Utrecht University

School of Economics

The Impact of Natural Disasters on Firm Growth in Vietnam

Interaction with Financial Constraints

Fujin Zhou
W.J. Wouter Botzen

U.S.E. Discussion Paper Series nr: 17-20

Tjalling C. Koopmans Research Institute
Utrecht University School of Economics
Utrecht University

Kriekenpitplein 21-22
3584 EC Utrecht
The Netherlands
telephone +31 30 253 9800
fax +31 30 253 7373
website www.uu.nl/use/research

The Tjalling C. Koopmans Institute is the research institute and research school of Utrecht University School of Economics. It was founded in 2003, and named after Professor Tjalling C. Koopmans, Dutch-born Nobel Prize laureate in economics of 1975.

In the discussion papers series the Koopmans Institute publishes results of ongoing research for early dissemination of research results, and to enhance discussion with colleagues.

Please send any comments and suggestions on the Koopmans institute, or this series to J.M.vanDort@uu.nl

How to reach the authors

Please direct all correspondence to the first author.

Fujin Zhou*
W.J. Wouter Botzen*#
*Utrecht University School of Economics
Kriekenpitplein 21-22
3584 TC Utrecht
The Netherlands.
Institute for Environmental Studies,
VU University Amsterdam, De Boelelaan 1085,
1081 HV Amsterdam
The Netherlands.
E-mail: f.zhou@uu.nl
Wouter.botzen@vu.nl

Utrecht University School of Economics
Tjalling C. Koopmans Research Institute
Discussion Paper Series 17-20

The Impact of Natural Disasters on Firm Growth in Vietnam: Interaction with Financial Constraints

Fujin Zhou[1]
W.J. Wouter Botzen[1,2,3]

[1]Utrecht University School of Economics,
Utrecht University.

[2]Institute for Environmental Studies,
VU University Amsterdam.

[3]Risk Management and Decision Processes Center, The Wharton School,
University of Pennsylvania.

18 December 2017

Abstract
The theory on the disaster impacts on firm growth is ambiguous and the empirical evidence on this topic is scarce, which hampers the design of disaster risk reduction and climate change adaptation policies. This paper estimates growth models of the impacts of natural disasters on labour, capital, and value-added growth of firms in the short run, and identifies the role of financial constraints in shaping disaster outcomes. The analysis uses a comprehensive enterprise census data (2000-2009) and also two different types of disaster measures from Vietnam: the physical intensity measures and the socioeconomic damage measures. We apply the Blundell-Bond generalized method of moments (GMM) to estimate firm level disaster impacts, and find robust evidence that natural disasters on average increase firm growth significantly. We also find stronger positive impacts in labour and output growth for more constrained firms. We argue that this occurs because financially more constrained firms substitute labour for capital during the reconstruction phase after a disaster.

Keywords: Natural disaster, disaster impact, firm growth, financial constraints, disaster measure

JEL classification: D22, D24, Q44, Q51, Q54, Q56

1. Introduction

Natural disasters such as storms, floods, droughts, are becoming more frequent and severe worldwide in recent decades, resulting in large socioeconomic consequences (IPCC, 2014). Many scientists tend to attribute this phenomenon largely to the increasing climate change risks and the concentration of wealth and population in disaster-prone regions (Bouwer, 2011; Estrada, Botzen, & Tol, 2015). Both developed and developing countries are vulnerable to the economic impacts of climate change, but it is expected that these impacts will be more severe in developing countries which have a more limited capacity to adapt to climate change (Tol, 2017). Hence it is important and urgent to adapt to changes in climate and limit the effects of changes in the intensity and/or frequency of natural hazards on economic development.

For adapting to climate changes and enhancing the preparedness and resilience of a society against natural disasters, it is essential to have a good understanding on the relationship between natural disasters and economic activities in the short and long run. Disaster impacts can be divided in direct impacts, like property losses, and indirect economic impacts, such as effects on economic growth. The former are relatively well understood, while insights into economic growth impacts of natural disasters are more uncertain (Lazzaroni & van Bergeijk, 2014). It is important to estimate the indirect losses to assess the consequences of natural disasters on welfare, as has for example been emphasized by Hallegatte and Przyluski (2010). However, the evidence for the disaster impacts on economic growth are inconclusive and are mostly obtained from highly aggregated macroeconomic data at the country or regional levels (Klomp & Valckx, 2014; Lazzaroni & van Bergeijk, 2014). This inconsistency in results is in part related to the failure in fully accounting for the differences in disaster types, locations, economic and financial development, institutional quality, time period used for the analysis, disaster cost definitions, and assessment methodologies (Loayza, Olaberría, Rigolini, & Christiaensen, 2012; Cavallo, Galiani, Noy, & Pantano, 2013; Felbermayr & Gröschl, 2014).

To improve our understanding of how disasters impact the economy, one may turn to study at the microlevel the relationship between business activities and natural disasters, for which there remains very limited evidence so far (Leiter, Oberhofer, & Raschky, 2009; Cole, Elliott, Okubo, & Strobl, 2015; Tanaka, 2015). This is because firms play an important role in the economy by generating wealth and jobs for the society and hence also play an increasingly important role in disaster resilience. Firms themselves may be directly impacted by natural disasters, and further create spillover effects to the rest of the society.

Therefore, we investigate in this paper, the impact of natural disasters on firm growth in the short run with firm level data. We focus on Vietnam, a developing country particularly vulnerable to climate change and

natural disasters.[1] According to the World Bank report (2010), the country has lost 1-1.5 percent of GDP annually between 1989 and 2008 due to natural disasters, which hinders the social and economic development of the country. With a coastline of 3440 kilometers, Vietnam is prone to a wide range of disasters including floods, typhoons, landslides and droughts, among which floods and typhoons are the most frequent and destructive occurrences with the highest number of fatalities and economic damage between 1990 and 2014 (EMDAT, 2016).[2] As an illustration, in 2006 typhoon Xangsane hit 15 provinces in the central region and caused damages of USD 1.2 billion, which is equivalent to approximately 1.9 percent of total GDP (CCFCS damage database);[3] the floods that occurred in 2008 affected north and central Vietnam caused damages of USD 479 million in assets; and typhoon Ketsana swept through central Vietnam in 2009 killing 163 people and causing a total economic loss of USD 785 million (EMDAT, 2016).

This paper contributes to the limited micreconomic evidence on post-disaster firm recovery or firm growth (Section 2) with firm level panel census data for the period 2000-2009. Specifically, natural disasters are incorporated into the firm growth model as exogenous shocks. The growth models are further estimated by the Blundell-Bond (1998) system generalized method of moments (GMM) to control for potential measurement error and endogeneity issues. We find significant positive disaster impacts on firm growth in terms of labor, capital, and value-added by floods and storms/typhoons.

Financial constraints have a large impact on firm survival and growth (Musso and Schiavo, 2008). But whether and to what extent natural disasters interact with financial constraints to affect firm survival and growth remains unknown.Therefore, we quantify the heterogeneous disaster impacts on firm growth for firms with different degrees of financial constraints, and reveal a financial constraint channel through which natural disasters generate heterogeneous disaster outcomes. This is done in three steps. First, we estimate a structural investment Euler equation with borrowing constraints to obtain a time-varying and continuous financial constraint index for each firm. The financial constraint index captures the relative shadow price of financing. Next, we identify a negative impact on firm growth by financial constraints, corroborating the important role of financial development in firm growth. Furthermore, we obtain empirical evidence for the heterogeneous disaster impacts across firms with different degrees of financial constraints.

Another contribution of this paper is that we are the first to evaluate and compare the performance of different disaster indicators in measuring impacts on firm performance, with one based on the physical

[1] Vietnam is ranked by the World Bank as one of the most vulnerable countries (6th) to climate change according to land area impacted, population affected, and economic loss (The World Bank, 2010).
[2] Floods and storms are recurring disasters that heavily impact the north central and delta region. Floods occur primarily in the central plain, along the Red River basin and Mekong delta, and account for more fatalities. whereas Storms strike along the coastal areas and cause more physical damages. The north central region is often hit by storms and typhoons that are accompanied by heavy rain, coastal flooding, and landslides.
[3] CCFSC: Central Committee for Flood and Storm Control. http://www.ccfsc.org.vn.

intensities (e.g. wind speed) and the other based on damage records (death tolls and economic losses). Most studies on disaster impact have relied on the damage measures which can cause an endogeneity issue,particularly for cross-country growth studies, because a high income may be positively related with high natural disaster damage records (Felbermayr & Gröschl, 2014). They instead build a comprehensive natural disaster database with physical intensities from primary geophysical and meteorological information. Felbermayr and Gröschl (2014) find a substantial negative and robust average impact effect of disasters on economic growth if the physical disaster indicators are used as explanatory variables, but not when instead the economic impact indicators are used. But there is no literature directly verifying the performances of different disaster measures in the context of micro-level disaster impacts on firms. Hence we provide a direct comparison of the performances of two types of disaster measures on the same group of firms in this paper. On average, we find similar positive disaster impacts for both disaster measures.

The paper is organized as follows. We start out by presenting a literature review for the impacts of natural disasters, with a focus on the indirect costs. Next, we discuss the determinants for firm growth based on the theoretical and empirical literature on firm growth and formulate some hypotheses for testing. Third, we introduce in detail the firm-level panel data and the disaster databases used for the analysis. Fourth, we present and discuss the estimation results for labor, capital, and output growth. Finally, the paper ends with a conclusion section.

2. Literature Review on the Impact of Natural Disasters

Natural disasters not only cause direct human and physical damages, but also have indirect impacts on the economy. Indirect disaster impacts can be further divided into short run impacts (up to three years) and long run impacts (beyond five years). Empirical evidence for the indirect impacts can be inferred from microeconomic data of firms or a specific sector which often focusses on impacts from single catastrophe events or using cross-country macroeconomic panel data which often examines multiple natural disasters (Klomp J. K., 2014; Lazzaroni & van Bergeijk, 2014). In this section, we briefly review the main literature on the disaster impacts, with a focus on the indirect economic consequences of disasters.

The studies on direct natural disaster impacts are in general consistent in the finding that such impacts are negative direct costs (Lazzaroni and Bergeijk, 2014). The immediate consequences of disasters include mortality, morbidity, and loss of physical infrastructure, like roads, telecommunication, and electricity networks, and damages to residential housing and other buildings and their contents, as well as capital stock and inventories of companies. The size of the direct costs is related to the nature and the physical intensity of the disaster but also to the so-called societal resilience against disasters, like early warning systems, evacuation plans, building codes, prevention measures in place, and quality of government institutions (Kahn, 2005).

These initial direct disaster impacts are followed by consequent indirect impacts on the economy. These indirect impacts can be indirect costs, like business interruption costs, but also indirect benefits, for example when businesses that are not directly affected by a disaster take over reduced supply from business of which production is impaired by the disaster (Hallegatte & Przyluski, 2010). Moreover, during the recovery process some firms may experience increased demand which is met by increasing production. An example, is the construction sector which often is in high demand when damaged properties need to be repaired. Noy and Nualsri (2007) show that standard neoclassical growth models with exogenous technical progress predict that the destruction of capital caused by a natural disaster results in more rapid capital accumulation. This is reflected in higher growth rates which sustain temporarily until steady state balanced growth is reached.

Growth theories with endogenous technical change result in mixed predictions of growth implications of disasters. Endogenous growth models with increasing returns of scale in production predict that technological change is increasing in the stock of human or physical capital, which implies lower growth after disasters reduce these capital stocks (Romer, 1986; Romer, 1990). In contrast, in line with the creative destruction theory of Schumpeter (1934), there may be a positive effect on long run economic growth when the capital stock after a disaster is updated with new more efficient technologies, which has been called creative destruction (Leiter, Oberhofer, & Raschky, 2009). For human capital, Skidmore and Toya (2002) expect human capital to increase to substitute for lost physical capital after a disaster, which can contribute to growth and ultimately also increase physical capital investments. In the short run, natural disasters may trigger reallocation of labor across sectors. For example, Kirchberger (2017) finds evidence for sectoral reallocation of workers as well as significant and persistent wage premia between agriculture and construction sectors after an earthquake in Indonesia. But labor supply can be reduced if people migrate out of disaster-stricken areas (Belasen & Polachek, 2009). However, for low-income countries, natural disasters tend to reduce human capital accumulation in the long run (Cuaresma, 2010; Baez, De La Fuente, & Santos, 2010; McDermott, 2012). Moreover, disasters may spur innovation to reduce and cope with the risk which enhances a country's adaptive capacity. This is illustrated by Miao and Popp (2014) who show that droughts, earthquakes and floods increase short and long-run patenting activities for technologies that mitigate risks.

The sign and size of the indirect costs, moreover, depend on the nature and physical intensity of the disasters and on the macroeconomic resilience of a society (Noy, 2009). The latter depends on a series of economic, social, and political characteristics, such as the level of economic development, financial market development, institutional quality, education attainment, trade openness, et cetera (Anbarci, Escaleras, & Register, 2005; Raschky, 2008; Toya & Skidmore, 2007; Noy, 2009; Cavallo & Noy, 2010) . Hallegatte and Przyluski (2010) point out two more factors for the conflicting assessment results, including the

differences in the definitions of disaster costs and the assessment methodologies and approaches used. Accordingly, there is no consensus in the literature for the sign and magnitude of the short- and long- run indirect costs following natural disasters (Klomp & Valckx, 2014; Lazzaroni & van Bergeijk, 2014). Specifically, Lazzaroni and Bergeijk (2014) systematize 64 primary studies published in 2000–2013 on the macroeconomic impact of natural disasters and conclude that disasters have on average an insignificant impact in terms of indirect costs. Similarly, Klomp and Valckx (2014) perform a meta-regression analysis of studies examining the relationship between economic growth per capita and natural disasters using more than 750 estimates in the literature. But they instead find a negative genuine effect of natural disasters on economic growth, which is increasing over the period of analysis. Further they find that climatic disasters in developing countries have the most significant adverse impact on economic growth. Both meta-analyses above find some degree of publication bias for a large part of the negative disaster impacts in the literature and the influence of time periods studied.

The literature on disaster impacts mostly use cross-country macroeconomic panel data for analysis, which may bias the estimate for the disaster impacts due to the large variations across countries in macroeconomic dynamics and shocks. Several papers pursue similar investigations but use more detailed panels at the county, region, or the state level within a single country. Strobl (2011) uses differences in hurricane impacts on coastal counties in the United States and finds negative impacts on growth at the county level, but no effect beyond the county level. Noy and Vu (2010) use provincial data in Vietnam to evaluate the macroeconomic disaster impacts and find support that disasters that destroy more property and capital actually appear to boost the economy in the short-run while lethal disasters decrease economic production. RodríguezOreggia et al. (2013) use municipal data from Mexico and find that general shocks, especially from floods and droughts, lead to significant drops in the social indicators for both human development and poverty levels.

Most studies on disaster impacts on economic growth have estimated the overall disaster impacts with aggregate data and arrived at inconclusive results (Lazzaroni & van Bergeijk, 2014; Klomp & Valckx, 2014). Very little is known about business vulnerability to natural disasters, loss-reduction measures adopted by businesses, disaster impacts on businesses, and business recovery after a disaster (Tierney, 2007). Firms receive much less attention in the public debate and also in the literature about disaster impacts, compared to households.[4] For instance, most disaster aids from governments and international organizations are directed towards households rather than firms.

[4] The literature on the disaster impact (risk coping and consumption smoothing) is rich (Wisner, Blaikie, Cannon, & Davis, 2003). However, a review of the literature for the disaster impact on households is beyond the scope of this paper.

A few publications address the interaction between supply chains and natural disasters and their impact on economic growth or firm recovery. Using firm level panel data from Worldscope for 53 countries for the period 1990-2004, Altay and Ramirez (2010) find that disasters impacts all sectors within a supply chain, and damage by windstorms and floods seem to be dramatically different from that of an earthquake. Accordingly, they suggest a supply chain–wide mitigation strategy rather than a company-specific one, as well as a disaster-specific approach rather than an all-hazard approach for reducing natural disaster risks. Todo et al. (2015) find a positive net effect of supply chain networks on firm recovery after the Kobe Earthquake by using firm-level data in Japan. Carvalho et al. (2016) provides a systematic quantification of the role of input-output linkages as a mechanism for the propagation and amplification of shocks and find that the propagation of the shock over input-output linkages can account for a 1.2 percentage point decline in Japan's gross output in the year following the 2011 Great East Earthquake.

There are a few studies that examine the post-disaster firm or plant survival and growth. For example, Leiter et al. (2009) analyze the short run impact of floods (in 2000) on firm growth using firm level data from Europe (AMADEUS). They find evidence that, in the short run, companies in regions hit by a flood show on average higher growth of total assets and employment than firms in regions unaffected by flooding. The positive effect prevails for companies with larger shares of intangible assets (e.g., R&D, patents, software, trademarks), which are less exposed to floods than tangible assets. But a negative flood effect is observed for firms' productivity (value-added), which declines with an increasing share of intangible assets. They argue that intangible assets are often an outcome of R&D activities and may act as a multiplier promoting (softening) positive (negative) tendencies. Apart from capital structure, financial conditions or access to capital is also an important factor for the post-disaster recovery of small businesses or microenterprises (Webb, Tierney, & Dahlhamer, 2002; Runyan, 2006; De Mel, McKenzie, & Woodruff, 2012).

Both Tanaka (2015) and Cole et al. (2015) analyze the impact of the Kobe earthquake on plant survival and growth, and find evidence against the creative destruction hypothesis. Specifically, Tanaka (2015) finds that the surviving plants experience lower employment and value-added growth than plants in unaffected areas during the subsequent three years of the Kobe earthquake. Cole et al. (2015) generate a measure of the damages incurred by individual buildings and show that the damage caused by the Kobe earthquake increases the likelihood of exiting the market for plants with unproductive, small, young and employing low-skilled workers; and reduces employment and value-added, but temporarily increases productivity of surviving plants; and boosts the birth of new firms in areas with severe damages.

Similar to Leiter et al. (2009), Tanaka (2015), and Cole et al. (2015), this paper aims to identify the growth impact at the firm level caused by natural disasters. However, the three studies above focus on single disaster events from developed countries (EU and Japan), while we analyze the short run impacts of

multiple floods and typhoons with firm level panel data from Vietnam, a developing country vulnerable to natural disasters and climate change. Moreover, this paper has two more methodological innovations. First, we directly verify the performances of two different disaster measures (damages and physical intensity) in the context of micro-level disaster impacts on firms. Second, we obtain more accurate estimates for the disaster impacts by applying the Blundell-Bond (1998) system generalized method of moments (GMM), which largely improves upon the commonly used methods (e.g. difference in difference and matching) in the literature by accounting for firm dynamics, endogeneity, and measurement errors with the use of lagged values as instruments.

3. The Definition and Determinants of Firm Growth

In this paper, we investigate the disaster impact on firm growth, and identify how natural disasters interact with financial constraints to affect firm performance in the short run. Hence this paper is also closely related to the literatures on firm growth and on financial constraints. Firm growth is difficult to predict and is highly heterogeneous across firms. In this section, we first discuss different measures for firm growth; describe the determinants for firm growth based on the relevant empirical literature; and accordingly formulate hypotheses for testing.[5]

The choice of which measure(s) for firm growth to use depends on specific research topics, data availability, and data quality. Firm size is most commonly measured by employment, total sales, value added (VA), and total assets in empirical analysis (Delmar, 1997; Weiss, 1998). Accordingly, firm growth can be measured as labor growth, sales growth, VA growth, and capital accumulation. Financial measures (sales, VA, and capital) may contain larger measurement errors caused by deflators,[6] compared to employment. In addition, there may be some manipulation in reported sales and profits by firms, especially for small firms. Sales growth may mirror best the short- and long- term changes in the firm. But sales may overstate the size of the firm as sales does not only reflect the value-added of a company, but also external shocks (e.g. on input prices). Asset or capital accumulation may be problematic for industries with a large share of intangible assets. Using employment as a size measure facilitates comparison across industries.

In this paper, we demonstrate how natural disasters affect labor growth, capital growth, and VA growth, similar to Leiter et al. (2009) and Tanaka (2015).[7] The empirical model for firm growth is built upon the

[5] There is a large gap between the empirical evidence and theory for firm growth. The economic theories for firm growth cannot fully explain the stylized facts for firm growth (see Coad 2007 for more details).

[6] Financial variables are mostly deflated with sectoral deflators, which can be very different from firm-specific prices, creating measurement errors. More productive firms tend to charge lower prices and hence their growth rates may be understated. It is the opposite for less productive firms.

[7] The measurement error in VA may be larger compared to labor growth because VA is calculated as the sum of profit, labor costs, and depreciation. We also consider sales growth in appendix A4 as robustness checks.

empirical literature of firm growth and firm size and age. We proceed to discuss the empirical specification for firm growth below.

Natural disasters work as external shocks on firms' physical assets and outputs. For instance, disasters like earthquakes, typhoons, and floods may disrupt production and reduce subsequent outputs by damaging physical assets, inventories and raw materials, causing power cuts and road destruction, and interrupting sales networks and supply chains, et cetera. On the other hand, the destruction of private assets and public facilities may also stimulate more demand for capital and labor for reconstruction purpose (and in some cases result in upgrades of capital), and ultimately increase outputs. Moreover, not directly impacted firms may experience increases in output when they take over part of the lost production from firms that are directly impacted by the disaster. Overall, the sign and magnitude of the disaster impacts on firm growth are uncertain, depending on the type and severity of the natural disasters, and other firm-specific and industry-specific resilience against disasters.

Financial constraints play a substantial role in shaping and conditioning firm decisions underlying growth and survival (Musso & Schiavo, 2008). Financial constraints increase exit probability, hold back innovation, and negatively affect firm growth (Hyytinen & Toivanen, 2005; Musso & Schiavo, 2008) . Lack of access to credit may hinder firms' investment to (fully) capture any growth opportunities. Natural disasters may worsen a firm's financial constraint status by reducing/destroying firms' collaterals (i.e. tangible assets) necessary for borrowing. If firms fail to replace their damaged assets with new ones, they may not be able to (fully) recover to the pre-disaster level or in the worst case be forced to exit the market. The disaster impact may be quite different for financially unconstrained firms with easy access to capital. Therefore, it is interesting to investigate whether or not the impact on firm growth by natural disasters may be different across firms with different degrees of financial constraints. There are different measures for financial constraints in the empirical literature. We discuss the relevant literature and our chosen proxy for financial constraints in appendix A3.

We summarize the expected effects of disasters and the role of financial constraints on firm growth in terms of capital, labor, and value added by the following five hypotheses for testing:

H1: natural disasters increase labor growth

H2: natural disasters increase capital growth

H3: natural disasters reduce value-added growth

H4: firm growth decreases with financial constraints

H5: the disaster impacts decrease with financial constraints for labor and capital growth but increase with financial constraints for value-added growth

Apart from natural disasters and financial constraints, other factors also matter for firm growth. These include firm size, firm age, ownership structure, and other firm-specific factors (Coad, 2007).[8] Gibrat's Law states that firm size does not matter for firm growth. There is mixed evidence for the Gibrat's Law. Hall (1987) finds evidence for Gibrat's Law, while Evans (1987) rejects the Gibrat's Law for large US manufacturing firms. Recent empirical literature shows that the growth rate is lower for large firms than small firms (Cabral, 1995). On the other hand, Bentzen, Madsen, and Smith (Bentzen, Madsen, & Smith, 2012) find a positive correlation between firm size and firm growth for Danish firms for the period of 1990 and 2004.[9] For firm age, the negative dependence of growth rate on age appears to be a robust feature of industrial dynamics (Coad, 2007). Young firms in general grow faster than old firms.

There is mixed evidence for the autocorrelation of firm growth in the literature. For instance, the autocorrelation of growth rates is positive for US manufacturing (Bottazzi & Secchi, 2003), but is negative for both Italian manufacturing (Bottazzi, Secchi, & Tamagni, 2006) and French manufacturing (Bottazzi, Coad, Jacoby, & Secchi, 2011). Still other studies have failed to find any significant autocorrelation in growth rates, e.g. Lotti et al. (2003). Further investigation by Coad (2006) shows that small firms tend to exhibit negative correlation, while large firms tend to show positive autocorrelation which means that large firms are more likely to sustain their growth.

Firm growth may vary across industries and with different macroeconomic factors (Coad, 2007). For instance, the disaster impact may differ across industries with different capital intensity. In most empirical research on firm growth, industry-specific factors are controlled away by using industry dummies that take into consideration the total combined influence of all industry-specific variables put together. Fixed effect and time dummies are often included in the model to capture both the time-invariant and time-varying macro factors.

4. Data Description

To analyze the short run disaster impact on firm growth, we use the annual Enterprise Census Data between 2000 and 2009 from Vietnam matched with multiple disaster databases. We describe the datasets for use in details below.

[8] Firm specific factors include innovation, ownership structure, the nature of firms' activity, the characteristics of management, et cetera. Many of which are not available in the data we use for analysis. The time-invariant part is captured by firm fixed effect.

[9] With panel data models, the initial firm size is time invariant and can be captured by the firm fixed effect.

4.1 The Enterprise Census Data (2000-2009)

The firm level census data was collected annually by the General statistical office (GSO) of Vietnam since 2000. We have access to the data up till 2009.[10] This dataset covers all state-owned enterprises (SOEs) and foreign firms, and also all private firms with 10+ employees in Vietnam. Another 10% of the private firms with less than 10 employees are randomly selected into the census. In this paper we focus on manufacturing firms. The census data collects information on sales, labor costs, the beginning and end of period values for employment size, fixed/liquid/total assets, debts, depreciation, and inventory.

With the census data, we can use sales, employment, and total assets to measure firm size. In addition, we can calculate the value added of a firm by summing up labor costs, profits, and depreciation. But VA growth may be noisier than other growth measures, because the reported profits may be heavily manipulated (especially for small firms). Since the majority of firms in our sample for analysis are small firms, labor growth may be a more robust measure for firm growth. Nevertheless, we also study capital growth, and VA growth from the perspective of productivity growth.[11]

Financial constraints are not directly observable but can be approximated. The empirical literature on financial constraints use either indirect proxies (such as having a credit rating or paying dividends) or one of the three popular financial constraint indices based on linear combinations of observable firm characteristics (e.g. the Kaplan-Zingales, Whited-Wu, and Hadlock-Pierce indices, see Farre-Mensa and Ljungqvist (2016)). With panel census data, we follow Whited and Wu (2006) to estimate a structural investment Euler equation with borrowing constraints. The non-negative multipliers associated with the borrowing constraints capture the shadow values of external financing. The Whited-Wu financial constraint index (WWI for short hereafter) captures the relative shadow price of external financing[12], which is approximated by variables that either capture financial constraints or growth opportunities.[13] The WWI varies across firms and over time. The WWI ranges from 0 to 1, with values close to zero indicating small financial constraints and values close to 1 indicating severe financial constraints.

Firms sorted by the predicted WWI exhibit patterns consistent with our expectation. The predicted values decrease with firm size and age, namely small and young firms in general experience more financial constraints than large and more mature firms. It is widely noted that private firms in Vietnam experience

[10] Zhou (2015) documents the data cleaning details for the enterprise census data.

[11] Firm growth is calculated as the log of the ratio of current period over previous period firm size (relative growth).

[12] The relative shadow value of financing for firm i at period t+1 is a function of the multipliers $\Lambda_{it+1} = \frac{1+\lambda_{it+1}}{1+\lambda_{it}}$.

[13] The final model for predicting financial constraint is $\widehat{\Lambda} = 1 - .045 * \mathrm{LNTA} + .104 * \mathrm{DAR} - .849 * \mathrm{IDAR} + .039 * \mathrm{ISG} - .040 * \mathrm{SG} - .245 * \mathrm{CKK}$, where LNTA is log of total assets, DAR and IDAR refer to individual and industry debt asset ratio, SG and ISG refer to sales growth and industry sales growth, and CKK is the ratio of liquid assets on total assets. Appendix A3 documents the details of estimating the Whited-Wu financial constraint index.

more severe financial constraints than SOEs and foreign firms. Financial institutions are mostly state-owned and prefer lending to SOEs, while foreign firms typically have easy access to capital abroad. We find on average lower predicted index values for SOEs and foreign firms than private firms. The mean index values also decrease with firm panel length. This implies that firms that survive longer in the data experience lower financial constraints than firms that exit earlier.

4.2 Three Disaster Databases

There are three major disaster databases available for use. The international disaster database EM-DAT (Emergency Event Database) is so far the most widely used database for analyzing the disaster impacts in the literature.[14] EM-DAT contains essential core data on the occurrence and effects of over 22,000 mass disasters in the world from 1900 to the present day. The database is compiled from various sources, including UN agencies, non-governmental organizations, insurance companies, research institutes and press agencies. A disaster is recorded in EM-DAT if it satisfies one of the following: 1) death toll 10 or more, 2) affected population 100 or more, 3) declaration of a state of emergency, 4) call for international assistance. This collection of natural disasters is mostly based on insurance claims or news stories, which are potentially related with large measurement errors. Felbermayr and Gröschl (2014) highlighted two issues with EM-DAT data in a cross-country GDP growth regression, namely both monetary damage and insurance coverage are correlated with GDP per capita, which causes an endogeneity issue for the disaster measures. But the endogeneity issue is less problematic here because we analyze the disaster impact on firms in a single country Vietnam, where the variation of income levels and the insurance coverages is much smaller across different provinces, than between countries.

The second source of disaster data is the ifo Geological and Meteorological Events (GAME) database (1979-2010). The dataset collects information on geological and meteorological events from primary information and translates them into natural hazards and disaster events on a country-level basis.[15] It covers earthquakes, volcanic eruptions, storms, extreme temperature events, floods and droughts on a monthly and yearly basis. GAME covers the whole world and various types of natural disasters and captures the physical intensity of disaster events. An advantage is that this data of physical indicators of natural disasters is exogenous to economic activity (Felbermayr and Gröschl, 2014). In this paper, we construct disaster measures from the primary data instead of directly using the country-level (GAME) database for Vietnam.[16]

[14] EM-DAT is collected by the center for research on the epidemiology of disasters (CRED), Université catholique de Louvain in Belgium.
[15] The GAME available in ifo website is a county-level database covering a rich collection of variables.
[16] There are two data sources for wind speed: the International Best Track Archive for Climate Stewardship (IBTrACS) and the Global Surface Summary of Day (GSOD) data. Precipitation data are recorded by the Goddard Space Flight

A drawback of the GAME data is that it uses precipitation as an indicator for flood. Precipitation may not accurately signal whether a flood event has occurred, for example, because high precipitation may not cause flooding when adequate flood protection infrastructure is in place. Moreover, the intensity and duration of rainfall, the geographical location, climate, and land-surface characteristics (e.g. topography, geomorphology, type and quality of soils, et cetera) all play important roles in flood occurrence. Hence we use a third disaster database which is the Dartmouth Flood Observatory (DFO), a Global Active Archive of Large Flood Events since 1985 collected by the University of Colorado.[17] DFO detects, maps, measures, and analyzes extreme flood events worldwide using satellite remote sensing. Imaging of selected river reaches is used to detect floods and extreme low flow conditions. The database provides information about flood catalog numbers, centroids, area affected outlines, and other attribute information such as begin and end dates, duration, death toll, monetary damage, population affected, affected square kilometers, and main cause. Much of the information (e.g. death toll and monetary damage) is derived from news, governmental, instrumental, and remote sensing sources.

We first merge the three disaster databases by date. The disaster data recorded in EM-DAT and DFO are for each disaster. There could be multiple disasters in a year, and we choose the most severe one in terms of physical intensity, death, and/or economic damages. With GAME primary data, the physical intensity measures for windspeed are recorded per grid cell (50 km by 50 km). If there are multiple observations with windspeed above our chosen thresholds, then we also choose the one with the highest values. Up till here, the unit of observation is per disaster in the three disaster databases. But the impact of a disaster can spread largely across different areas (e.g. provinces, cities, towns). Therefore, we further convert the disaster data into per year per province basis. With the above conversion, we may have multiple observations from different provinces for the same disaster. This conversion facilitates the merge with firm level data census for analysis, in which firms' location information is available at provincial level.[18]

Next, we match the merged disaster databases with the cleaned enterprise census data (by province and year) for further analysis. We focus on floods and storms/typhoons when analyzing the impact of disasters on firm growth. This is because floods and storms/typhoons are the two most frequent and destructive natural disasters in Vietnam, accounting for the majority of death tolls and economic damages.[19] Storms

Center of the National Aeronautics and Space Administration (NASA) in the Global Precipitation Climatology Project (GPCP).

[17] The link for the data is http://floodobservatory.colorado.edu/Archives/index.html.

[18] Data conversion is documented in appendix A2. For more information on the primary data, visit the website for codebook: https://www.cesifo-group.de/ifoHome/facts/EBDC/Ifo-Research-Data/Ifo_GAME_Dataset.html.

[19] For the data on frequency, mortality, and economic damage by natural disasters in Vietnam, visit http://www.preventionweb.net/countries/vnm/data/.

and floods are typically periodic and more predictable than earthquakes. The majority of storms and floods in Vietnam occur between July and November in a year.

We define three different disaster dummies, all of which incorporate both storms/typhoons and floods. Typhoons/storms and floods are closely related to each other in the sense that floods often occur after typhoons/storms strike. All disaster dummies are defined at the provincial level. The first disaster dummy (DIS_1) is defined using the wind speed data from GAME and the ratio of the affected area over provincial size by floods (DFO).[20] Specifically, DIS_1 is equal to one if 1) wind speed is 64 knots or above (Saffir-Simpson Hurricane Wind Scale)[21], or 2) the ratio of affected square kilometers over province size is above 1; and zero otherwise. We do not define floods by precipitation as precipitation data can be a poor proxy for floods. Extreme precipitation may not always cause floods, as discussed above. Moreover, extreme precipitation may occur in one place but cause flooding of riverss in another place. Therefore, the affected geographical size (in square kilometers) by floods recorded in DFO may be a better proxy for floods.

The second/third dummy (DIS_2/DIS_3) is defined based on the death tolls/estimated direct economic damages for typhoons and/or floods from EM-DAT and/or DFO for Vietnam. DIS_2 is equal to 1 if death toll is above 50, which is close to the median of the death tolls by natural disasters in Vietnam. The median nonzero damages by various storms and floods in Vietnam are 44 and 35 respectively. Therefore, DIS_3 is equal to 1 if the estimated direct damage is above 50 million US dollars, and zero otherwise.[22]

The three disaster measures only partially identify the same disasters simultaneously. The correlation between DIS_1 and two other disaster dummies are .43 and .45 respectively. Out of the 630 observations (per year per province),[23] one third of them (218) have at least one disaster dummy equal to one. The number of disasters simultaneously identified are respectively: 51 by DIS_1 and DIS_2, 43 by DIS_1 and DIS_3, 100 by DIS_2 and DIS_3, and finally 39 by all three disaster dummies.

One limitation with the census data is that we do not know the detailed locations of the firms. Hence we cannot pin down firms that are directly impacted by natural disasters. We have to make the assumption that all firms located in the provinces hit by natural disasters are equally affected. This may not be true given the highly local nature of many disaster events. For firms not directly affected in the same province, there may be positive spillover effects if they take over the production shortfalls from directly affected firms. For

[20] The data on wind speed is available per 50km by 50 km grid cell. We transform the data from grid cell to provincial level per month by taking the weighted average from all cells in a province. Then we take the maximum out of the values from the 12 months as our final measure for further analysis.
[21] 58 out of 326 observations (one observation per province/year/month) with non-missing maximum wind speed data have wind speed equal or above 64 knots while only 11 observations have wind speed equal or above 83 knots.
[22] As robustness checks, we later on also vary the threshold values for defining disaster dummies.
[23] The disaster data is aggregated to one observation per province per year. There are 63 provinces and 10 years.

directly affected firms, the disaster impacts may be negative in the immediately after the disaster but can turn positive later. Hence the coefficient for the disaster dummy defined captures the combined disaster impact for firms that are directly and indirectly affected.

Finally, we proceed to present some key statistics such as firm growth rate, (initial) firm size, age, ownership status, financial constraints, et cetera. The summary statistics below are produced after the top 1% and bottom 1% of the growth values are trimmed off. Variables in the table exhibit different degrees of between and within variation. The within (time) variation is larger than between (cross-section) variation for growth measures and disaster dummies. For other firm characteristics (e.g. WWI, age, fraction of female workers), between variation is larger than within variation. Among the four measures for firm growth, the mean and the standard deviation for capital growth are the smallest, while they are much larger for sales and VA growth. Both could reflect to some extent larger measurement errors in sales growth and VA growth.

Table 1
Summary Statistics

Variable		Mean	Std. Dev.	Min	Max	Observations
VA growth (growthV)	overall	.17	.55	-1.69	2.12	N = 20844
	between		.31	-1.54	2.05	n = 5449
	within		.49	-1.91	2.22	T-bar = 3.83
Employment growth (growthL)	overall	.06	.32	-1.10	1.27	N = 20853
	between		.19	-1.10	1.21	n = 5454
	within		.28	-1.21	1.48	T-bar = 3.82
Capital growth (growthK)	overall	.02	.04	-.07	.19	N = 20844
	between		.03	-.06	.17	n = 5460
	within		.03	-.11	.18	T-bar = 3.82
Sales growth (growthS)	overall	.16	.42	-1.26	1.69	N = 20883
	between		.24	-1.12	1.59	n = 5449
	within		.37	-1.31	1.61	T-bar = 3.83
financial constraint index	overall	.52	.08	.27	.87	N = 15804
	between		.08	.28	.82	n = 5464
	within		.02	.36	.68	T-bar = 2.89
age	overall	7.66	7.75	1.00	64.00	N = 26732
	between		6.97	2.00	61.50	n = 5464
	within		1.75	-.01	15.99	T-bar = 4.89
female	overall	.39	.26	0	1	N = 26732
	between		.24	0	1	N = 5464
	within		.08	-.38	1.03	T-bar = 4.89
DIS_1 (by physical intensity)	overall	.30	.46	0	1	N = 18788
	between		.32	0	1	n = 5464
	within		.36	-.60	1.19	T-bar = 3.44
DIS_2 (by death toll)	overall	.33	.47	.00	1.00	N = 18160
	between		.29	.00	1.00	n = 5464
	within		.41	-.50	1.21	T-bar = 3.32
DIS_3 (by damage in $)	overall	.23	.42	.00	1.00	N = 17566
	between		.28	.00	1.00	n = 5464
	within		.35	-.60	1.11	T-bar = 3.21
LnS: log of initial sales		8.07	1.80	2.40	13.33	26732
lnVA: log of initial VA		6.40	1.74	.75	11.67	26732
LnL: log of initial employment		4.12	1.37	0	9.17	26732

Source: Enterprise census data (2000-2009) and 3 disaster databases: GAME, EM-DAT, and DFO.

5. Empirical Estimation Results

5.1 Empirical Model Specifications

In this section, we present the estimation results for the firm growth model. Based on the firm growth literature, we can express the initial empirical models for labor, capital, and VA growth as follows:

$$GR_{i,t} = b_0 + \sum_{l=1}^{L} b_{1l}\, GR_{i,t-l} + b_2 age_{i,t} + b_3 findex_{i,t-1} + b_4 DIS_{i,t} + b_5 DIS_{i,t} * dfindex_{1_{i,t}} + b_6 DIS_{it} * dfindex_{3_{i,t}} + \beta X_{i,t} + \eta_i + d_t + \varepsilon_{i,t} \quad (1)$$

In equation (1), GR denotes firm (labor, capital, output) growth. The indepdent variables in the growth model include lagged growth rates ($GR_{i,t-l}$) up to L lags, firm age, a proxy for financial constraints (findex), [24] a disaster dummy ($DIS_{i,t}$), its interaction with two financial constraint dummies ($dfindex_1$&$dfindex_2$), and any other available time-varying controls X related to firm growth (e.g. the share of female workers, lagged disaster dummy, and its interaction with lagged financial constraint dummies),[25] a time invariant individual effect η_i, and year dummies controlling for common macroeconomic patterns. Finally, ε_{it} is i.i.d error term capturing any other unexplained effects.

With natural experiments, the disaster dummy is exogenous and uncorrelated with other firm characteristics.[26] The coefficient for the disaster dummy (b_4) captures the short-run impact of natural disasters on firm growth, which may be heterogeneous across firms. For instance, the disaster impact on firm growth may differ across firms with different degrees of financial constraints. With this hypothesis, firms are further sorted into three subgroups using the cutoff values of the 33rd and 66th percentiles for the predicted Whited-Wu index values for each year. The dummy $dfindex_1$ ($dfindex_3$) is equal to one for firms in the bottom (top) 33% in terms of financial constraint index values, and zero otherwise; $dfindex_2$ is equal to one for firms with financial constraint index values between the 33rd and the 66th percentile thresholds, and zero otherwise.[27]

Firm growth exhibits some degrees of autocorrelation when $b_{1l} \neq 0$. The growth models then become dynamic panel models. To consistently and efficiently estimate the dynamic panel growth models, we adopt the system generalized method of moments (GMM) proposed by Arellano-Bond (1991), Arellano-Bover (1995), and Blundell-Bond (1998).[28]

---

[24] The proxy for financial constraints are derived and predicted by estimating a structural investment Euler equation with financial constraints.
[25] The inclusion of lagged disaster dummy can test whether the disaster impact expands to the next year or not.
[26] The disaster risks differ across different areas and provinces and may affect the location choices of new entrants.
[27] Later on we also vary the cutoff values to check if the results are robust.
[28] Roodman (2006) illustrates in detail how to implement system GMM estimation in Stata.

The five hypotheses (H1-H5) specified in section 3 can be formulated equivalently as testing the signs of the coefficients in equation (1) as follows (with the superscript x referring to L/K/VA):

H1: $b_4^L > 0$; H2: $b_4^K > 0$; H3: $b_4^{VA} < 0$; H4: $b_3^x < 0$; H5: $b_6^x > 0, b_7^x < 0$

5.2 Estimation Results for Labor Growth and Capital Growth

Table 2 below presents the estimation results for both labor growth (columns (1)-(2)) and capital growth (columns (3)-(4)). AR(2) test is not rejected. Hansen over-identifying test is not rejected, indicating the validity of the lagged instruments used. Hence both labor and capital growth models fit the data well.

For the autocorrelation of firm growth, there is mixed evidence in the literature. Small firms tend to exhibit negative autocorrelation while large firms tend to show positive autocorrelation (Coad, 2006; Coad, 2007). Hence the growth pattern is more erratic and less persistent for small firms but more sustainable for large firms. The adjustment cost of labor is also relatively small compared to capital. Here we find negative and significant autocorrelation with its first lag for labor growth. This is consistent with our expectation as small and medium firms (SMEs, with less than 250 employees) take up almost 80% in our sample. High growth in one period is more unlikely to persist for small firms.

Labor growth significantly decreases with firm age (-.16) and the degree of financial constraints (-.53). Labor growth is significantly smaller for firms with larger fraction of female workers. The fraction of female workers may not only reflect firm-level differences but also industry-level differences in productivity and capital intensity. Industries with large shares of female workers tend to be more labor intensive compared to industries with lower shares of female workers. The average share of female workers is around 40% but with large variations across industries. For instance, the shares of female workers are the highest for industries related to wearing apparels (78.3%) and tanning and dressing of leather products (69.9%) and the lowest for basic metal (15.7%) and machinery and equipments (20.6%).

The coefficient for the disaster dummy is positive and significant (see column (1)). Firms in provinces hit by floods/typhoons on average experience significantly higher labor growth than firms in provinces without disasters (confirming H1). The demand for labor increases after natural disasters strike as recovery demands more labor input. This is feasible as many industries in Vietnam are labor intensive. The picture also holds when we define disasters by death and damage, although the magnitude is slightly smaller.[29]

To further identify whether the disaster impact differs across firms with different degrees of financial constraints, we include the interaction terms between disaster dummy and financial constraint dummies.

[29] We also add in lagged disaster into the model to see if there is longer term disaster impact. But the coefficient is small and insignificant. The same is true for capital growth.

We find evidence for the heterogeneous disaster impact on firm labor growth across firms with different degrees of financial constraints (see column (2)). Specifically, we find a significant positive effect for firms experiencing medium financial constraints (.059), but zero net effect (.059-.058=.001) for firms with least financial constraints (bottom 33% in terms of financial constraints). For most constrained firms, the disaster impact is not significantly different from the firms with medium financial constraints. These results imply that firms overall increase labor input after a disaster, and that this effect is stronger for firms experiencing medium and high financial constraints, but is negligible for firms with low financial constraints (H5 is rejected). This suggests that access to financial capital, which can be used for repairing damaged capital goods and technologies, acts as a substitute for labor after a disaster occurs.

Table 2
Estimation Results for Firm Growth

	(1) Labor	(2) Labor	(3) Capital	(4) Capital
L.growthL	-.122**	-.122**		
	(.00)	(.00)		
L2.growthK			.042**	.041**
			(.00)	(.00)
age	-.160**	-.156**	-.010**	-.011**
	(.00)	(.00)	(.00)	(.00)
female	-.073**	-.069**	-.010**	-.010**
	(.00)	(.00)	(.00)	(.00)
findex	-.611**	-.526**	-.054**	-.067**
	(.00)	(.01)	(.03)	(.01)
DIS	.032**	.059**	.005**	.005*
	(.00)	(.00)	(.00)	(.08)
DIS*dfindex$_1$		-.058**		-.004
		(.03)		(.36)
DIS*dfindex$_3$		-.030		.006
		(.30)		(.19)
_cons	.072	.119		
	(.53)	(.31)		
N	15300	15300	10007	10007
ar1p	.000	.000	.000	.000
ar2p	.789	.790	.934	.996
hansenp	.390	.358	.227	.283

Note: p-values in parentheses; * $p < 0.10$, ** $p < 0.05$. The growth model is estimated by system GMM method. In columns (2) & (4), we include the interaction terms of natural disaster dummy with two financial constraints dummies. The default group for comparison is the firms with financial constraint index between 33rd and 66th percentiles.

Columns (3) and (4) present the results for capital growth. The coefficient for disaster dummy is positive and significant (H2 is confirmed). This implies that firms located in provinces with natural disasters on average have significantly higher capital growth than firms in provinces not hit by natural disasters, confirming the creative destruction hypothesis. When decomposing the picture, we find significant positive impacts on growth for firms with medium and high level financial constraints (.005 and .011 respectively,

and H5 is again rejected), but nearly no disaster impact on capital growth for firms with least financial constraints (.005-.004=.001).

Different from labor growth, capital growth exhibits positive auto-correlations. Specifically, the autocorrelation is positive but insignificant with its first lag, and is positive and significant with its second lag. The positive autocorrelation may be partly related to the investment spikes observed in data caused by convex and non-convex capital adjustment costs (Doms & Dunne, 1998; Cooper & Haltiwanger, 2006).[30] Similar to labor growth, capital growth decreases with firm age, the fraction of female workers, and the degree of financial constraints.

Up till here, we have examined the immediate short run impact of natural disasters on firm growth. Most of the typhoons and floods we studied for Vietnam occur between September and November in a year. It is interesting to find out whether the disaster impact lasts for multiple periods. To check this, we include lagged disaster dummies into the model. For instance, the one-lag disaster dummy indicates whether there was any disaster occurred in the previous period. We find small and insignificant coefficients for the lagged disaster dummy for both capital and labor growth. Hence the disaster impact on firm labor growth and capital growth is only present in the current period but does not last to the following year.

5.3 Estimation Results for Value Added Growth

We proceed to investigate the determinants for VA growth (see table 3 below). The empirical specification for VA growth is slightly different from the capital and labor growth above. Both AR(2) test and Hansen J test are not rejected, indicating a good fit of the model to the data. Consistent with labor and capital growth, VA growth decreases with firm age, the fraction of female workers, and the degree of financial constraints (comfirming H4). But different from labor and capital growth, VA growth is more persistent. Specifically, VA growth is negatively and significantly auto-correlated with its first and second lags (auto-correlated of degree two).

Natural disasters have on average positive and significant impact on VA growth (.055, rejecting H3). Note that the positive disaster impact we find is opposite to Leiter et al. (2009) for VA growth.[31] The impact on VA growth by natural disasters again differs across firms with different degrees of financial constraints. The disaster impact on VA growth is positive but insignificant for firms with medium level financial constraints (default group for comparison). The disaster impact on VA growth is negative for firms with least financial constraints but positive for firms with most severe financial constraints (H5 is rejected). The

[30] When a firm makes an (dis)investment decision, the investment pattern is likely to sustain for multiple periods due to convex and fixed capital adjustment costs.

[31] One potential explanation is that EU firms in Leiter et al. (2009) are less financially constrained than firms in Vietnam.

difference from the default group is significant. Unlike capital and labor growth, the disaster impact on VA growth lasts to the next period. Moreover, the lagged impact is also heterogeneous across firms with different degrees of financial constraints. Specifically, the impact on VA growth is negative for firms with least financial constraints (-.032), but is positive and significant for firms with medium and most financial constraints (.065 and .14 respectively).

Table 3
Value Added (VA) growth

	(1)	(2)	(3)
L.growthV	-.237**	-.239**	-.236**
	(.00)	(.00)	(.00)
L2.growthV	-.037**	-.037**	-.037**
	(.03)	(.02)	(.02)
L.findex	-.953**	-1.052**	-1.086**
	(.00)	(.00)	(.00)
age	-.250**	-.251**	-.259**
	(.00)	(.00)	(.00)
female	-.090**	-.090**	-.087**
	(.00)	(.00)	(.00)
DIS	.055**	.039	.037
	(.00)	(.17)	(.19)
L.DIS	.067**	.066**	.065**
	(.00)	(.00)	(.02)
DIS*L.dfindex$_1$		-.117**	-.122**
		(.01)	(.01)
DIS*L.dfindex$_3$		.135**	.137**
		(.00)	(.00)
L.DIS*L.dfindex$_1$			-.098**
			(.02)
L.DIS*L.dfindex$_3$			.075*
			(.08)
_cons	.113	.047	.044
	(.34)	(.70)	(.72)
N	9962	9962	9962
ar1p	.000	.000	.000
ar2p	.601	.571	.624
hansenp	.295	.440	.470

Note: *p*-values in parentheses; * $p < 0.10$, ** $p < 0.05$. The model is estimated by system GMM. Columns (2)&(3) include the interaction term between (lagged) disaster dummy with two dummies indicating different degrees of financial constraints. The default group is the firms with medium financial constraints.

Why does disaster impact on productivity (VA) growth last longer than capital growth and labor growth? Natural disasters create investment demand in both labor and capital for recovery. Unlike labor which becomes immediately productive, it takes some time before new capital becomes productive. New capital installed in the previous period may become productive one period later. If there is any upgrade of machinery and equipment for production, it also leads to productivity growth beyond one period.

So far, the estimation results for the disaster impact on labor, capital, and VA growth are consistent with one another. To summarize, we find that firm growth decreases with firm age, financial constraints, and the share of female workers, and that natural disasters have mostly a positive impact on firm growth. The positive growth may be the result from the higher reconstruction demands for recovery after the natural disasters. For instance, empolyees may also work longer hours than before natural disasters. Labor supply may increase in manufacturing sectors if some labor shifts from agriculture to manufacturing sectors (Kirchberger, 2017). If some firms manage to upgrade their assets and technologies, their growth can also be higher. The immediate negative impacts on growth for directly affected firms can to some extent be offset by the positive spillover effects on firms not directly affected. The large significant negative impact on firm growth by financial constraints implies the importance of financial market development on economic growth.

The disaster impacts on firm growth are heterogeneous across firms with different degrees of financial constraints but the pattern is opposite to our expectation. Specifically, the disaster impact is positive for firms with more severe financial constraints but negative or zero for firms with least financial constraints.[32] To explain the higher labor growth for constrained firms, one could argue that, with limited access to capital, financially constrained firms may seek to substitute labor (partially) for lost or damaged capital to resume production (e.g. by working longer hours), whereas firms with low financial constraints can simply replace lost or damaged assets with new ones. For capital and value added growth, initially we expect larger growth impacts for least constrained firms. The argument is that firms with low financial constraints can replace damaged assets and resume production more quickly with their (easy) access to credit for recovery than firms with most financial constraints. One potential explanation for the opposite findings is that firms with least financial constraints may be more resilient to typhoons and floods, which could be related to firm size and age. Larger and older firms may be more capable of reducing disaster risks as they are equipped with risk-mitigating measures and facilities (buildings, and machinery and equipment), more disaster experience, and better trained workers. When disasters occur, they can react more efficiently to mitigate damages than more constrained firms. Besides, least constrained firms are more likely to locate in safer areas (e.g.

[32] But the difference across firms from the three subgroups is insignificant for capital growth.

industrial parks) than most constrained firms.[33] In the census data we do observe that least financially constrained firms are much larger and older than most financially constrained firms.

Following the arguments above, we test whether the heterogeneous disaster impacts across firms with different financial constraints are driven by the differences in firm size and age, by adding the interaction terms of the disaster dummy with the size and age dummies into the growth model. The results are presented in table 4.[34] The coefficient for the disaster dummy captures the average disaster impacts for the default group of firms with employment above 250, older than 5 years, and are least constrained. For the default group, the average disaster impacts are positive but insignificant for labor growth (.03), close to zero and insignificant for capital growth, but are significantly negative (-.08) for value added growth. However, the stronger positive disaster impacts for more constrained firms remain for labor and value added growth but are no longer true for capital growth. More constrained firms may indeed seek to substitute labor for capital for post-disaster reconstruction, rendering larger positive growth impacts in labor and output for more constrained firms.

Regarding the impact of firm size, small and medium firms (SMEs) have on average significantly lower labor growth (-.04 and -.13) but significantly higher capital growth (.01 and ,02) than large firms, ceteris paribus. Capital adjust costs may be smaller for SMEs than large firms, making it easier for them to adjust capital stocks, , and hence there is less need to substitute capital for labor. Another possibility is that many SMEs in Vietnam make use of informal credits for investment which may not necessarily be present in their formal balance sheet (Le & Nguyen, 2009). For VA growth, the disaster impacts are similar across firms of different sizes, which can be explained to some extent by the opposite disaster impacts on labor and capital growth. The average disaster impacts on labor and VA growth are significantly lower (-.04 and -.09) but are similar for capital growth relative to old firms.

Can we explain the larger positive disaster impacts on labor and output growth for more constrained firms than less constrained firms? We find in the data that most constrained firms are much more labor intensive than least constrained firms.[35] This is true even after controlling for differences in firm size and age. For reconstruction purpose, most constrained firms may seek to substitute labor for capital in the short run if they have difficulties accessing to capital necessary for recovery. It is relatively easier to hire new workers than replacing physical assets in the short run. Higher labor growth and similar capital growth combined may to some extent explain the larger value added growth for more constrained firms.

[33] Unfortunately we cannot check this argument because we have no detailed location data for different firms.
[34] We allocate firms into three size categories based on the number of employees: small if 50 or below, medium if between 51 and 250, large if above 250. The age dummy is equal to 1 if firms are 5 years old or younger, and zero otherwise.
[35] The average capital labor ratio for most (least) constrained firms is 29 (107).

Table 4
Disaster impact on firm growth: controlling for firm size and age

	Labor Growth	Capital Growth	Value Added growth
disaster	.028	-.003	-.076*
	(.24)	(.29)	(.07)
l.disaster			-.033
			(.32)
$dfindex_2$*disaster	.095**	-.001	.135**
	(.00)	(.84)	(.00)
$dfindex_3$*disaster	.121**	.000	.290**
	(.01)	(.99)	(.00)
l.$dfindex_2$*l.disaster			.098**
			(.02)
l.$dfindex_3$*l.disaster			.171**
			(.00)
young*disaster	-.036*	.001	-.088*
	(.08)	(.87)	(.09)
Medium*disaster	-.041**	.009**	-.007
	(.03)	(.01)	(.87)
Small*disaster	-.127**	.015**	-.029
	(.00)	(.00)	(.62)

Note: the growth models are estimated by system GMM method. To save space, we do not report the coefficient estimates for other variables, which are similar to the previous estimates from table 1 to table 3.

The positive disaster impact found on firm growth in Vietnam offers some insights to understand the short run macroeconomic disaster impact. First, we find positive impact on firm growth for at least two thirds of the firms in the sample and slightly negative or zero impact for the rest. The sign and magnitude of the aggregate impact by storms and floods on economic growth depends on the relative importance of the one third of firms with least financial constraints in the economy. If they do not take up a dominant share in the economy, then the aggregate disaster impact may end up being positive; and vice versa.[36] Recall that we find larger positive impact on firm growth for more constrained firms (top 66%) than least constrained firms. This implies that natural disasters (floods and typhoons to be precise) also trigger some extent of resource redistribution/reallocation among firms. Relatively more resources (labor and capital) are directed towards most constrained firms compared to the pre-disaster period. This should also bring positive aggregate output growth to some extent.

5.4 Alternative disaster dummies defined by damage measures

So far, we have presented the estimation results with the disaster variable defined by physical intensity measures (wind speed in knots and affected square kilometers). It is interesting to check the results with

[36] If bottom 33% of the firms (least constrained firms) take up a dominant share of aggregate output, the positive growth impact from the other 66% on the aggregate economy may be small as they do not play a large role in the economy.

two other damage measures (death and estimated economic damages) for natural disasters which are widely used in the literature. Therefore, we also estimate the growth model with the disaster dummies defined by either death toll (DIS_2) or estimated economic damages (DIS_3) for comparison. The estimation results are presented in panel A in table 5. Overall, we still find positive and signicant disaster impacts on firm growth. The impact is similar in scale when the disaster is defined by death toll and economic damages, but is slightly smaller than when disaster is defined by physical intensity measures.[37] However, the impacts of floods and typhoons on value added growth last to the next period only when natural disasters are defined by physical intensity measures but not by death tolls or estimated economic damages.

Table 5
Disaster impact on firm growth with different disaster dummies

	Labor growth	Capital growth	VA growth
	Panel A: original cutoff values for disaster definitions		
DIS_1 ($L.DIS_1$)	.032**	.005**	.055**(.067**)
DIS_2 ($L.DIS_2$)	.022**	.004**	.043**(-.009)
DIS_3 ($L.DIS_3$)	.021**	.003**	.042**(.019)
	Panel B: increase the cutoff values for disaster definitions		
DIS_1 ($L.DIS_1$)	.026**	.004**	.063**(.074**)
DIS_2 ($L.DIS_2$)	.031**	.005**	.088**(.120**)
DIS_3 ($L.DIS_3$)	.023**	.002*	.045**(.016)
	Panel C: decrease the cutoff values for disaster definitions		
DIS_1 ($L.DIS_1$)	.027**	.004**	.055**(.080**)
DIS_2 ($L.DIS_2$)	.025**	.003**	.048**(.050**)
DIS_3 ($L.DIS_3$)	.023**	.002**	.038**(.028)

Note: the cutoff values for wind speed, the ratio of the affected square kilometers over province size by floods, death by floods and typhoons, and the estimated economic damages in panel A/B/C are respectively 64/83/55, 1/2/.5, 50/100/30, and 50/100/30 million VND.

5.5 Robustness Checks

In this section, we perform several robustness checks for the (heterogeneous) disaster impacts on firm growth. We first vary the cutoff values used to define our disaster dummies. Next, we decompose the natural disasters into typhoons and floods respectively. Third, we check the disaster impacts for firm growth in terms of sales. Finally, we investigate the disaster impacts with alternative definitions of financial constraints.

5.5.1 Varying the cutoff values for defining disaster dummies

Although the cutoff values for defining the three disaster dummies are close to sample medians, the choices are arbitrary. Therefore, we perform additional tests by the varying of the cutoff values for defining the disaster dummies to see if the results are robust. We present the estimation results with higher and lower cutoff values for all three disaster dummies in table 4 (panels B and C). When we increase/decrease the

[37] The estimation results are robust to the changes in cutoff values used to define disaster dummies.

cutoff values for defining disasters, we in fact look at the impacts for more or less severe floods and typhoons in terms of physical intensities, death tolls, and estimated economic damages. The number of observations experiencing disasters will be smaller and larger respectively. Overall, the positive impacts on firm growth are robust to the changing in the cutoff values for disaster definitions.

5.5.2 Decomposing natural disasters into floods and storms/typhoons

We have grouped floods and typhoons/storms together into one single disaster dummy. The overall disaster impact can be caused by floods (typhoons) alone or by both. Therefore, it is interesting to identify the individual impacts of floods and typhoons respectively. We run the three growth models with the disaster dummy replaced by a flood dummy and a typhoon dummy. The table below presents the estimation results. Both floods and typhoons have positive and significant impact on firm growth in terms of labor, capital, and value added. The positive impacts are slightly higher by typhoons than floods. Interestingly, we also find that the positive impacts by floods last longer than typhoons. Floods occurred in the previous year have significant positive impacts on firm growth in the current period.

Table 6

Impacts on Firm Growth by Floods and Typhoons separately

	labor growth	capital growth	VA growth
flood	.031**	.004**	.055**
	(.01)	(.002)	(.02)
typhoon	.052**	.007*	.064
	(.02)	(.004)	(.04)
L.flood	.021**		.084**
	(.01)		(.02)

Note: the flood and the typhoon dummies are defined by the physical intensity measures from DFO and GAME respectively.

5.5.3 Alternative definition of firm growth: sales growth

We also perform the same analysis on sales growth. Sales growth does not solely reflect production growth but also incorporates influences from other external factors such as demand shocks. Without sufficient controls for other external factors, one should be very cautious in making direct inference based on the findings. Nevertheless, we obtain similar findings in that sales growth decreases with firm age, share of female workers, and financial constraints. Sales growth also exhibits negative autocorrelation with its first lag. The impact on sales growth by natural disasters does not last to the period after. Although we also observe heterogeneous disaster impact across firms with different degrees of financial constraints, the picture looks slightly different. With sales growth, we find positive and significant disaster impacts for firms with medium and least financial constraints, but negative impacts for firms with most financial constraints (confirming H5). Most constrained firms are much smaller and younger than firms with medium

and least financial constraints. Most constrained firms may be more vulnerable to natural disasters in terms of supply chain networks. They may mostly serve for local markets. When natural disasters hit local areas, local sales network may be temporarily distrupted, rendering negative sales growth by natural disasters for most constrained firms. But the disaster impact on sales growth does not last to the next year.

Table 7
Determinants for Sales Growth

	(1)	(2)	(3)
DIS_1	.020*	.067**	.067**
	(.07)	(.00)	(.00)
DIS_1*$dfindex_1$		.016	.016
		(.58)	(.57)
DIS_1*$dfindex_3$		-.131**	-.131**
		(.00)	(.00)
$L.DIS_1$			.003
			(.78)

Note: *p*-values in parentheses: * $p < .10$, ** $p < .05$. See appendix A4 for the full estimation results.

5.5.4 Robustness of the heterogeneous disaster impacts for firms with different financial constraints

We further perform extra robustness checks to see if the heterogeneous disaster impacts on firm growth across firms are robust. For example, the heterogeneous disaster impacts remain robust when we define financial constraint dummies by the cutoff values for the 25th and 75th percentiles (rather than 33rd and 66th percentiles). Moreover, instead of including interaction terms between disaster dummy and the financial constraint dummies, we directly include the interaction term between disaster dummy and the (continuous) financial constraint index. But the estimated coefficients for both the disaster dummy and the interaction term become insignificant due to multicollinearity issue between the interaction term and the disaster dummy with a correlation coefficient of as high as .96.

The financial constraint dummies may be endogeneous as they are defined based on the contemporaneous financial constraint index values. If so, the interaction terms between disasters and financial constraints may be endogeneous as well. To reduce the potential endogeneity concern, we split the whole sample into three subgroups based on firms' first available financial constraint index values.[38] The downside is that such sample splitting criterion does not account for switching of a firm's financial constraint statuses over time. But the ratios of the annual financial constraint index over the initial financial constraint index do not exhibit a large variation.[39] Therefore, we expect only a small fraction of firms to experience switching in their financial constraint statuses between the least and the most constrained.

[38] The endogeneity issue is still present if there is not much variation in financial constraint index over time.
[39] The maximum value for the ratio is 1.4.

Nevertheless, we still find systematic differences for firms from the three subgroups defined by the initial financial constraint index (see table A4.1 in the appendix A4). More constrained firms also tend to be smaller in terms of employment, capital stock, and value-added and younger than less constrained firms. Labor growth and VA growth on average decrease slightly with the degrees of financial constraints while capital growth remains similar across groups. The averages for the three disaster dummies increase slightly with the degrees of financial constraints. It could imply that more constrained firms tend to be located in disaster-prone areas than less constrained firms. The average fraction of female workers is the lowest for most constrained firms.

We then estimate the growth models for the three subsamples of firms (see appendix A4 for the estimation results). The results are mostly consistent with the model with interaction terms, e.g. the impact of firm age, financial constraints, and fraction of female workers, as well as the degree of autocorrelation. The results also confirm the positive disaster impacts on firm growth, which are heterogeneous across firms with different degrees of financial constraints, although with a less clear-cut pattern.

Finally, it is interesting to check the impacts of initial firm size and ownership on firm growth. To do this, we first predict the residuals from the three (labor/capital/VA) growth models, and then regress the predicted residuals on time-invariant variables such as initial firm size, initial firm age, ownership dummies, and sector and regional dummies.[40] The coefficients for the proxies of initial firm size are all negative and significant, rejecting the Gribat's law. We also find negative and mostly significant coefficients for the dummies of state-owned firms and foreign firms, implying that private firms on average experience higher growth than SOEs and foreign firms. The results are consistent with the findings in previous studies that private firms perform better than state-owned firms (Goldeng, Grünfeld, & Benito, 2008; Nguyen & van Dijk, 2012).

6. Conclusion

We investigate in this paper how typhoons and floods interact with firms' heterogeneous financial conditions to impact firm labor, capital, and value-added growth. This is done by testing five hypotheses using the enterprise census panel dataset which is matched with three different disaster databases from Vietnam. We find positive and significant short-run impacts of typhoons and floods on the growth of labor, capital, and valued added. Moreover, contrary to our expectations, we find stronger positive disaster impacts for financially more constrained firms. This pattern is robust for labor and VA growth, but not for capital growth when accounting for the differences in firm size and age. One explanation for the finding is that more financially constrained firms substitute labor for capital for post-disaster reconstruction, rendering

[40] The estimation results are available upon requests.

larger labor and output growth. The results are robust to different definitions for disasters and financial constraints. Notably, we find stronger positive disaster impacts for less (rather than more) constrained firms on sales growth, although one should be cautious in interpreting the results.

The paper has two methodological contributions to the literature. First, we pioneer to estimate the firm-level disaster impacts by the GMM method that efficiently accounts for endogeneity and measurement errors that can otherwise be problematic in firm growth models. The successful application of the method can be extended to data from other countries to generate more insights into disaster impacts. Second, we make the first attempt to compare the performance of different disaster measures defined by physical intensities and damages (death and estimated economic damages) with firm level data, and find similar impacts for the different disaster measures. This implies that both physical and damage measures are reliable proxies for disasters that can be used in firm level studies on disaster impacts.

While on average we find that disasters are positively related with labor and output growth, more detailed analyses show this is mainly the case for older firms, but not for young firms which have a significantly lower growth after a disaster. This could be due to a lack of experience and knowledge about disaster management by young compared to old firms. A policy recommendation is to better inform young firms about the disaster risk they face and measures they can take to limit these risk. For example, the government can intervene by organizing workshops about disaster preparation and management for startups.

A limitation of this paper is that we only examine impacts from storms and floods. We are aware of the different nature of different disasters and do not seek to generalize the findings to all types of natural disasters. Second, the disaster measures used in this paper cannot precisely identify firms directly hit by natural disasters. The disaster dummies are defined at provincial levels, because we do not have information on the specific location of firms in the census data, whereas disaster events typically have local impacts which perhaps occur in smaller areas than a province. An advantage of this approach is that we learn more about the aggregated impacts of a disaster on firms in a region, including substitution effects experienced by not directly impacted firms. A disadvcantage is that we cannot separate effects between directly versus indirectly impacted firms in a region. We suggest to extend the study to other countries with a broader variety of natural disasters to obtain a more complete picture of the firm level impacts by different types of natural disasters in the future. Moreover, future research can complement our study and provide more detailed insights into the disaster impacts and mitigating factors by conducting a firm level survey, which collects more detailed information on natural disaster impacts, such as whether firms are directly or indirectly affected by a natural disaster and the associated damages.

Reference

Altay, N., & Ramirez, A. (2010). Impact of Disasters on Firms in Different Sectors: Implications for Supply Chains. *Journal of Supply Chain Management*, Volume 46, Issue 4, pp 59-80.

Anbarci, N., Escaleras, M., & Register, C. (2005). Earthquake Fatalities: the Interaction of Nature and Political Economy. *Journal of Public Economics*, vol. 89, issue 9-10, 1907-1933.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies*, Vol. 58, pp. 277–297.

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, Vol. 68, pp. 29–51.

Baez, J., De La Fuente, A., & Santos, I. (2010). Do Natural Disasters Affect Human Capital? An Assessment Based on Existing Empirical Evidence. *IZA DP NO. 5164*.

Beck, T., Demirguc-Kunt, A., & Maksimovic, V. (2005). Financial and Legal Constraints to Growth: Does Firm Size Matter? *Journal of Finance*, VOL. 60 NO. 1, pp. 137-177.

Belasen, A. R., & Polachek, S. W. (2009). How Disasters Affect Local Labor Markets: The Effects of Hurricanes in Florida. *The Journal of Human Resources*, Volume 44, Issue 1, pages. 251-276.

Bentzen, J., Madsen, E., & Smith, V. (2012). Do firms' growth rates depend on firm size? *Small Business Economics*, Volume 39, Issue 4, pp 937–947, https://doi.org/10.1007/s11187-011-9341-8.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, vol. 87, pp. 115–143.

Bottazzi, G., & Secchi, A. (2003). Common Properties and Sectoral Specificities in the Dynamics of U.S. Manufacturing Companies. *Review of Industrial Organization*, vol. 23, issue 3, 217-232.

Bottazzi, G., Coad, A., Jacoby, N., & Secchi, A. (2011). Corporate growth and industrial dynamics: evidence from French manufacturing. *Applied Economics*, Volume 43, Issue 1, pp. 103-116.

Bottazzi, G., Secchi, A., & Tamagni, F. (2006). Productivity, Profitability and Financial Fragility: Evidence from Italian Business Firms. *LEM Papers Series, Sant'Anna School of Advanced Studies, Pisa, Italy*.

Bouwer, L. (2011). Have disaster loses increased due to anthropogenic climate change? . *Bulletin of The American Meteorological Society*, January: 39-46.

Brückner, M., & Ciccone, A. (2011). Rain and the Democratic Window of Opportunity . *Econometrica*, Volume 79, Issue 3, pp. 923–947.

Cabral, L. (1995). Sunk Costs, Firm Size and Firm Growth. *The Journal of Industrial Economics*, Vol. 43, No. 2, pp. 161-172.

Carvalho, V. M., Nirei, M., Saito, Y. U., & Tahbaz-Salehi, A. (2016). Supply Chain Disruptions: Evidence from the Great East Japan Earthquake. *Columbia Business School Research Paper No. 17-5*.

Cavallo, E., & Noy, I. (2010). The Economics of Natural Disasters: A Survey. *IDB Working Paper Series, No. IDB-WP-124*.

Cavallo, E., Galiani, S., Noy, I., & Pantano, J. (2013). Catastrophic Natural Disasters and Economic Growth. *Review of Economics and Statistics*, Volume 95, Issue 5, p.1549-1561.

Coad, A. (2006). A Closer Look at Serial Growth Rate Correlation. *Working paper*.

Coad, A. (2007). Firm Growth: A Survey. *working paper*.

Cole, M. A., Elliott, R. J., Okubo, T., & Strobl, E. (2015). Natural Disasters and Plant Survival: The impact of the Kobe earthquake. *RIETI Discussion Paper Series 13-E-063*.

Cooper, R. W., & Haltiwanger, J. (2006). On the Nature of Capital Adjustment Costs. *Review of Economic Studies*, vol. 73, issue 3, pp. 611-633.

Cuaresma, J. C. (2010). Natural disasters and human capital accumulation. *World Bank Economic Review*, Volume 24, Issue 2, Pages 280-302.

De Mel, S., McKenzie, D., & Woodruff, C. (2012). Enterprise recovery following natural disasters. *The Economic Journal*, Volume 122, Issue 559, pp 64-91.

Delmar, F. (1997). Measuring growth: methodological considerations and empirical results. In R. Donckels, & A. Miettinen, *Entrepreneurship and SME Research: On its Way to the Next Millennium* (pp. pp. 199-216). Aldershot, England: Ashgate.

Doms, M., & Dunne, T. (1998). Capital Adjustment Patterns in Manufacturing Plants. *Review of Economic Dynamics* , vol. 1, pp. 402-429.

EMDAT. (2016). *International Disaster Database; www.emdat.be.* Brussels - Belgium.: CRED: The OFDA/CRED, Université catholique de Louvain.

Estrada, F., Botzen, W., & Tol, R. (2015). Economic losses from US hurricanes consistent with an influence from climate change. *Nature Geoscience*, 8: 880-884.

Evans, D. (1987). The Relationship between Firm Growth, Size, and Age: Estimates for 100 Manufacturing Industries. *Journal of Industrial Economics,*, vol. 35, issue 4, 567-81.

Farre-Mensa, J., & Ljungqvist, A. (2016). Do Measures of Financial Constraints Measure Financial Constraints? *Review of Financial Studies* , Vol. 29, no. 2, pp. 271-308.

Felbermayr, G., & Gröschl, J. (2014). Naturally negative: The growth effects of natural disasters. *Journal of Development Economics*, Volume 111, pages 92–106.

Gilchrist, S., & Himmelberg, C. (1998). Investment: Fundamentals and Finance. *NBER Macroeconomics Annual*, Vol. 13, pp. 223-262.

Goldeng, E., Grünfeld, L. A., & Benito, G. R. (2008). The Performance Differential between Private and State Owned Enterprises: The Roles of Ownership, Management and Market Structure. *Journal of Management Studies*, Vol. 45, No. 7, pp. 1244-1273.

Hall, B. (1987). The Relationship between Firm Size and Firm Growth in the U.S. Manufacturing Sector. *Journal of Industrial Economics*, vol. 35, issue 4, 583-606.

Hallegatte, S., & Przyluski, V. (2010). The Economics of Natural Disasters: concepts and methods. *World Bank Policy Research Working paper 5507*, pages 1-31.

Hansen, L. (1982). Large Sample Properties of Generalized Method of Moment Estimators. *Econometrica*, Vol. 50, issue 4, pp. 1029-1054.

Hansen, L., & Singleton, K. (1982). Generalized Instrumental Variables Estimation of Nonlinear Rational Expectations Models. *Econometrica*, Vol. 50, issue 5, pp. 1269-86.

Hayakawa, K., Matsuura, T., & Okubo, F. (2015). Firm-level Impacts of Natural Disasters on Production Networks: Evidence from a Flood in Thailand. *Journal of the Japanese and International Economics*, Volume 38, pp 244-259.

Huang, Y., Ma, Y., Yang, Z., & Zhang, Y. (2016). A fire sale without fire: an explanation of labor-intensive FDI in China. *Journal of Comparative Economics*, Volume 44, Issue 4, pp. 884-901.

Hyytinen, A., & Toivanen, O. (2005). Do financial constraints hold back innovation and growth?: Evidence on the role of public policy. *Research Policy*, Volume 34, issue 9, pages 1385-1403.

IPCC. (2014). *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.* Cambridge, U.K. and New York: Cambridge University Press.

Kahn, M. E. (2005). The Death Toll from Natural Disasters: The Role of Income, Geography, and Institutions. *Review of Economics and Statistics*, Volume 87, Issue 2, pages 271-284.

Kirchberger, M. (2017). Natural disasters and labor markets. *Journal of Development Economics*, Volume 125, pages 40–58.

Klomp, J. K. (2014). Natural disasters and economic growth: A meta-analysis. *Global Environmental Change* , Volume 26, issue 0, pages 183-195.

Klomp, J., & Valckx, K. (2014). Natural disasters and economic growth: A meta-analysis. *Global Environmental Change*, Volume 26, issue 0, pages 183-195.

Lazzaroni, S., & van Bergeijk, P. A. (2014). Natural disasters' impact, factors of resilience and development: A meta-analysis of the macroeconomic literature. Ecological Economics. *Ecological Economics*, Volume 107, pages 333-346.

Le, N. T., & Nguyen, T. V. (2009). The Impact of Networking on Bank Financing: The Case of Small and Medium-Sized Enterprises in Vietnam. *Entrepreneurship: Theory and Practice*, Volume 33, Issue 4, pp. 867–887.

Leiter, A. M., Oberhofer, H., & Raschky, P. A. (2009). Creative Disasters? Flooding Effects on Capital, Labour and Productivity within European Firms. *Environmental and Resource Economics*, Volume 43,Issue 3, pp 333-350.

Lin, Ma, & Xuan. (2011). Ownership structure and financial constraints: evidence from a structural estimation. *Journal of Financial Economics*, Vol.102, pp. 416-431 .

Loayza, N. V., Olaberría, E., Rigolini, J., & Christiaensen, L. (2012). Natural Disasters and Growth: Going Beyond the Averages. *World Development*, Volume 40, Issue 7, Pages 1317-1336.

Lotti, F., Santarelli, E., & Vivarelli, M. (2003). Does Gibrat's Law hold among young, small firms? *Journal of Evolutionary Economics*, Volume 13, pp. 213-235.

Love, I. (2003). Financial Development and Financing Constraints: International Evidence from the Structural Investment Model. *The Review of Financial Studies*, Volume 16, Issue 3, pp. 765–791.

McDermott, T. K. (2012). The Effects of Natural Disasters on Human Capital Accumulation. *IIIS Discussion paper, No. 391*.

Miao, Q., & Popp, D. (2014). Necessity as the mother of invention: Innovative responses to natural disasters. *Journal of Environmental Economics and Management*, Volume 68, issue 2, pages 280-295.

Miguel, E., Satyanath, S., & Sergenti, E. (2004). Economic Shocks and Civil Conflict: An Instrumental Variables Approach. *Journal of Political Economy*, vol. 112, no. 4, pp. 725-753.

Musso, P., & Schiavo, S. (2008). The impact of financial constraints on firm survival and growth. *Journal of Evolutionary Economics*, Volume 18, issue 2, pages 135-149.

Newey, W., & West, K. (1987). A Simple, Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica*, Vol. 55, issue 3, pp. 703-08.

Nguyen, T. T., & van Dijk, M. A. (2012). Corruption, growth, and governance: Private vs. state-owned firms in Vietnam. *Journal of Banking & Finance*, Vol. 36, pp. 2935–2948.

Noy. (2009). The Macroeconomic Consequences of Disasters. *Journal of Development Economics*, Volume 88, pages 221-231.

Noy, I., & Nualsri, A. (2007). *What do Exogenous Shocks Tell Us about Growth Theories?* Manoa: Department of Economics, University of Hawaii.

Noy, I., & Vu, T. (2010). The economics of natural disasters in a developing country: the Case of Vietnam. *Journal of Asian Economics* , Volume 21, pages 345–354.

Raschky, P. A. (2008). Institutions and the losses from natural disasters. *Natural Hazards and Earth System Science*, Volume 8, Issue 4, pp.627-634 .

Rodriguez-oreggia, e., De La Fuente, A., De La Torre, R., & Moreno, H. A. (2013). Natural Disasters, Human Development and Poverty at the Municipal Level in Mexico. *Journal of Development Studies*, Vol. 49, No. 3, 442–455.

Romer, P. (1986). Increasing returns and long-run growth. Journal of Political Economy, 94(5): 1002-1037. *Journal of Political Economy*, Volume 94, issue 5, pages 1002-1037.

Romer, P. (1990). Endogenous technological change. *Journal of Political Economy*, Volume 98, issue 5, pages 71-102.

Runyan, R. C. (2006). Small Business in the Face of Crisis: Identifying Barriers to Recovery from a Natural Disaster. *Journal of Contingencies and Crisis Management*, Volume 14, Issue 1, pp 12–26.

Schumpeter, J. (1934). *The Theory of Economic Development.* Cambridge: Harvard University Press.

Skidmore, M., & Toya, H. (2002). Do Natural Disasters Promote Long-Run Growth? *Economic Inquiry*, Volume 40, pages 664-687.

Strobl, E. (2011). The Growth Impact of Hurricane Activity: Evidence from US Coastal Counties. *Review of Economics and Statistics*, Volume 93, pages 575-589.

Tanaka, A. (2015). The impacts of natural disasters on plants' growth: Evidence from the Great Hanshin-Awaji (Kobe) earthquake. *Regional Science and Urban Economics*, Volume 50, pages 31–41.

The World Bank. (2010). *Weathering the Storm: Options for Disaster Risk Financing in Vietnam.* Washington DC.

Tierney, K. J. (2007). Chapter 16 Businesses and Disasters: Vulnerability, Impacts, and Recovery. In H. Rodriguez, E. L. Quarantelli, & R. R. Dynes, *Handbook of Disaster Research* (pp. pp 275-296). New York: Springer.

Todo, Y., Nakajima, K., & Matous, P. (2015). How do supply chain networks affect the resilience of firms to natural disasters? Evidence from the great east Japan earthquake . *Journal of Regional Science* , Volume 55, Issue 2, Pages 209–229.

Tol, R. (2017). Economic impacts of climate change. *Review of Environmental Economics and Policy* , (In press).

Toya, H., & Skidmore, M. (2007). Economic Development and the Impacts of Natural Disasters. *Economic Letters*, Volume 94, pages 20–25.

Webb, G. R., Tierney, K. J., & Dahlhamer, J. M. (2002). Predicting Long-term Business Recovery from Disaster: a Comparison of the Loma Prieta Earthquake and Hurricane Andrew. *Environmental Hazards*, Volume 4, pp 45-58.

Weiss, C. (1998). Size, Growth, and Survival in the Upper Austrian Farm Sector. *Small Business Economics*, Volume 10, Issue 4, pp. 305–312.

Whited. (1992). Debt, Liquidity Constraints, and Corporate Investment: Evidence from Panel Data. *The Journal of Finance*, Volume 47, Issue 4, pp. 1425–1460.

Whited, T., & Wu, G. (2006). Financial Constraints Risk. *Review of Financial Studies*, Vol. 19, issue 2, pp. 531-559.

Windmeijer, F. (2005). A finite sample correction for the variance of linear two-step GMM estimators. *Journal of Econometrics*,, Volume 126, Issue 1, pp. 25–51.

Wisner, B., Blaikie, P., Cannon, T., & Davis, I. (2003). *At Risk: natural hazards, people's vulnerability and disasters* .

Zhou, F. (2015). Capital Market Distortions in Vietnam: Comparing SOEs and Private Firms. *working paper*, pp. 1-52.

Appendices (A1-A4)

Appendix A1. The Enterprise Census Data (2000-2009)

The enterprise census was collected annually between March and May since 2000 by the General statistical office (GSO) of Vietnam. This data covers all state-owned enterprises (SOEs) and foreign firms, and also private firms with 10 plus employees in Vietnam from all industries. An additional 10% of the private firms with less than 10 employees are randomly selected as well. We have access to the census data between 2000 and 2009. In this paper we focus on manufacturing firms. For the documentation of data merging and preliminary cleaning, one can refer to Zhou (2015).[41] Below we document the data cleaning relevant to this paper briefly.

First, duplicates for selected key variables within each year and across years are removed. The selected key variables for within each year include (end of year) total and fixed capital, labor, and debt, and value added/sales.[42] Firms with duplicates across years by total and fixed capital, labor, debt, equity, and sales (no within variation) are eliminated as well.

Next, firms that switch locations across regions and from sectors with few observations are removed. Firms from the sectors of tobacco, coke and refined petroleum, office, accounting and computing machinery, and recycling with sector numbers 16, 23, 30, and 37 respectively are removed due to small number of observations.

Third, observations that are outliers and/or with missing or non-positive values for key variables are dropped. Outliers are with capital output ratio above 1000 or below .001, with wage output ratio above 100 or below .01, with capital labor cost ratio above 1000 or below .001, with mean wage rate above 250 or below .1.[43] Moreover, observations with missing or non-positive values for ownership, sector, region, sales and value added, wages, (end of year) fixed and total assets and labor, and with sales smaller than net sales and/or net sales smaller than profits are excluded.[44]

[41] The paper is available for download on Zhou's personal website: http://zyzyis.github.io/fujinzhou/.
[42] The reason for removing all observations with duplicates is that quite some observations have more than 5 duplicates (but have different panel identifiers), making it difficult to determine which duplicates to drop. Therefore, we drop all duplicates. We further remove the observations with duplicates in terms of (end of year) total and fixed capital, labor, and debt, and sales.
[43] The cutoff values for different variables are chosen based on their 99th and 1st percentiles.
[44] Net sales are equal to sales minus any deductions, such as excise duties, export tax, and direct VAT payable.

Fourth, outliers of the growth rates of capital, labor, labor costs, sales, value added are also removed. Growth rate is defined as the ratio of the end of year t real values over the end of year t-1 real values.[45] The outliers are defined with the growth rates above the user-defined upper bounds (50 for total capital, 100 for fixed capital, labor, wages, 200 for value added, and 250 for sales) or below the lower bounds (.02 for total capital, .01 for fixed capital and labor, wages, .005 for value added, and .004 for sales). We drop the outliers only if they also satisfy one of the following conditions: 1) firms only appear 2 consecutive years in the panel, 2) for each firm, there is only one outlier defined by each variable and this outlier either occurs in its first or last year in the data.[46] For the rest of the outliers, we then eyeball and handpick outliers to be dropped by checking firm sales, value added, labor, and capital simultaneously to avoid excessive data cleaning.

Furthermore, the top and bottom 1% of the data for the key variables such as value added, output growth, capital growth, and labor growth, wages, sales, and the end of year fixed and total capital, labor, and debt, are trimmed off. Also, all firms with gaps are dropped.

The cleaning above leaves out about 24% of the firm-year observations and the final sample size is 180181. All nominal values are deflated by 2-digit industry deflators with 1994 as the base year.

Appendix A2. Three Disaster Databases

In this appendix, we introduce three different disaster databases for use in the paper.

A2.1 The ifo Geological and Meteorological Events Database (GAME)

The ifo Geological and Meteorological Events (GAME) database is a country-level database covering a rich collection of variables for all countries worldwide from 1979 till 2010. The dataset collects information on geological and meteorological events including earthquakes, volcanic eruptions, storms, extreme temperature events, floods and droughts from primary information. GAME provides a unique dataset for economic analysis as the disaster measures feature variation that is presumably exogenous to economic outcomes. We use the primary information for two most frequent and disruptive disaster events, namely typhoons and floods, from Vietnam to construct disaster measures for analysis. We measure the severity of typhoons by wind speed.

Wind Speed Data

[45] In case of first time appearance in the data, the growth is defined by the ratio of the end of period values over the beginning of period values in the same year. Notice that the recall bias can be very large for beginning of period values relative to end of period values since the recall length is at least 15 months for the former.

[46] The reliability of panel identifiers across years is an issue. This simple data cleaning strategy can better identify any potential mismatch of observations based on firm panel identifiers. With only 2 years of data, it is easy to spot if the values of the key variables are very different between two consecutive years. Similarly, with more than 2 years, it is easy to implement the data cleaning when the *only* outlier occurs in the first or last appearance in the data. This helps to identify mismatches at the start/end of the panel. Data cleaning is difficult with multiple outliers.

GAME uses two primary data sources for hurricanes/storms/typhoons: the International Best Track Archive for Climate Stewardship (**IBTrACS**) and the Global Surface Summary of Day (GSOD) data. The IBTrACS data (version v03r03)[47] records data of individual hurricane events, positions (latitude and longitude) of hurricane centers at 6-hourly intervals, combined with intensity information (wind speed in knots and barometric pressure). The raw `best track' data give no indication on affected countries. GAME use geographic information system (GIS) software to map hurricane position data to affected countries. Not only do they consider positions (latitude and longitude) on land, but we also consider positions off the coastline of a country.

To capture tornadoes, and winter and summer storms (not captured by the IBTrACS data), the hurricane track data is matched to daily data of the **GSOD** data (version 7) on maximum wind speed and wind gust.[48] GSOD uses daily summaries of hourly observations contained in the Integrated Surface Data (ISD). They collapse daily extremes on wind speed and wind gust over all stations on a country basis. Combining both datasets, we obtain a measure that brings together wind speed from the hurricane track data and wind speed from GSOD.

The variable "hurrfield" records the maximum hurricane wind speed data in knots. We convert the monthly data from per grid cell (50 km by 50 km) to per province basis. Since storms/typhoons/hurricanes may occur multiple times in a month and in a year, we construct the data for storms/typhoons/hurricanes in a yearly basis by selecting the observations with maximum wind speed. We also record the hurricane frequency if the maximum wind speeds exceed the threshold of 64 knots multiple times in a year.[49] After conversion, we have 326 observations with non-missing data for "hurrfield" and only 69 observations with the maximum hurricane wind speed equal or exceed 64 knots.[50] The number is reduced to 35 between 2000 and 2009.

The conversion from per grid cell to per province basis has a few concerns. Note that the same typhoon can be recorded in multiple grid cells, a province often consists of multiple grid cells, and some grid cells may be located on the borders of multiple provinces. It is likely that the share of the affected area in a province hit by a typhoon with high wind speed is small. Therefore, the final wind speed for a province can be calculated as the weighted average of the wind speed for multiple cells, with the weight equal to the ratio

[47]The IBTrACS data is provided by the National Climatic Data Center of the National Oceanic and Atmospheric Administration (NOAA). The data incorporate information from a variety of sources, such as reconnaissance aircraft, ships, and satellites.

[48] This dataset includes records of wind speed from over 9000 worldwide stations and is produced by the National Climatic Data Center (NCDC).

[49] The Saffir-Simpson Hurricane Wind Scale is a 1 to 5 rating based on a hurricane's sustained wind speed. 64 knots is the threshold value for scale 1 hurricane.

[50] After conversion there are 12 observations per year per province (total 63 provinces) between 2000 and 2014. Hence there are in total 11340 observations in the 15-year period.

of the grid cell size over the size of the province in which the cell is located.[51] But the potential downward bias is large if some part of the province has low wind speed, resulting in too few severe hurricanes/storms/typhoons. We take an alternative strategy of calculating the weighted average of wind speed equal or above the threshold of 64 knots for the grid cells in a province with their relative sizes in a province above 10%.[52] Table A2.1 presents the distribution of raw and weighted wind speed data.

Table A2.1
Distribution of Wind speed in knots

Percentiles	Hurrfield	Hurrfield (>=64kt)	Hurrfield_w
1%	34	64	64
25%	40	67	68
50%	48	71	73
75%	60	78	78
99%	92	99	101
Obs. (2000-2014)	326	69	58
Obs. (2000-2009)	170	35	29

Precipitation Data

Precipitation data are recorded by the Goddard Space Flight Center of the National Aeronautics and Space Administration (NASA) in the Global Precipitation Climatology Project (GPCP). The GPCP combines weather station rainfall gauge measures and satellite information. Total monthly precipitation data are provided in millimeters (mm) for 2.5 latitude and longitude degree grid nodes. The data is further brought to the country level by matching rainfall estimates per node to the corresponding country using GIS software and they average rainfall across nodes to produce an estimate of total monthly rainfall per country (Miguel, Satyanath, & Sergenti, 2004; Brückner & Ciccone, 2011). If no degree node fell within the national boundaries of a country, they assigned the rainfall measures from the nearest node(s) to their borders. The principal measure of weather variation is the difference in monthly rainfall in mm, which is defined as the proportional (positive) deviation of total monthly rainfall from average monthly rainfall of the entire available time period (1979-2010).[53] Some grid cells may be located on the border of two or multiple provinces and some provinces may consist of multiple grid cells, each of which has different values. We match the grid cells to corresponding provinces using GIS software. Similar to hurricane wind speed data, the precipitation data also need to be converted into one observation per year per province similar to the conversion of wind speed data.

[51] The grid cell may be partialy or fully located in a province.
[52] The threshold is based on the Saffir-Simpson Hurricane Wind Scale with 5 categories defined by wind speed in knots: 64-82, 83-95, 96-112, 113-136, 136+.
[53] They create an indicator variable for droughts, which takes the value of unity if at least three subsequent months have rainfall below 50% of the long-run average monthly mean, or if at least five months within a year have rainfall below 50% of the long-run monthly mean, and zero otherwise. A single dry month usually does not cause a drought.

The precipitation data can be a poor proxy for floods and extreme precipitation may not always cause floods. Whether heavy precipitation will cause floods or not depends on the intensity and duration of rainfall, the geographical landscape (degree of urbanization, vegetation, and soil saturation, and steepness, et cetera), and other factors. Extreme precipitation may occur in one region but causes floods in other regions.

A2.2 The Emergency Event Database (EM-DAT)

The second disaster database for use is the international disaster database EM-DAT (Emergency Event Database), which is collected by the center for research on the epidemiology of disasters (CRED), Université catholique de Louvain, Brussels, Belguim. EM-DAT contains essential core data on the occurrence and effects of over 22000 mass disasters worldwide from 1900 to the present. The database is compiled from various sources, including UN agencies, non-governmental organizations, insurance companies, research institutes and press agencies. A disaster is recorded in EM-DAT if it satisfies one of the following: 1) death toll 10 or more, 2) affected population 100 or more, 3) declaration of a state of emergency, 4) call for international assistance. This collection of natural disasters is mostly based on insurance claims or news stories, while GAME is based on primary geophysical and meteorological data. This database is so far most widely used for analyzing the disaster impact in the literature.

The data is collected per disaster event by aggregating information for death, damage, and affected population from all areas affected in a country. We also need to convert the data in EM-DAT for Vietnam into one observation per province per year. This is possible as EM-DAT records the locations affected by natural disasters. But we do not have disaggregate disaster data for the same disaster at the provincial level. Furthermore, we cannot identify which firms in a province are directly impacted by the natural disasters.

A2.3 Dartmouth Flood Observatory (DFO)

Since the precipitation data from GAME cannot capture flood events properly, we use a third disaster database for floods, namely the Dartmouth Flood Observatory (DFO) to measure the intensity of floods. DFO is a Global Active Archive of Large Flood Events since 1985.[54] DFO detects, maps, measures, and analyzes extreme flood events worldwide using satellite remote sensing. Imaging of selected river reaches is used to detect floods and extreme low flow conditions. The database provides information about flood catalog numbers, centroids, area affected outlines, and other attribute information such as begin and end dates, duration, death toll, monetary damage, population affected, affected square kilometers, and main cause. The information for floods is derived from news, governmental, instrumental, and remote sensing sources. Similar to EM-DAT, we need to convert each flood event into one observation per province in

[54] G.R.Brakenridge, "Global Active Archive of Large Flood Events", Dartmouth Flood Observatory, University of Colorado, http://floodobservatory.colorado.edu/Archives/index.html.

year, if the flood affects multiple provinces. We use the affected square kilometers scaled by provincial size to measure the severity of a flood for a province.

A2.4 Data Matching and Comparison

For further analysis and comparison, we first bring together the three disaster databases for storms/typhoons/hurricanes and floods.

Storms/Typhoons/Hurricanes: Matching GAME with EM-DAT

We first match GAME with EM-DAT for storms/typhoons/hurricanes in Vietnam between 2000 and 2014 per province per year. GAME contains 263 observations, 56 of which have wind speed data equal to or above 64 knots. EM-DAT contains 123 observations. In total, 51 observations are jointly identified by both databases.[55] There are more than half of the storms/typhoons/hurricanes in EM-DAT not identified by GAME. It is likely that some storms/typhoons with wind speed below 64 knots may cause death or damage that meets the criteria for being recorded in EM-DAT. Note that the 51 observations are not equivalent to 51 storms and typhoons. This is because the same storm/typhoon may affect multiple provinces and hence are recorded multiple times across different provinces in a year.

Floods: Matching EM-DAT with DFO

We use the affected geographical size (in square kilometers) by floods documented in DFO to capture the severity of floods. Specifically, we construct a flood dummy to be equal to 1 if the ratio of the geographical size affected by a flood over the provincial size is above 1, and zero otherwise. The flood observation is also constructed as one observation per province per year. The DFO flood data is then merged with EM-DAT flood records.

Appendix A3. The Proxy for Financial Constraints: Whited-Wu Financial Constraint Index

This appendix documents the theoretical and empirical details of approximating financial constraints using firm-level (unbalanced) panel census data (2000-2009) from Vietnam.

Financial constraints are not directly observable but are expected to vary over time and across firms with different characteristics. The empirical literature on financial constraints use either indirect proxies (such as having a credit rating or paying dividends) or one of the three popular financial constraint indices (Kaplan-Zingales, Whited-Wu, and Hadlock-Pierce indices) based on linear combinations of observable firm characteristics (Farre-Mensa & Ljungqvist, 2016). We choose to approximate the financial constraints with the Whited-Wu financial constraints index (2006), which captures the variation of financial

[55] Strictly speaking, there are 51 observations with non-missing wind speed data. We do not include the hurricane wind speed data for which the relative cell size to the provincial size is below 10%.

constraints across firms and over time. The index value increases with the degree of financial constraints. In case of no financial constraints, the value of the financial constraints index is zero. With severe financial constraints, the index value is positive and large.

We first present the theoretical framework for the Whited-Wu index, and then illustrate the empirical approximation, estimation, and the prediction of the index.

The Theoretical Framework/Model

In a frictionless capital market, firm investments respond immediately to growth opportunities. Financial constraints dampen the sensitivity of investments in relation to economic shocks and changed growth opportunities. Following Whited (1992) and Whited and Wu (2006), we derive a structural investment Euler equation for analysis from the standard investment model of a firm with financial constraints. In the model, a firm maximizes expected present discounted value of future dividends subject to a budget constraint and an external financing constraint (e.g. dividends issuance cannot exceed a threshold), while taking factor prices and output prices as given (in a partial-equilibrium framework). The expected present discounted value of future dividends is given by:

$$V_t(K_{it}, \xi_{it}) = \max_{\{I_{it+s}\}_{s=0}^{\infty}} (D_t + E_t[\textstyle\sum_{s=1}^{\infty} \beta_{t+s-1} D_{it+s}]) \quad (1)$$

Subject to the following constraints:

$$D_{it} = \Pi(K_{it}, \xi_{it}) - \psi(I_{it}, K_{it}) - I_{it} \quad (2)$$

$$K_{it+1} = (1 - \delta_i)K_{it} + I_{it} \quad (3)$$

$$D_{it} \geq 0 \quad (4)$$

Where K_{it} is the beginning of period t capital stock, I_{it} is firm investment in period t, ξ_{it} is a productivity shock in period t, β_{t+s-1} is a discount factor from the period t+s to period t,[56] $\Pi(K_{it}, \xi_{it})$ is the restricted profit function (already maximized with respect to variable costs), $\psi(I_{it}, K_{it})$ is a function of investment adjustment cost. Equation 2 represents the budget constraint of dividends, equation 3 represents the development of the capital stock and equation 4 imposes that dividends cannot be negative. Let λ_{it} be the multiplier associated with equation (4).[57] It can be interpreted as the shadow cost of external finance, namely, raising new equity. If the dividend constraint is not binding $\lambda_{it} = 0$, otherwise $\lambda_{it} > 0$. For our estimate of a firm's financial constraint we focus on identifying the Lagrange multiplier on the dividends

[56] The discount factor is defined as the inverse of annual inflation rate plus one.
[57] The dividend issuance threshold is not restricted to zero, but threshold values do not change the results.

constraint and do not consider the possibility of a borrowing (debt) constraint, because it is difficult to simultaneously identify the two Lagrange multipliers associated with debt and dividend constraints.[58]

Following the literature, we assume that the capital adjustment costs take the following form:[59]

- $\psi(I_{it}, K_{it}) = \left[\alpha_0 + \sum_{m=2}^{M} \frac{1}{m} \alpha_m \left(\frac{I_{i,t}}{K_{i,t}}\right)^m\right] K_{it}$

where α are parameters of the costs function, M is a truncation parameter that sets the highest power of $\frac{I_{i,t}}{K_{i,t}}$ in the expansion. In the literature M is typically set to be 3 (e.g. Whited 1998; Love 2003; Whited and Wu 2006).[60] The structural investment Euler equation is derived from the maximization w.r.t investment, assuming rational expectation:

$$\beta_{t,t+1}\Lambda_{it+1}\{\pi_K(K_{i,t+1}, \xi_{i,t+1}) - \psi_K(I_{i,t+1}, K_{i,t+1}) + (1-\delta_i)(\psi_I(I_{i,t+1}, K_{i,t+1}) + 1)\} = \psi_I(I_{i,t}, K_{i,t}) + 1 + \eta_i + \varepsilon_{it+1} \quad (5)$$

Where $\Lambda_{it+1} = \frac{1+\lambda_{it+1}}{1+\lambda_{it}}$ captures the relative shadow costs of external finance (in period t+1 relative to period t), η_i is the firm fixed effect, and ε_{it+1} is the rational expectation error.[61] The identification of the structural model (eq. (5)) relies on the variation of Λ_{it+1} over time.[62] The right-hand side of equation (5) represents the marginal adjustment and purchasing costs of investing today. The left-hand side represents the marginal expected discounted cost of waiting to invest until tomorrow, which consists of the two components of the marginal product of capital, namely the forgone marginal change in production and the marginal change in installation costs due to a change in the capital stock. Second, the cost of waiting with investment includes the expected discounted value of the marginal purchasing and installation costs of investing tomorrow. Optimal investment implies that on the margin, the firm must be indifferent between investing today and transferring those resources to tomorrow.

Following Love (2003), we approximate marginal product of capital (MPK) by the sales to capital ratio

- $\pi_K(K_{i,t+1}, \xi_{i,t+1}) = \theta \frac{S_{i,t+1}}{K_{i,t+1}}$

[58] See Whited (1992) and Whited and Wu (2006) for more details regarding the identification.
[59] The flexible functional form taken in the literature is linearly homogeneous but allows for nonlinearities in the marginal adjustment cost function.
[60] Higher values of M are typically rejected by the test developed by Neywey and West (1987).
[61] The time dummies are jointly insignificant and hence are dropped from the final model.
[62] If financial constraints do not vary over time ($\Lambda_{it+1} = 1$), then the financial constraints do not matter for investment despite large cross-sectional variation in λ_{it}.

Where $\theta = \frac{\alpha_k}{\mu}$ with $\mu = 1.3, \alpha_k = .3 \Rightarrow \theta = .23$.[63,64] Plugging the capital adjustment function and the approximation for MPK back to equation (5), one derives the investment Euler equation for estimation:

$$\beta_{t,t+1}\Lambda_{it+1}\left\{\theta\frac{S_{i,t+1}}{K_{i,t+1}} - \left[\alpha_0 - \sum_{m=2}^{3}\frac{m-1}{m}\alpha_m\left(\frac{I_{i,t+1}}{K_{i,t+1}}\right)^m\right] + (1-\delta_i)\left[\sum_{m=2}^{3}\alpha_m\left(\frac{I_{it+1}}{K_{it+1}}\right)^{m-1} + 1\right]\right\} =$$
$$\sum_{m=2}^{3}\alpha_m\left(\frac{I_{it}}{K_{it}}\right)^{m-1} + 1 + \eta_i + \varepsilon_{it+1} \qquad (6)$$

Subject to a non-negativity constraint that the expected shadow value of external financing should be non-negative ($E(\lambda) \geq 0$). This non-negativity constraint also implies that the relative shadow cost of external finance should also be non-negative ($E(\Lambda) \geq 0$).[65]

Estimation of the Structural Investment Euler Equation (6)

The structural investment Euler equation (6) is nonlinear with an inequality constraint in addition to constraints (2-4), namely that the shadow cost of external financing cannot be negative. Estimation is performed on the first difference equation to remove individual fixed effect (η_i). Nonlinear GMM outlined by Hansen and Singleton (1982) and Hansen (1982) is applied to estimate the conditional moment conditions of the form:

$$E_{t-1}[z_{it-1} \otimes (e_{it+1} - e_{it})]$$

with an optimal weighting matrix proposed by Newey and West (1987). With dynamic panel data model, all of the variables in the Euler equation with proper lags can be used as instruments for estimation. Additional panel-style instruments include the (lagged) net changes of inventory and depreciation within a year (both are scaled by total assets).[66]

Empirical Approximation of the Shadow Value of External Finance

The identification of financial constraints on investment depends on the variation of financial constraints over time. Without time variation in financial constraints, firm investment behaviors do not change and therefore financial constraints do not matter and the relative shadow cost of external finance Λ_{it+1} is always equal to one. Following the literature on estimating a financial constraint index (Whited, 1992; Love, 2003; Whited & Wu, 2006; Lin, Ma, & Xuan, 2011; Huang, Ma, Yang, & Zhang, 2016), we parameterize Λ_{it+1}

[63] α_k, μ, η refer to the capital share in output, markup, and return to scale respectively. In the literature, MPK is approximated by $\frac{Y_{i,t+1} - \mu C_{i,t+1}}{K_{i,t+1}}$ or $\eta\frac{Y_{i,t+1}}{K_{i,t+1}} - \mu\frac{C_{i,t+1}}{K_{i,t+1}}$ or $\theta\frac{S_{i,t+1}}{K_{i,t+1}}$. But data for the first two measures are not available.

[64] See Gilchrist and Himmelberg (1998) for the derivations and arguments for this measure over other measures.

[65] Recall that $\Lambda_{it+1} = \frac{1+\lambda_{it+1}}{1+\lambda_{it}}$, with λ being non-negative. When $\lambda_{it} > \lambda_{it+1} \geq 0$, $\Lambda > 1$. When $0 \leq \lambda_{it} < \lambda_{it+1}$, $1 > \Lambda > 0$. But our estimation results later show that this non-negativity constraint $\Lambda \geq 0$ is not binding.

[66] Apart from inventories and depreciation, Whited and Wu (2006) included other instruments such as current assets, current liabilities, the net value of the capital stock, and tax payments, all of which are normalized by total assets.

by observable contemporaneous firm characteristics capturing the degrees of financial constraints. Since growth opportunities also affect firm investment, the proxy for growth opportunities is also included.

To make the estimation more efficiently, we perform the following transformation: $\Lambda = 1 + \Lambda^n$, with $\Lambda^n = \frac{1+\lambda_{it+1}}{1+\lambda_{it}} - 1$.[67] The initial full parameterization for Λ^n_{it+1} is written as:

$$\Lambda^n = b_0 + b_1 LNTA + b_2 DAR + b_3 IDAR + b_4 CFK + b_5 ISG + b_6 SG + b_7 CKK$$

where LNTA is log of end of previous period total assets and a proxy for firm size. The idea is that large firms (with more collateral) may experience lower financial constraints than small firms. DAR and IDAR are respectively debt asset ratio and 3-digit industry debt asset ratio. The shadow price of external finance increases with debt asset ratio DAR as higher DAR implies higher default risk. The effect of IDAR is a priori ambiguous. Firms in industries with more external finance dependence (high IDAR) can be more likely to experience financial constraints than firms in industries with lower external financing dependence. On the other hand, ceteris paribus (e.g. for a given DAR level), firms in industries with more external finance dependence may experience less financial constraints than firms in industries with lower external finance dependence. [68]

Cash flow over total assets (CFK) is a proxy for firm profitability and is expected to have a negative sign. This is because more profitable firms can save more quickly to grow out of financial constraints and therefore may experience less severe financial constraints. But if cash flow also captures firm growth opportunities, cash flow may have positive sign instead since fast growing firms may have high demand for investments funds and experience financial constraints. Therefore, the sign for cash flow is unclear. SG and ISG are firm sales growth and 3-digit industry sales growth respectively.[69] Industry sales growth (ISG) may be another proxy for growth opportunities and is expected to have positive sign. Rapid individual sales growth (SG) brings in more revenues[70] and hence is expected to reduce firm financial constraints (SG negative sign).

Finally, CKK is defined as the ratio of liquid assets and short run investments over end of previous period total assets, including account receivables, inventory, and cash and other liquid assets. In the literature it is typically defined as cash over total assets. However, there is no information available in the data to

[67] This renormalization is necessary for estimation purpose, because without imposing the renormalization, one can simply set all coefficient estimates to zero to minimize the criterion function, which is not desirable. Whited (1992) define $\Lambda^n = 1 - \frac{1+\lambda_{it+1}}{1+\lambda_{it}}$ instead, and hence $\Lambda = 1 - \Lambda^n$.

[68] We also replace DAR by a ratio of DAR over IDAR in the model for estimation. The idea is that firms with borrowing higher than industry average are expected to be riskier and may experience more severe financial constraints. But the results are similar whether using DAR or the ratio of DAR over IDAR.

[69] The definitions of variables are documented in the appendix.

[70] Firms may experience idiosyncratic positive demand shocks.

distinguish between cash and other types of liquid assets. For instance, trade credit is prevalent and important for firms in Vietnam and in other developing countries and is included as liquid assets in CKK. Trade credit relieves financial constraints for many private firms. In this respect CKK should have negative coefficient. But the prevalence of trade credit may also imply that firms cannot find alternative financing and have to resort to trade credit to get business done. In addition, if inventory takes a large share of CKK, it may also increase firm financial constraints. Hence the sign for CKK is ambiguous.

Summary Statistics of Key Variables for Use

Before presenting the results, we first describe some statistics of the key variables across ownership and firm sizes. First, state-owned enterprises (SOEs) and foreign firms take up the majority of large firms while most private firms are of small and medium sizes (SMEs). SOEs have on average the highest DAR and the lowest sales growth, while foreign firms have the lowest CKK on average.[71] Both private and small firms have on average much lower debts. Compared to large firms, small firms have on average higher investment rates, higher sales growth, higher ratio of liquid assets, lower debt asset ratios and cash flow, and are more labor intensive and smaller in terms of capital.

The average investment rates (IKx) are large, especially for private firms. The mean investment rates are much larger than the median values, indicating that the investment data is heavily right-skewed.[72] The variation of mean investment rates is larger than the medians across groups. Both the debt asset ratio (DAR) and the industry debt asset ratio (IDAR) are quite large. One potential explanation is that debt is defined as the end of period accumulated debt, which includes both long term and short-term debts. We do not have additional information to distinguish between short-term and long-term debts. But in Vietnam it is common for firms to have short-term debts.

Table A3.1
Summary Statistics

ownership		IKx	SK	LNTA	DAR	SG	CFK	CKK	ISG	IDAR
private	Mean	.43	7.00	7.92	.43	.18	.06	.57	.09	.56
	median	.13	2.89	7.79	.44	.16	.04	.59	.09	.57
SOEs	Mean	.31	4.28	9.85	.61	.09	.09	.55	.07	.56
	median	.12	2.36	9.91	.63	.10	.07	.56	.08	.57
foreign	Mean	.21	2.92	9.99	.47	.16	.08	.47	.08	.56
	median	.08	1.44	9.99	.47	.14	.07	.46	.09	.56
Small	Mean	.42	7.02	7.25	.35	.16	.06	.57	.09	.56
	median	.10	2.58	7.20	.32	.15	.04	.59	.09	.56
Medium	Mean	.36	5.47	9.00	.51	.17	.07	.55	.08	.57
	median	.12	2.46	9.00	.53	.15	.05	.55	.09	.57

[71] It implies that foreign firms on average have lower ratios of liquid assets (such as cash, inventories, and account receivables) than private firms and SOEs.

[72] The investment rates calculated from directly reported investment are larger than the investment rates inferred from the balance sheet. Here the investment rates are calculated after trimming off top and bottom 1% of investment rates. But they remain large if we trim off the top and bottom 5% of investment rates instead.

Large	Mean	.31	4.41	10.30	.57	.15	.08	.51	.08	.56
	median	.13	2.11	10.39	.59	.14	.06	.51	.09	.57
Total	Mean	.37	5.91	8.52	.45	.16	.07	.55	.08	.56
	median	.11	2.42	8.49	.47	.17	.05	.56	.09	.57

Note: small/medium/large firms are defined by employment size: less than 50/between 50 and 250/larger than 250 employees respectively. IKx is defined as the difference between the end of current and previous years' fixed capital plus depreciation and then scaled by the fixed capital from the end of previous year ($\mathbf{IKx_{it}} = \frac{\mathbf{FK_{it} - FK_{it-1}}}{\mathbf{FK_{it-1}}}$). SK is the ratio of sales over the fixed capital from the end of previous year.

Estimation Results for the Structural Investment Euler Equation by nonlinear GMM

Table A3.2 presents the estimation results for the structural investment Euler equation by nonlinear GMM. Column (1) are one-step estimators and the rest are two-step estimators. Hansen J-test rejects the full specification in column (2). The model is not rejected when cash flow is dropped (see column (3)). But the L-test rejects the dropping of industry sales growth (ISG) from the model (see column (4)). Therefore, we take column (3) as our final specification for predicting financial constraints. The signs of all coefficients in table A3.2 are consistent with the findings in the literature. Financial constraints decrease with firm size and firm sales growth but increase with debt asset ratios and industry sales growth. The impact of cash flow on financial constraints is small and insignificant. A priori, the signs for industry debt asset ratio IDAR and CKK are ambiguous, and they are both negative and significant here. Ceteris paribus, firms in industries with more external finance dependence or with higher ratio of liquid assets and short-term investment to total assets experience less financial constraints.

Predicting Financial Constraints Index

Using the estimated coefficients (column (3) of table A3.2), we can calculate the financial constraint index values with the equation below:

$$\widehat{\Lambda} = 1 - .045 * \mathrm{LNTA} + .104 * \mathrm{DAR} - .849 * \mathrm{IDAR} + .039 * \mathrm{ISG} - .040 * \mathrm{SG} - .245 * \mathrm{CKK}$$

The predicted values for the financial constraint index are all positive, indicating that all firms experience financial constraints to some extent.

Table A3.2
Estimation Results for the Structural Investment Euler equation

	(1)	(2)	(3)	(4)
	1-step estimator	2-step estimator	2-step estimator	2-step estimator
$\boldsymbol{\alpha_0}$	2.136**	1.697**	1.731**	1.678**
	(.135)	(.042)	(.048)	(.049)
$\boldsymbol{\alpha_2}$	.013	.014	.022	.023*
	(.038)	(.011)	(.012)	(.012)
$\boldsymbol{\alpha_3}$	-.006	-.006**	-.005**	-.006**
	(.007)	(.002)	(.002)	(.003)
LNTA	-.048**	-.044**	-.045**	-.043**
	(.012)	(.003)	(.003)	(.003)
DAR	. 112**	.111**	.104**	.098**
	(.042)	(.012)	(.014)	(.013)
IDAR	-.888**	-.896**	-.849**	-.897**
	(.146)	(.046)	(.054)	(.050)
CFK	.071	.034	----	----
	(.111)	(.038)		
ISG	.073	.045**	.039**	----
	(.060)	(.021)	(.019)	
SG	-.041**	-.039**	-.040**	-.036**
	(.020)	(.007)	(.007)	(.007)
CKK	-.219**	-.231**	-.245**	-.227**
	(.065)	(.021)	(.022)	(.023)
observations	15804	15804	15804	15804
p-value of J-test	na	.022	.108	.137
p-value of L-test	na	na	.307	.004

Note: The structural investment Euler equation is estimated in first difference by nonlinear GMM on an unbalanced panel census data 2000-2009. **/* indicate significance at 5%/10% respectively. **α** is the investment adjustment cost parameter. The instruments used include: L(3/4). IKx, L(2/3).(SK beta LNTA DAR IDAR CFK ISG SG CKK DINV DEPK), where SK is sales over capital ratio (a proxy for MPK), DINV and DEPK refer to changes in inventory and depreciation within a year.[73] We also correct the potential downward bias for the standard errors based on Windmeijer **(2005)**.

Table A3.3 presents the distribution of the predicted financial constraints index values across firm sizes, ownership types, age groups, regions, et cetera. The predicted financial constraint index values decrease with firm size and age, implying that small and young firms in general experience more financial constraints than large and more mature firms. The predicted financial constraint index values show that SOEs and foreign firms have lower index values on average than private firms, which is consistent with our expectation. It is widely noted that private firms in Vietnam experience more severe financial constraints than SOEs and foreign firms. Financial institutions are state-owned and prefer lending to SOEs, while foreign firms typically have access to capital abroad. The mean index values also decrease with firm panel length. This implies that firms that survive longer in the data experience lower financial constraints than firms that exit earlier. The yearly averages of the predicted financial constraints index decrease steadily since 2002 with a slight rebound in 2009. This rebound may reflect to some extent the financial

[73] We also estimate the model assuming away financial constraints. The unconstrained model is rejected by Hansen J-test. The results are not reported here.

crisis occurred in late 2008. The results presented above are robust in a multivariate regression analysis of the predicted financial constraint index on dummies of ownership, sizes, regions, et cetera.[74]

We further compare the key statistics between least and most constrained firms sorted based on the predicted financial constraint index values in table A3.4 below. Compared to least constrained firms, most constrained firms are on average smaller in terms of total assets, have lower leverage (debt asset ratios), much lower sales growth, and lower ratios of liquid assets over total assets. This pattern is consistent with the literature on financial constraints (Beck, Demirguc-Kunt, & Maksimovic, 2005; Whited & Wu, 2006).

Table A3.3
Distribution of the Predicted Financial Constraint Index

		mean	St.d	min	max
Ownership	private	.545	.080	.273	.871
	SOEs	.461	.068	.291	.672
	Foreign	.463	.058	.272	.695
Firm size	Small	.584	.068	.343	.871
	Medium	.502	.062	.272	.747
	Large	.444	.059	.273	.687
Age	age<5	.543	.078	.313	.822
	Age≥5&age≤10	.515	.081	.280	.799
	Age>10	.490	.088	.272	.871
Region	Red River Delta	.522	.085	.272	.871
	South East	.504	.076	.288	.805
	Mekong River Delta	.566	.101	.321	.822
	Other Regions	.539	.085	.292	.808
Length of Panel	4 years	.540	.088	.291	.793
	5 years	.533	.082	.295	.805
	6 years	.520	.081	.297	.871
	7 years	.514	.075	.306	.722
	8 years	.506	.083	.273	.748
	9 years	.497	.079	.300	.758
	10 years	.475	.070	.272	.742
Total		.519	.084	.272	.871

Source: Vietnam census data 2000-2009.

Table A3.4
Summary statistics by the predicted financial constraint index

	Least constrained		Most Constrained	
	mean	median	mean	median
Investment rate IKx	.25	.27	.30	.32
Total assets (log) LNTA	11.07	9.64	8.52	7.06
Debt asset ratio DAR	.62	.55	.50	.33
Cash flow asset ratio CFK	.08	.07	.06	.06
Sales growth SG	.20	.14	.11	-.01
Liquid/total assets CKK	.60	.59	.58	.53
Industry sales growth ISG	.10	.08	.09	.08
Industry debt asset ratio IDAR	.58	.58	.57	.56

[74] The average index values overall decrease over time. The results of multivariate regression on predicted financial constraint index are reported at the end of this appendix (see table A3.7).

Robustness checks with subsamples

We further examine the performance of the structural investment Euler equation in different subsamples defined by regions and ownership types to check parameter stability. The idea is that capital adjustment parameters may differ across industries with different production technologies and different types of capital. Moreover, the relative importance of variables used to approximate the shadow cost of external finance may vary across regions with different economic environment and across ownership types.

We first check the stability of the coefficient estimates across subsamples defined by regions and ownership types and the results are robust across subsamples (see table A3.5 for the results). We divide Vietnam broadly into four regions (Red River Delta, South East, Mekong River Delta, and the rest). The investment environment, local institutional quality, and the economic development vary largely across the four regions. Due to smaller sample sizes, some coefficients (e.g. the capital adjustment coefficients α_2 and α_3) lose significance. Overall, the signs of the coefficients are more or less consistent with the results for the whole sample. Most of the coefficients do not change signs in subsamples, although Hansen J tests are rejected for some subsamples.

Table A3.5
Estimation of Structural Investment Euler Equation in Subsamples

	Whole sample	Red River Delta	South East	Mekong River Delta	Other regions	Private	SOEs	Foreign
$\boldsymbol{\alpha_0}$	1.73**	1.44**	1.21**	2.52**	1.65**	1.76**	1.62**	1.26**
$\boldsymbol{\alpha_2}$	.02	.01	.01	-.04**	-.02*	-.01	-.00	-.01**
$\boldsymbol{\alpha_3}$	-.01**	.00	-.00	.003**	.00	.00	-.00**	.00
LNTA	-.05**	-.02**	-.02**	-.06**	-.05**	-.05**	-.07**	-.06**
DAR	.10**	.08**	.02*	.18**	.01	.11**	.03**	-.03**
IDAR	-.85**	-.81**	-.50**	-.76**	-.66**	-.86**	-.06**	-.51**
ISG	.04**	-.08**	-.07**	-.14**	-.14**	.04*	.04**	-.01
SG	-.04**	.03**	-.06**	-.01**	-.09**	-.03**	-.01**	-.03**
CKK	-.25**	-.43**	-.59**	-.25**	-.22**	-.24**	-.30**	-.14**
J-stat	162.1	164.6	205.7	156.2	127.8	164.6	156.9	181.9
p-value	.11	.09	.00	.18	.78	.09	.17	.01

Some Extra Notes for the Estimation of Financial Constraint Index (appendix A3)

Table A3.6 present the definitions of key variables for use.

Table A3.6
Variable Definitions

IKx	Net change of fixed capital in a year plus depreciation, scaled by end of previous period fixed capital
SK	Sales scaled by end of previous period fixed capital
Beta	Discount factor
LNTA	Log of end of previous period total assets
DAR[75]	End of period accumulated debts scaled by end of previous period total assets
IDAR	3-digit industry debt asset ratio
CFK	Cash flow scaled by end of previous period total assets
SG	Sales growth (log of sales ratios between today and yesterday)
ISG	3-digit industry sales growth
CKK	End of year liquid assets and short-term investment, scaled by end of previous period total assets
DINV	Net changes of inventories in a year, scaled by end of previous period total assets
DEPK	Net changes of depreciation in a year, scaled by end of previous period total assets

Note: all variables are deflated first with appropriate deflators.

About L-test

L-test assesses whether a variable or a set of variables belong in the Euler equation by comparing the minimized GMM objective functions for the most general and for a more parsimonious model (using the same set of instrumental variables and therefore having the same weighting matrices in the GMM objective functions). The difference is distributed as chi-squared with degrees of freedom equal to the number of excluded variables. A small p-value from the L-test indicates that the omitted variables belong to the Euler equation and should not have been excluded from the model.

Multivariate Regression of Predicted Financial Constraint Index

Table A3.7
Regression of Predicted Financial Constraint Index

	Coef.	Std.Err	t	P>|t|	95% conf. Interval	
SOEs	-.036	.002	-2.30	.000	-.040	-.033
Foreign	-.042	.001	-33.21	.000	-.044	-.039
Medium	-.070	.001	-62.07	.000	-.072	-.067
Large	-.119	.001	-86.70	.000	-.121	-.116
Age (5-10)	-.010	.001	-9.31	.000	-.012	-.008
Age (>10)	-.014	.001	-1.23	.000	-.017	-.012
Red River Delta	-.001	.001	-1.20	.228	-.004	.001
South East	.027	.002	11.65	.000	.022	.031
Mekong River Delta	.033	.002	13.25	.000	.028	.038

Note: year dummies are included in the regression.

[75] In the literature DAR is typically defined as total long-term debt to asset ratio but it is not possible to distinguish between long-term and short-term debts in our data. However, there is plenty of anecdotal evidence that most private firms in Vietnam have short-term debts but hardly any long-term debts.

Appendix A4. Extra Estimation Results and Robustness Checks

A4.1 The estimation results for sales growth

Table A4.1
Estimation Results for Sales Growth

	(1)	(2)	(3)
L.growthS	-0.029**	-0.028**	-0.028**
	(0.03)	(0.03)	(0.03)
findex	-0.434**	-0.415**	-0.418**
	(0.01)	(0.01)	(0.01)
age	-0.168**	-0.167**	-0.167**
	(0.00)	(0.00)	(0.00)
female	-0.049**	-0.053**	-0.053**
	(0.00)	(0.00)	(0.00)
DIS_1	0.020*	0.067**	0.067**
	(0.07)	(0.00)	(0.00)
DIS_1*$dfindex_1$		0.016	0.016
		(0.58)	(0.57)
DIS_1*$dfindex_3$		-0.131**	-0.131**
		(0.00)	(0.00)
L.DIS_1			0.003
			(0.78)
_cons	0.244**	0.256**	0.254**
	(0.01)	(0.01)	(0.01)
N	15316	15316	15316
ar1p	0.000	0.000	0.000
ar2p	0.622	0.544	0.540
hansenp	0.268	0.226	0.226

A4.2 The estimation results for subgroups defined by initial financial constraint index values

We split the whole sample into three subgroups with the **initial** financial constraint index values.[76] If the sample splitting criterion is systematically correlated with unobserved firm characteristics, subsamples of firms may be systematically different from one another. With this (predetermined) sample splitting criterion, we hope to reduce the endogeneity issue to some extent.[77] However, this splitting does not account for the likelihood that firms change financial constraint statuses over time. We check the distribution of the ratio of the annual financial constraint index values over the initial index values and find mostly reasonable variation.[78] Therefore, only a small fraction of firms have undergone dramatic changes in financial constraint statuses.

We find systematic differences among the three subgroups split by the initial financial constraint index values. The proxy for firm size (employment, capital stock, and VA) and firm age decrease with financial constraints. Labor growth and VA growth on average decrease slightly with financial constraints while

[76] The first available financial constraint index values for each firm.
[77] The endogeneity issue is still present if there is not much variation in financial constraint index over time.
[78] The maximum value for the ratio is 1.4.

capital growth remains similar across groups. The averages for the three disaster dummies increase slightly with the degrees of financial constraints. It could imply that more constrained firms are located in disaster-prone areas than less constrained firms. The average share of female workers is the lowest for most constrained firms. But overall the variations of the variables are similar across the three groups.

Table A4.2
Summary Statistics for subsamples split by initial financial constraint index

	Mean			Standard deviation		
	Least	Medium	Most	Least	Medium	Most
lnL	5,46	4,29	3,22	1,19	1,10	0,96
LNTA	10,29	8,45	6,83	1,05	0,94	0,99
lnVA	8,50	6,76	5,32	1,32	1,20	1,12
age	9,34	7,29	6,35	9,22	7,45	5,91
findex	0,44	0,52	0,61	0,04	0,04	0,05
female	0,42	0,41	0,35	0,26	0,26	0,25
growthL	0,08	0,06	0,04	0,28	0,33	0,35
growthK	0,02	0,03	0,03	0,03	0,04	0,05
growthV	0,19	0,17	0,16	0,54	0,54	0,56
DIS_1	0,17	0,17	0,22	0,37	0,37	0,41
DIS_2	0,20	0,22	0,25	0,40	0,41	0,43
DIS_3	0,13	0,15	0,17	0,34	0,36	0,38

Table A4.3 below presents the estimation results for the growth model for the three subsamples of firms. The same specification does not perform equally well across all subsamples. Minor modifications have been done in the empirical specifications to achieve a better fit for some subsamples. The results are mostly consistent with the model with interaction terms, e.g. the impact of firm age, financial constraints, and fraction of female workers, as well as the degree of autocorrelation. The results also confirm the positive disaster impacts, and the differential disaster impacts across firms with different degrees of financial constraints, albeit with a less clear-cut pattern.

Table A4.3

Firm Growth: Robustness Checks with Subsamples split by initial financial constraint index

	Labor Growth			Capital Growth			VA growth		
	Least	Medium	Most	Least	Medium	Most	Least	Medium	Most
L.growthL	-0.106**	-0.135**	-0.131**						
	(0.00)	(0.00)	(0.00)						
L2.growthK				0.033*	0.043**	0.044*			
				(0.09)	(0.05)	(0.07)			
L.growthV							-0.205**	-0.194**	-0.138**
							(0.00)	(0.00)	(0.00)
age	-0.170**	-0.182**	-0.095**	-0.011**	-0.012**	-0.012**	-0.224**	-0.400**	-0.184**
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)	(0.00)
female	-0.035*	-0.060**	-0.067**	-0.003	-0.012**	-0.001	-0.030	-0.014	-0.080**
	(0.05)	(0.00)	(0.01)	(0.15)	(0.00)	(0.89)	(0.38)	(0.66)	(0.02)
findex	-0.550**	-0.399	-0.843**	-0.049**	-0.086**	-0.102**		-0.908**	-1.682**
	(0.02)	(0.18)	(0.01)	(0.00)	(0.00)	(0.00)		(0.02)	(0.00)
L.findex							-1.120**		
							(0.00)		
DIS	0.009	0.041**	0.027*	0.001	0.001	0.009**	0.050	0.050*	0.019
	(0.50)	(0.01)	(0.06)	(0.62)	(0.71)	(0.00)	(0.13)	(0.06)	(0.40)
L.DIS							0.021	0.044*	0.044*
							(0.44)	(0.08)	(0.07)
_cons	0.093	0.249	-0.118				-0.252	0.376*	-0.291
	(0.60)	(0.12)	(0.38)				(0.23)	(0.10)	(0.17)
N	5397	5148	4755	3747	3427	2833	3709	5147	4841
ar1p	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ar2p	0.821	0.832	0.357	0.695	0.444	0.700	0.938	0.186	0.988
hansenp	0.434	0.745	0.762	0.059	0.524	0.572	0.333	0.149	0.363

Note: *p*-values in parentheses; * $p < 0.10$, ** $p < 0.05$. Firms are split into three groups with least/medium/most financial constraints by the cutoff points for the 33rd and 66th percentiles of the initial financial constraint index values. The models are estimated by system GMM. The models are not entirely the same with minor modifications to achieve better fit.