes are perceived to be low-probability events, certain countries due to their climate or geographic location carry significantly higher probabilities of occurrence (e.g., mudslides in the Philippines, hurricanes in the Atlantic, earthquakes in the Aegean Sea or sandstorms in North Africa are common events). Firms outsourcing from these regions should seriously consider the possibility of major disruptions seriously and plan accordingly.

Limitations of Secondary Data

In this research we used secondary data and some of the concerns that are inherent to the EM-DAT database must be addressed. First, it is difficult to compare the quality of the sources of information, especially for earlier events (EM-DAT data starts in 1900). Here the issue is not only the emphasis different sources give to different data but also the frequency of reporting. The institutional infrastructure of disaster aid significantly improved throughout the 20th century. Thus, it is reasonable to assume that data on catastrophic events have been collected more systematically by authorities in the later part of the century. Furthermore, multiple sources of information reporting on the same event but with minute differences in numbers occasionally cause duplicate entries of the same incident in the database. Because the time period of our panel data represents the end of the 20th century we are confident that the above-mentioned issues do not impose a systematic bias to our results.

Another concern with the EM-DAT data is that differences in nations' buying power and fluctuations in currency exchange make one-to-one comparisons difficult. For example, the damage estimate of the Kobe earthquake in 1995 was US$114 billion based on simple currency exchange rates. When purchasing parity is taken into consideration, however, the cost estimate decreases to US$64 billion (Horwich 2000). Because our monetary proxy is normalized by the country GDP in USD without adjusting for purchasing power parity, this issue should not be of concern in our results.

Finally, periodic occurrences of certain events may inject systematic bias to our data. For instance, earthquakes tend to happen randomly throughout the year whereas floods and windstorms (mostly accompanied with hurricanes/cyclones) happen consistently in a given season of the year. We believe that this is another compelling reason to separate disasters by type rather than reporting collectively in our study.

Future Research Directions

Within the supply chain literature, we feel that it would be of interest to address the following issues: We only considered four major industry sectors (extraction, manufacturing, wholesale and retail) in this paper. But another interesting question is how disasters impact firms that connect the echelons of supply chains and the consequences reflected on the supply chain itself. We are referring to service industries such as transportation, telecommunication, information technology services and financial services. These services essentially link firms in a supply chain to each other enabling movement of product, information and cash. Disruptions of these sectors undoubtedly affect supply chain operations. The question is how.

Given that our study is based on an indirect approach to understand effects of disasters on supply chain echelons, it would be interesting to see if our findings are confirmed based on direct approaches. Another area of potential interest lies with the timing and duration of the effects. Does the impact of a disaster have a long-term effect? A longer time series dataset would be required. In our study we look at what firms do after the event. It would be interesting to know if firms do change before the event takes place. In other words, do companies domiciled in disaster prone areas behave differently than those residing in areas that are not subject to disasters?

Outside of the supply chain arena our research tackles interesting problems in disaster research leading to three distinct research directions: First, the debate on all-hazards versus hazard-specific mitigation and preparedness strategies continues. In this paper we showed that different types of disasters impact industry sectors in different ways, suggesting that an all-hazard approach may not be the best route to take in order to understand the impact of disasters on business and society. More research support is needed in understanding the underlying differences of different disasters from a supply chain management standpoint.

Second, we found that not all existing and commonly used measures for disaster damage are useful in explaining the impact of disasters. More research is needed to test different and new impact measures and their explanatory powers. Third, we found that even a rudimentary composite measure seems to precipitate stronger results than individual measures. Thus, more research is needed to develop better composite measures.

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APPENDIX

Variables and Sources

Variable	Definition	Source
Dependent variables		
Leverage	Financial Leverage, the ratio of total debt to total assets. Debt and asset figures are at the end of each year in local currency.	*Worldscope* 1990–2004
Operational Cash Flow	Operational Cash Flow, the ratio of cash from operational activities over total assets. Cash flow and asset figures are at the end of each year in local currency.	*Worldscope* 1990–2004
Total Asset Turnover	Total Asset Turnover, the ratio of total sales over total assets. Sales and assets figures are at the end of each year in local currency.	*Worldscope* 1990–2004
Independent variables		
Extract	Extraction Sector Damage Indicator. Dummy variable that takes the value of 1 if the firm year observation belongs to agriculture or mining and if damage proxy >0 (dam/gdp or aff/pop).	*Worldscope* 1990–2004
Basic	Basic Manufacturing Sector Damage Indicator. Dummy variable that takes the value of 1 if the firm year observation belongs to basic manufacturing and if damage proxy >0 (dam/gdp or aff/pop).	*Worldscope* 1990–2004
Advanced	Advanced Manufacturing Sector Damage Indicator. Dummy variable that takes the value of 1 if the firm year observation belongs to advanced manufacturing and if damage proxy >0 (dam/gdp or aff/pop).	*Worldscope* 1990–2004
Whole	Wholesale Sector Damage Indicator. Dummy variable that takes the value of 1 if the firm year observation belongs to wholesale and if damage proxy >0 (dam/gdp or aff/pop).	*Worldscope* 1990–2004
Retail	Retail Sector Damage Indicator. Dummy variable that takes the value of 1 if the firm year observation belongs to Retail and if damage proxy >0 (dam/gdp or aff/pop).	*Worldscope* 1990–2004

APPENDIX Continued

Variable	Definition	Source
Firm level controls		
GROWTH	Growth opportunities, market capitalization plus total assets plus total liabilities over total assets. Figures are in local currency at the end of each year.	*Worldscope* 1990–2004
L_ASSETS	Log of total assets; total assets in local currency converted to USD at the end of each year.	*Worldscope* 1990–2004 and IMF
International Financial Statistics		
NDTS	Non Debt Tax Shelter; The sum of depreciation plus research and development over total assets. Figures are in local currency at the end of each year.	*Worldscope* 1990–2004
TANGI	Tangibility of assets; The ratio of property, plant and equipment net over total assets. Figures are in local currency at the end of each year.	*Worldscope* 1990–2004
CASH	Cash Holdings; The ratio of cash and short-term investments over total assets. Figures are in local currency at the end of each year.	*Worldscope* 1990–2004
BUSRISK	Business Risk; The standard deviation of a firm's net income over the sample period.	Own calculation based on *Worldscope* 1990–2004
Country level controls		
GDPCAP	GDP per capita in USD at the end of each year.	IMF — *International Financial Statistics* 1996–2004
COUNTRY RISK	Index based on ratings of countries according to seven types of country risk: growth vulnerability, foreign currency and liquidity crisis, external over indebtedness, sovereign financial vulnerability, banking sector's fragilities, political and institutional instability, and firms' payment behavior. High scores mean high country risks.	Calculated using ordinal rating from http://www.coface.com
CORRUPTION	Corruption perception index. To form this index, Transparency International compiles surveys that ask business people and analysts their perceptions of how corrupt a country is. A low value implies less corruption.	Transparency International
BANK_GDP	Relative size of banking sector. Deposit money bank over GDP.	Beck, Demirguc-Kunt and Levine (1999)
Natural disaster variables		
Criteria for disaster	Ten or more people reported killed, one hundred or more people affected, declaration of state of emergency, or call for international assistance.	EM-DAT, Emergency Disaster Database
Killed	Persons confirmed as dead and persons missing and presumed dead.	
Affected	People requiring immediate assistance during a period of emergency, i.e., requiring basic survival needs such as food, water, shelter, sanitation and medical assistance; it can also include displaced or evacuated people.	
Damage	The sum in millions of USD of each year of the estimated economic damage. Damage can be direct: damage to infrastructure, crops, housing, or indirect: loss of revenue, unemployment.	