Understanding Volatility Spillover Using Disaster Shocks

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Abstract

Does stock market volatility in a country raise that in other countries? To answer this question, I conduct two types of empirical exercises. I fit a simple bivariate vector augoregressions (VAR) to see the persistent positive response of domestic volatility to a shock in external volatility. In addition, I run a two stage least square on domestic volatility to resolve the problem of endogenous explanatory variable. Disaster shocks are used as the instrument for external volatility. I find that international spillover does exist in stock markets. In particular, one standard deviation increase in external volatility raises domestic volatility by 0.3 standard deviation. Moreover, I show that disaster shocks are valid and robust instrument for volatility. To the best of my awareness, this is the first work addressing the issue of endogeneity in international stock markets with instrument variables.

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1 Introduction

Global equity markets are so highly integrated that market performances are closely related. Thus, a shock in a single country affects stock markets around the world. To be specific, both the first moment and the second moment of stock indices co-move to some extent. However, it is hard to gauge to what extent this relation is causal due to the contemporaneous movements in stock markets. This paper identifies the causal relation in stock market volatility across countries by using disaster shocks to instrument volatility.

Terms such as contagion, interdependence or spillovers are widely used in the literature and there are debates on definitions of these terms. In this paper, I define volatility spillover as a causal relation in volatility. To investigate if there is cross-country causality in volatility, I fit a simple bivariate vector augoregressions (VAR), which show a persistent positive response of domestic volatility to a shock in external volatility. In addition, I run two stage least square regression on domestic volatility to resolve the problem of endogenous explanatory variable. Disaster shocks are used as the instrument for external volatility. I find that international spillovers do occur in the stock market. In particular, one standard deviation increase in external volatility raises domestic volatility by 0.3 standard deviation. Moreover, I show that disaster shocks are a solid instrument for volatility.

Earlier works on financial market integration and interdependence both in terms of return and volatility assess the extent of cross-country financial market integration differently. King et al (1994) point out that there is no trend increase in the inter-market correlation coefficients from 1970 to 1988, using a multivariate factor model in GARCH for 16 advanced countries. Forbes and Rigobon (2002) show that correlation coefficients are biased by heteroskedasticity. After correcting this, adjusted correlation coefficients suggest no strong increase in correlation during major crises.

Some recent works adjust correlation coefficients according to Forbes and Rigobon (2002) to test whether there are correlation in return and volatility spillovers from mature markets to emerging markets. In particular, Beirne et al (2009) address the question in this paper using a GARCH-in-mean specification for emerging countries. They show that their GARCH measures of volatility do spill over from advanced to emerging markets. Diebold and Yilmaz (2009) build an index of volatility spillovers by decomposing the VAR covariance matrix of forecast errors into own variance share and cross variance share. Their measure of volatility spillover is substantial in its size and tend to rise during economic crises. However, it is hard to identify the direction of causation from VAR approach. When the volatility in a country rises together with that in another country, it is very likely that something drives both in the same direction in the integrated financial markets. By using an exogenous variable to proxy volatility, the causal effect can be identified, if there is any. To the best of my awareness, this is the first work to focus on causation in volatility using instruments to control for endogeneity.

There is a growing volume of literature on the relationship on uncertainty on the one hand and growth, investment and asset prices on the other hand. Considering the level of stock market volatility as a proxy for uncertainty as carefully illustrated in Bloom (2009), these works make the question posited in this paper more interesting. Volatility spillover, if it exists, will affect real economic activities, hence leading to a loss in welfare.

The paper proceeds by describing three types of data used in this empirical work in section 2. Section 3 consists of five subsections. The first subsection considers the specification of a Vector Autoregression (VAR) on external and domestic volatility. In the second subsection, I conduct a principal component analysis to investigate if disaster shocks can instrument volatility suitably. In the following two subsections, I use disaster shocks to instrument endogenous external volatility in a two state least square(2SLS) setup for a panel data and for individual country's data respectively. Finally, a number of different specifications are considered in the fifth subsection to check the robustness. Section 4 concludes and suggest some directions for future research.

2 Data

This paper uses three types of data sets, stock market data, disaster shock data and economic indicators.

2.1 Stock Market Data

The stock market data are collected for 60 countries during the period of 1970 - 2011. Stock indices representing total market capitalization are preferred, but indices built from major stocks are used when preferred index is not available or provides only limited time-series. Among 60 countries, 21 are advanced and 39 are emerging economies. The full list of countries and stock indices is provided in the appendix. In terms of economic size, advanced countries account for three quarters of the GDP on average. Daily stock index is scaled by its CPI so that we have real returns and real volatilities. The weekly returns are from Friday to Friday and are the changes in the log of stock indices. For countries where the equity market opens Sunday to Thursday or Saturday to Wednesday, the weekly return is from Thursday to Thursday and Saturday to Saturday, respectively. Table 1 shows some descriptive statistics for weekly return and volatility. The mean of weekly return is equivalent to an annualized return of 3.5 per cent, while it varies greatly from country to country. If the U.S. mean return is normalized to unity, it is as low as - 9 for Ecuador[1], -3 for Kenya and Romania. On the other side, the average return is six times the U.S. or higher in Chile, Brazil, Mexico and Peru. Descriptive statistics of each country is provided in the appendix. The weekly volatility is computed a la Garman and Klass(1980)[2] which provides an efficient analytic scale-invariant estimator for σ^2:

$$\tilde{\sigma}^2 = 0.511(H-L)^2 - 0.019[(C-O)(H+L-2O) - 2(H-O)(L-O)] - 0.383(C-O)^2$$

where H is the high, L is the low, O is the open and C is the close. From underlying

[1] This is a combination of stock market boom and bust since the country launched its stock exchanges in early 90s and high inflation in late 90s at the average rate of 30%

[2] By adopting this meghod, we are assuming that volatility is constant within a week, but variable across weeks. The computed stock market volatility is strongly correlated with a measure of implied volatility from options(VIX). The coefficients of correlation between the computed volatility and implied volatility(VIX) are 0.724 for the US and 0.63 for Korea.

daily close prices, I use the highest close, the lowest close, the first close and the last close of a week for H, L, O and C. All prices are in natural logarithms. Weekly volatilities are modestly variable across countries. Emerging countries have 30 per cent higher level and 40 per cent higher standard deviation of volatility than advanced economies. From the Table 1, it is clear that neither returns nor volatilities are normally distributed. The combination of the negatively skewed return variables and positively skewed volatility variables indicates the presence of rare disasters with low return and high volatility.

For each country, I compute external return and volatility as the weighted average of 59 countries' returns and volatilities. Bilateral trade volume is used to build country weights. A portfolio of 59 countries is typically well diversified such that mean of external return and external volatility is fairly low compared to those of individual countries.

2.2 Disaster Shock Data

The disaster shocks data are taken from Baker and Bloom(2013) in which various specifications of panel growth regression are conducted to see the effects of uncertainty on economic growth. In particular, they collect information for date, fatality, monetary costs, and location of disasters from various sources and classify them into five types: natural disasters, terrorist attacks, political shocks, revolutions, and accidents. Political shocks include successful coup d'états and other political regime changes according the definitions by the Center for Systemic Peace and revolutions include a revolutionary war or violent uprising. Based on the date and location of events, they build an attention index from volume of media citation on the origin country of the shock to measure the degree of each shock. In particular, they weight each event by the increase in daily newspaper word counts of the effected country in the five days after the event compared to the five days before the event. For example, 700 per cent increase in the count of the word "Japan" is observed in five days after March 11th, 2011 tsunami compared to the five days before the shock. In this fashion, Katrina in the U.S. in August 2005 shows 130 per cent. The tsunami in the Indian Ocean affects India and Indonesia by 200 per cent and 90 per cent, respectively. For some events, the citation index is less consistent with the importance of disasters. For instance, terrorist attack in September 2001 in the U.S. shows only 53per cent. Admittedly, the total volume of news in the U.S. is likely to be stable while their contents are heavily weighted on disasters. Thus, it is possible not to see a proportionate jump in the volume of news on the U.S. after a disaster. From this point, searching for news on the U.S. from foreign news providers can be considered to supplement and probably improve the disaster shock data.

In building a weekly disaster shock index, I allow only one event during a week in a country by taking the event with largest jump in media release, if multiple events occur. In particular, $\{\{nat_i, ter_i, rev_i, pol_i, acc_i\}_{t=1}^{T}\}_{i=1}^{I}$, the series of natural disasters, terrorist attacks, revolutions, political shocks, and accidents are constructed as the following. If a disaster occurs at time t in country i, the value of percentage increase in news citations is assigned. If the volume of news rather decreases after the shock, the value of zero is assigned, instead. Naturally, the series have the value of zero in periods with no shocks. During $1970 - 2011$, there are $3,474$ observations of disasters with positive increase in news citations. Among the observed disasters, 70 per cent are natural disasters and each of the other four types of disasters account for less than 10 per cent of the total. Descriptive statistics for disasters data are provided in Table 1.

These series are averaged over countries in order to represent disaster shocks of a group of countries. For example, the disaster series of each country are averaged using GDP as weights to produce $\{nat, ter, rev, pol, acc\}_{t=1}^{T}$ when they are used as instruments for principal components in stock market volatilities of sample countries in Section 3.2. On the other hand, the disaster series of each country are averaged using bilateral trade volume with country i as weights to produce external disasters that the county i faces, $\{\{nat_{-i}, ter_{-i}, res_{-i}, pol_{-i}, acc_{-i}\}_{t=1}^{T}\}_{i=1}^{I}$ in Section 3.3. and Section 3.4. In these sections, this series of external disasters will instrument external stock market volatility.

Table 1: Descriptive Statistics

	Domestic Return	Domestic Volatility	External Return (Trade Weighted)	External Volatility (Trade Weighted)	External Return (GDP Weighted)	External Volatility (GDP Weighted)	Disasters
Mean	0.0007	0.0123	0.0004	0.0113	0.0003	0.0113	0.828
Median	0.0012	0.0092	0.0018	0.01	0.0018	0.01	0.461
Std. Dev.	0.0351	0.0113	0.0196	0.0059	0.01788	0.0054	1.38
Skewness	-0.239	2.961	-0.9775	2.977	-1.148	3.249	6.877
Kurtosis	9.496	16.909	11.366	18.84	12.873	22.27	74.305
Minimum	-0.2161	0.0001	-0.2108	.0011	-0.1960	0.0023	0.04
Maximum	0.2044	0.1064	0.1406	.0819	0.1014	0.0675	25
Observations	86236	86237	131460	131460	131460	131460	3474

2.3 Economic Data

Several economic indicators are used in re-scaling stock market index and computing country weights. CPI data are from the IMF except for China and Taiwan. I got CPI for these two countries from the OECD and the Taiwan Directorate-General of Budget, Accounting and Statistics. Annual GDP data are from OECD World Economic Outlook database. Lastly, annual bilateral trade data are from the IMF Direction of Trade Statistics (DOTS) database except for Taiwan, whose data are collected from the Taiwan Ministry of Finance.

3 Empirical Specification

The empirical approach follows two paths. First, I estimate a simple vector autoregressions (VAR). Second, I run least square (OLS) and two stage least square (2SLS) regressions using disaster shocks as instruments for external volatility. Before I estimate the 2SLS regressions, I investigate how good the disaster shocks are to instrument stock market volatility, using principal component analysis. Then, the OLS and 2SLS estimation are conducted under both panel and country by country setup in the following two sections. Finally, a number of extensions and robustness checks are introduced.

3.1 Vector Autoregressions

As the first step to understand how stock market volatility in a country responds to external volatility, I fit a simple bivariate-VAR with external volatility and domestic volatility and recover the orthogonalized impulse response function from a Cholesky decomposition. In doing so, I impose an identifying assumption that external volatility moves in advance of domestic volatility when a shock occurs in a foreign country.

The VAR model of order p for each country $i = 1, 2, \cdots 60$ takes the form

$$y_t = v + (A_1 L + \cdots + A_p L^p) y_t + u_t \tag{1}$$

where $y_t = (external\ vol_t, domestic\ vol_t)'$, A_j are fixed (2×2) coefficient matrices, L is lag operator, $v = (v_1, v_2)'$ is the vector of intercept terms allowing for the possibility of a nonzero mean $E(y_t)$. t is number of weeks since the first week of 1970. Finally, $u_t = (u_{1t}, u_{2t})'$ is an innovation process. The country subscript i is dropped for simplicity.

The VAR model equation by equation has the form

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} v_1 \\ v_2 \end{pmatrix} + \begin{pmatrix} a_{11}^1 & a_{12}^1 \\ a_{21}^1 & a_{22}^1 \end{pmatrix} \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \end{pmatrix} + \cdots + \begin{pmatrix} a_{11}^p & a_{12}^p \\ a_{21}^p & a_{22}^p \end{pmatrix} \begin{pmatrix} y_{1t-p} \\ y_{2t-p} \end{pmatrix} + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}$$

Four-week backward moving averages of both domestic and external volatilities are used to deal with substantial noise in high frequency stock market data and to alleviate potential problems from outliers.[3]

A number of criteria for VAR order selection choose order of three for the half of sample countries and four or longer for the others. Taking this result into consideration, I apply order of four to every country for comparative purposes. In the results of the VAR, one-

[3]Stock markets are too volatile to be explained by true investment values as shown in Shiller (1987) among many others. In consequence, the series of volatility contain many outliers and extreme observations. While there is a vast literature on handling with these outliers from robust modelling to smoothing filters as in Tsay (1988) or Croux et al (2009), four-week backward moving average is chosen for simplicity. The VAR results do not vary a lot when the unsmoothed volatility data are used instead.

week-lagged external volatility positively affects domestic volatility for all but 14 countries. That is, coefficients a_{21}^{1} is significant for 46 countries at the ten per cent level, and its average is 0.15.[4]

By covariance stationarity, the moving average (MA) representation of the equation (1) can be written as

$$y_t = \mu + \Phi(L)u_t$$

where $\mu = (\sum_{i=0}^{\infty} \Phi_i)\nu$ and $\Phi(L) = (I - A(L))^{-1}$ given the definitions of $A(L) := A_1 L + \cdots + A_p L^P$ and $\Phi(L) := \sum_{i=0}^{\infty} \Phi_i L^i$. The MA representation can be rewritten as

$$y_t = \mu + \sum_{i=0}^{\infty} \Phi_i P P^{-1} u_{t-i} = \mu + \sum_{i=0}^{\infty} \Theta_i \omega_{t-i} \tag{2}$$

where $\Theta_i := \Phi_i P$ and $\omega_t := P^{-1}u_t$ is white noise with covariance matrix $\Sigma_\omega = P^{-1}\Sigma_u(P^{-1})' = I$. ω_t is called the vector of orthogonal innovations.

Clearly, a shock in one country's stock market may be accompanied by a shock in another country in the same period. Therefore, the innovation covariance matrix Σ_u is likely to have positive off-diagonal terms. This is the reason why impulse response analysis is performed in terms of the MA representation. In (2), it is reasonable to assume that a change in one component of ω_t has no effect on the other components. Yet, it is important to keep in mind that the ordering of external volatility and domestic volatility is specified such, based on the assumption that the former has a potential immediate impact on the latter. In fact, this issue is addressed in the following section by using disasters as instruments.

The impulse responses of 46 countries are depicted in Figures 1 and 2. Generally, the responses of advanced countries are notably greater than those of emerging economies. In the majority of countries, orthogonalized impulses responses jump around $0.1 - 0.2$ standard deviation in the same week of the shock, increase to about $0.2 - 0.35$ at the peak in two to three weeks, then die away slowly.

In Figure 1, I find strongly significant impact of external volatility on domestic volatility

[4] Or, the coefficient is significant at five per cent level for 44 countries.

among advanced economies. Among 21 sample countries, all but for Austria and Finland show an average of 0.18 on impact and 0.27 at peak. Netherlands, Sweden and Switzerland are most responsive while Luxemburg, New Zealand and Belgium are least responsive countries. For most of countries, the impact from external volatility is almost zero after 20th week.

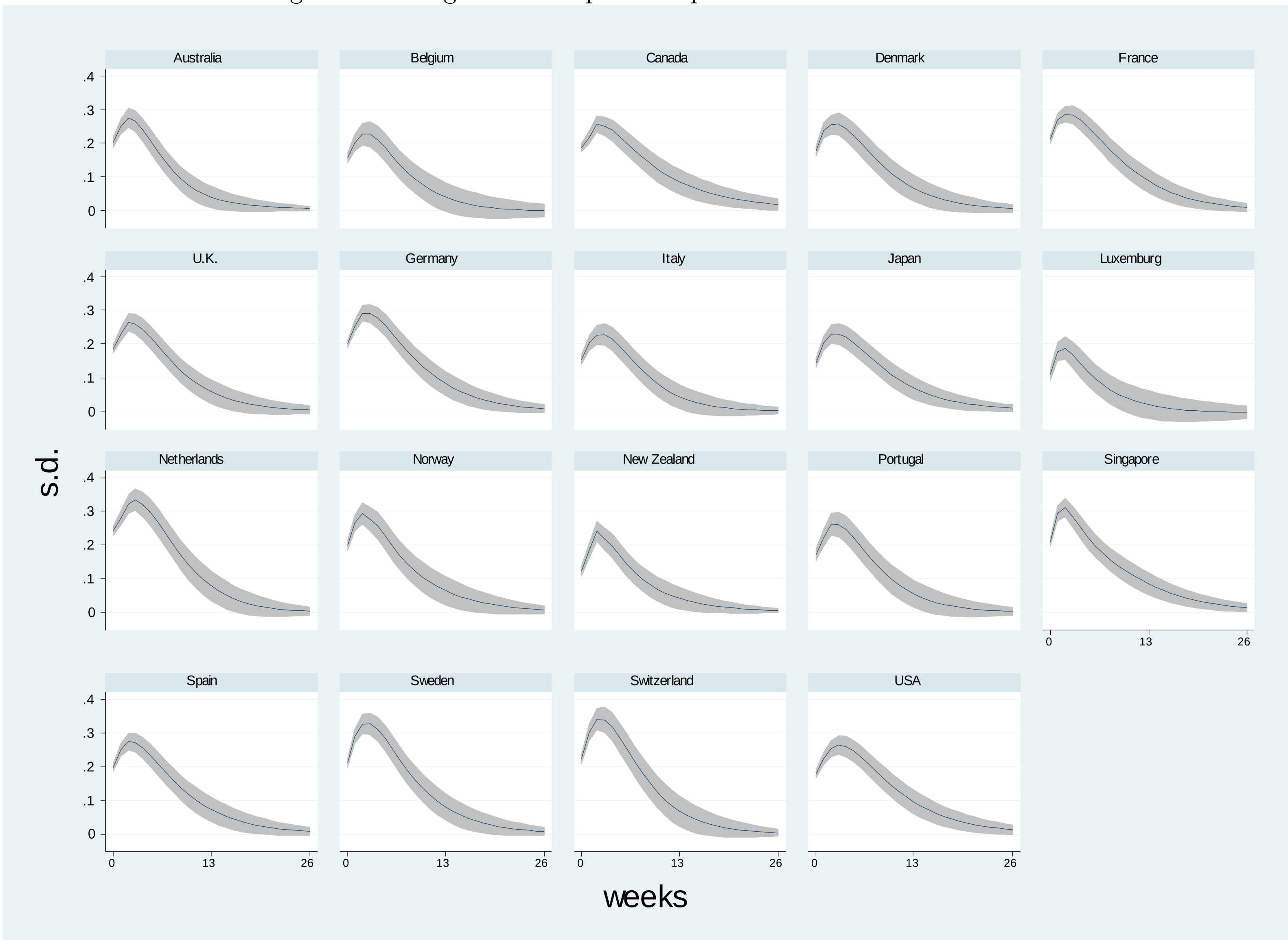
Figure 2 shows orthogonalized impulse response functions of emerging economies. 27 countries out of 39 exhibit significant positive coefficient on external volatility. The average response is 0.1 standard deviations on impact and 0.16 at peak in two to three weeks. The response vanishes after the 17th week. Among emerging countries, Ireland, Czech Republic, and Hungary are most responsive. On the other side, Bangladesh, Kuwait and Saudi Arabia show least responses.

Figure 3 shows how the 26 weeks' cumulative orthogonalized impulse responses are distributed among 19 advanced and 27 emerging economies for which coefficients of external volatility in VAR are significant. Both external and domestic volatilities are scaled to have standard deviation of one. The average cumulative orthogonalized impulse response is 2.7 for advanced economies, 1.5 for emerging economies, and 2.0 for all countries. That is, one standard deviation increase in external volatility would raise domestic volatility by two standard deviations in six months.[5] It may be surprising that the advanced economies respond by greater degree to external volatility than the emerging economies do. But it is important to remember that the standard deviation of domestic volatility in advanced economies are smaller than that of emerging economies. Even considering that, advanced economies seem to be more sensitive to external shocks than emerging economies and this finding is consistent with the IV results in the following section. A plausible explanation to interpret the result is provided in that section.

Lastly, results from Granger causality tests also suggest that external volatility contains useful information in predicting domestic volatility. External volatility Granger causes

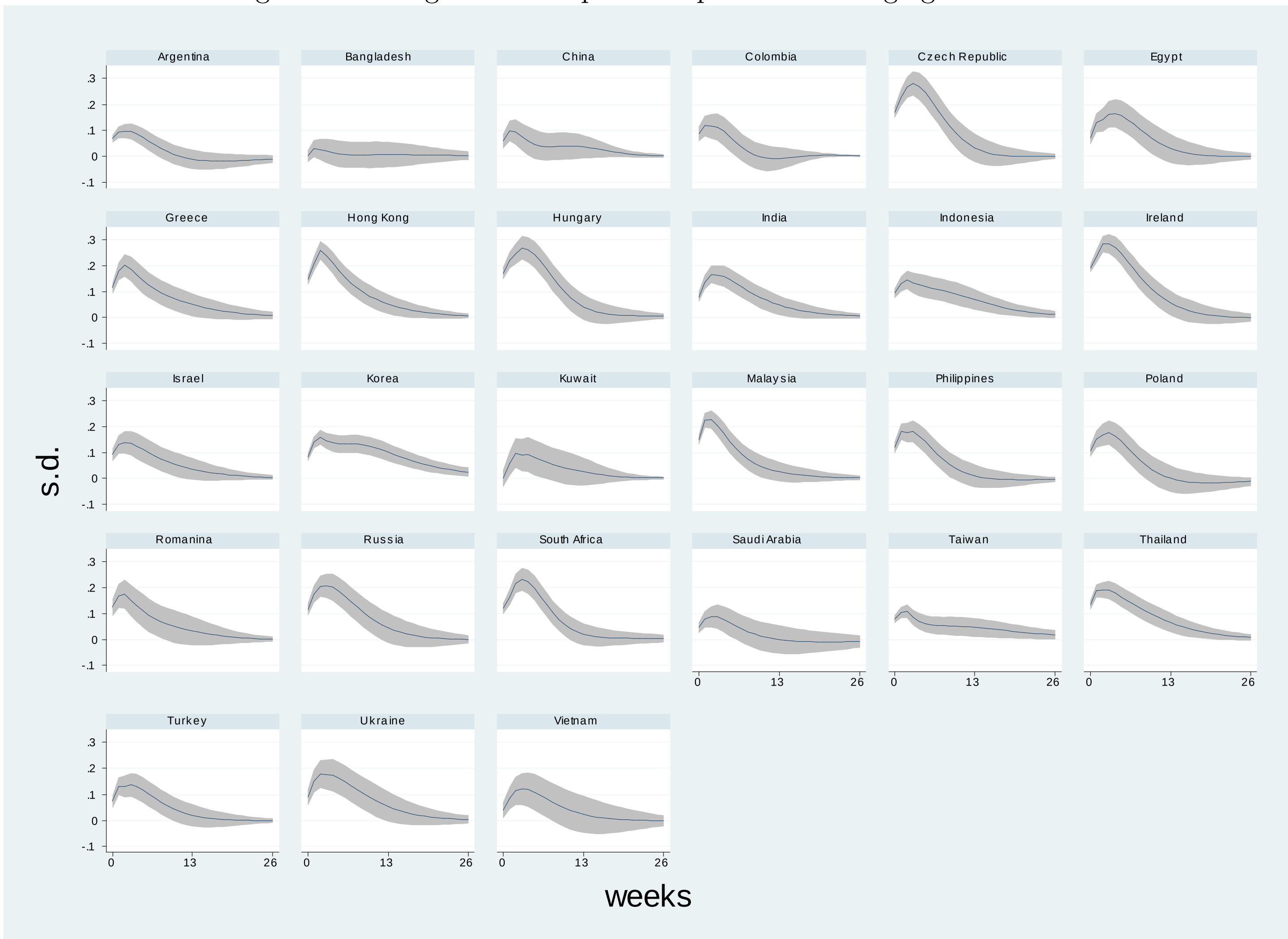
[5] If I use the opposite ordering so that domestic volatility moves in advance of external volatility, the effects of external volatility on domestic volatility are consistent but smaller. For example, the average COIRF is 1.7 and 0.8 for advanced and emerging economies respectively.

Figure 1: Orthogonalized Impulse Responses of Advanced Economies



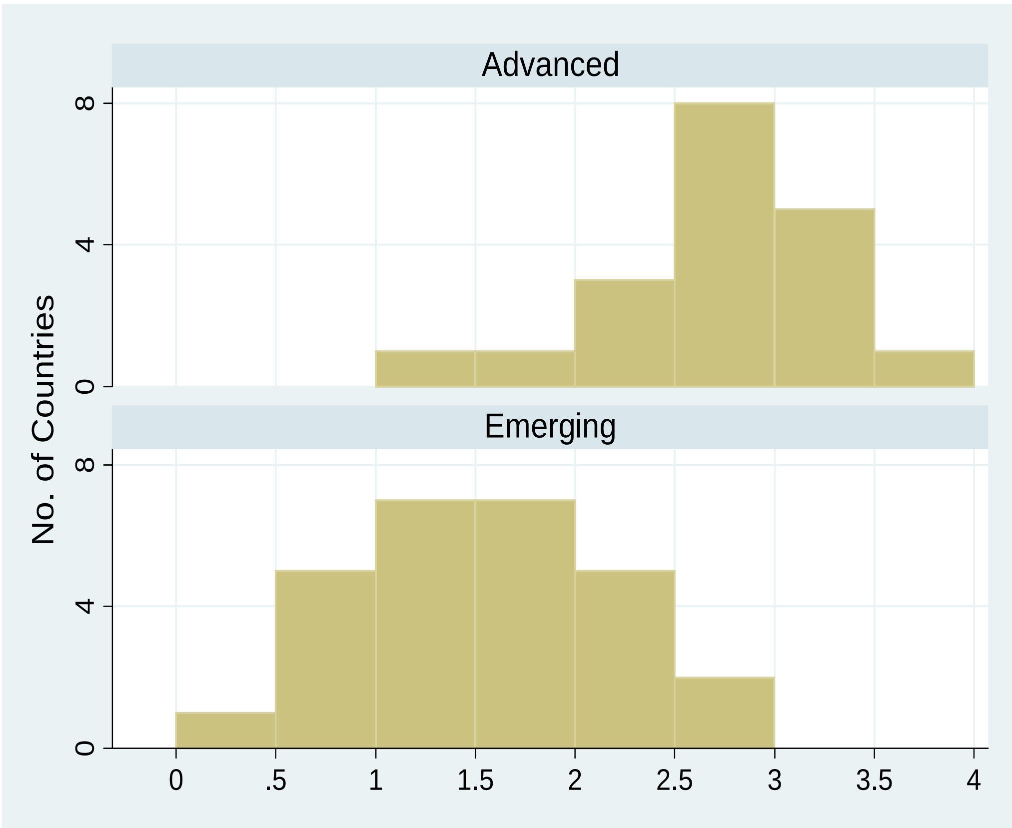
Notes: Impulse is one standard deviation increase in external volatility and response variable is domestic volatility of each country.

Figure 2: Orthogonalized Impulse Responses of Emerging Economies



Notes: Impulse is one standard deviation increase in external volatility and response variable is domestic volatility of each country.

Figure 3: Distribution of Cumulative Orthogonalized Impulse Responses



domestic volatility in 50 countries but the latter Granger causes the former in only 27 countries. Admittedly, it is not very likely that domestic volatility in such countries as Ireland and Romania causes external volatility. Instead, the Granger causality in both directions emphasizes that the issue of endogeneity can be substantial. At the same time, it also supports the conjecture of volatility spillover, as external volatility causes domestic volatility in most countries.

3.2 Relationship between Volatility and Disasters

In this section, the relationship between disaster shocks and stock market volatility is investigated before the spillover effects are estimated in the following sections. I calculate principal components of the volatility series $\{\{\tilde{\sigma}_{it}\}_{i=1}^{I}\}_{t=1}^{T}$ and call them $\{p_{1t}, p_{2t}, \cdots\}$. In order to have a perfectly balanced panel data, the sample for this analysis is limited to 21 countries during $1980-2011$. As a result of principal component analysis, the first principal component has variance 9.33, explaining 44%(9.33/21)[6] of the total variance. The second and third principal components have variance 11%(2.24/21) and 8%(1.58/21) of the total variance respectively. As a consequence, the first three components explain 63% of the total variance. Then, I estimate the following equation for each country i,

$$\tilde{\sigma}_{it} = \alpha_i + \beta_i p_{1t} + \delta_i p_{2t} + \gamma_i p_{3t} + e_{it} \tag{3}$$

where $\tilde{\sigma}_{it}$ is stock market volatility of country i in week t, and the principal components $\{p_{1t}, p_{2t}, p_{3t}\}$ are instrumented using five types of disaster series. The disaster series $\{nat, ter, rev, pol, acc\}_{t=}^{T}$ are GDP- weighted averages of disaster series of 21 countries. The first stage of this equation is of main interest, because it shows how much disaster shocks are related to stock market volatility. As the regressors and instrumental variables are common for all countries, the result of the first stage in the Table 2 applies to every equation. I find that disasters can instrument principal components of volatility suitably. Natural disasters, terrorist attacks and political shocks have significant impact on all the three principal components and the other two types are also significant for at least one component.

3.3 Panel OLS and 2SLS

The baseline equation in the least square has external volatility as an explanatory variable for domestic volatility.

$$\tilde{\sigma}_{it} = \beta \tilde{\sigma}_{-it} + c_i + e_{it} \tag{4}$$

where $\tilde{\sigma}_{i,t}$ is domestic volatility, $\tilde{\sigma}_{-it}$ is external volatility for country i at weekly time t, and c_i is the fixed effects for country i. The coefficient β is of main interest, as it reflects the degree of volatility spillover. External volatility is computed using bilateral trade volume as

[6] The volatility series of each country are standardized to have unit variance, making the total variance to be 21.

Table 2: Disasters and Volatility: First Stage Regressions

	p1	p2	p3
Natural Disasters	3.45***	-1.165*	-2.027***
	(.916)	.618	(.488)
Terrorist Attacks	113.9***	-37.95***	-10.02**
	(27.84)	(8.107)	(4.43)
Revolutions	-5953.1***	-5319.8***	-475.40
	(1047.3)	(246.38)	(492.06)
Political Shocks	-135.15***	97.888**	210.33***
	(30.31)	(41.77)	(21.74)
Accidents	2.5494	-2.148**	0.281
	(1.98)	(.8469)	(0.013)
F test	20.79	101.25	26.51
No. of obs	1670	1670	1670

1) * $p<0.1$ ** $p<0.05$ *** $p<0.01$

2) Robust standard errors are in parentheses

country weight on the assumption that external shocks are more important, the more the countries trade with the domestic country. The idea comes from a conjecture that the real linkages may play a role in explaining cross-country spillover.

There is considerable possibility that a common shock affects both the domestic volatility and external volatility in which case the least square estimate is inconsistent. In fact, the exogeneity of external volatility is rejected in various specifications. In particular, the test statistic is defined as the difference of two Sargan-Hansen statistics: one for the equation under the IV setup, where the external volatility is treated as endogenous, and one for the equation under the OLS setup, where the external volatility is treated as exogenous.[7] The null hypothesis is that external volatility is properly exogenous in this model. When various combinations in the five types of external disasters are used to instrument external volatility, the p-value of the test statistic is ranged from 0.008 to 0.27, suggesting that the data reject the use of OLS in favor of IV.

Table 3 summarizes the results from primary specifications. Every variable is normalized to have standard deviation of unity for interpretative purposes. From the OLS result, I find that external volatility has significant positive effects on domestic volatility. In addition, I

[7] This method is alike the *C test*, which is also known as *difference-in-Sargan test* or *distance difference test*.

find a significant causal effect of external volatility on domestic volatility in the IV result. The point estimate of external volatility in the IV regression is notably below the OLS estimate reflecting that OLS estimate may include effects from common shocks affecting both domestic and external volatility. To evaluate the validity of the instruments, result of a test of overidentifying restrictions is reported. Under the null hypothesis, all instruments are uncorrelated with residuals from 2SLS regression, that is, instruments are appropriately independent of the error process. Therefore, it is important not to reject the null hypothesis for valid instruments. All possible types of disasters are used as instruments and they appear to be independent of residuals. The first stage also passes a test of weak identification. The test statistic is much greater than the critical values for five per cent maximal IV relative bias and ten per cent maximal IV size.

The point estimates from the first stages of the Table 3 are largely sensible in that disasters are positive second moment shocks in general. I find that coefficients of three types of disasters - natural disasters, terrorist attacks and accidents- are positive and strongly significant, while revolutions show correct sign but lose significance. Interestingly, external political shocks have significant negative impact on external volatility. Baker and Bloom (2013) explain this due to the nature of political shocks. They are generally right-wing military coups which often take the power away from left-wing or communist governments. That is, stock market volatility actually falls after this type of successful military coups. In contrast, revolutions are generally arisen from left-wing or communist groups.

From these results, I point out that treating external volatility as an exogenous variable is likely to result in upward bias in estimates of cross-country volatility spillovers or interdependence. In addition, I find that a shock in a country does spill over to other countries by raising their stock market volatility. Lastly, estimation results confirm that disaster shocks serve as a solid instrument of volatility.

Table 3: Effects of External Volatility on Domestic Volatility

	(1) OLS	(2) IV
External Volatility	0.478***	0.392***
	(0.031)	(0.101)
First Stage		
Natural Disasters		0.047***
		(0.014)
Terrorist Attacks		0.241***
		(0.016)
Revolutions		0.009
		(0.049)
Political Shocks		-0.141***
		(0.009)
Accidents		0.296***
		(0.013)
Weak Identification F		131.27
Overidentification p-value		0.497
R-squared	0.267	0.258
Observations	86757	86757

1) * p<0.1 ** p<0.05 *** p<0.01

2) Robust standard errors are in parentheses and clustered by country

3) Cargg-Donald Wald F statistic provided for weak identification test.

4) P-value of Sargan-Hansen J statistic provided for overidentification test.
A rejection casts doubt on the validity of the instruments

3.4 OLS and 2SLS for Each Country

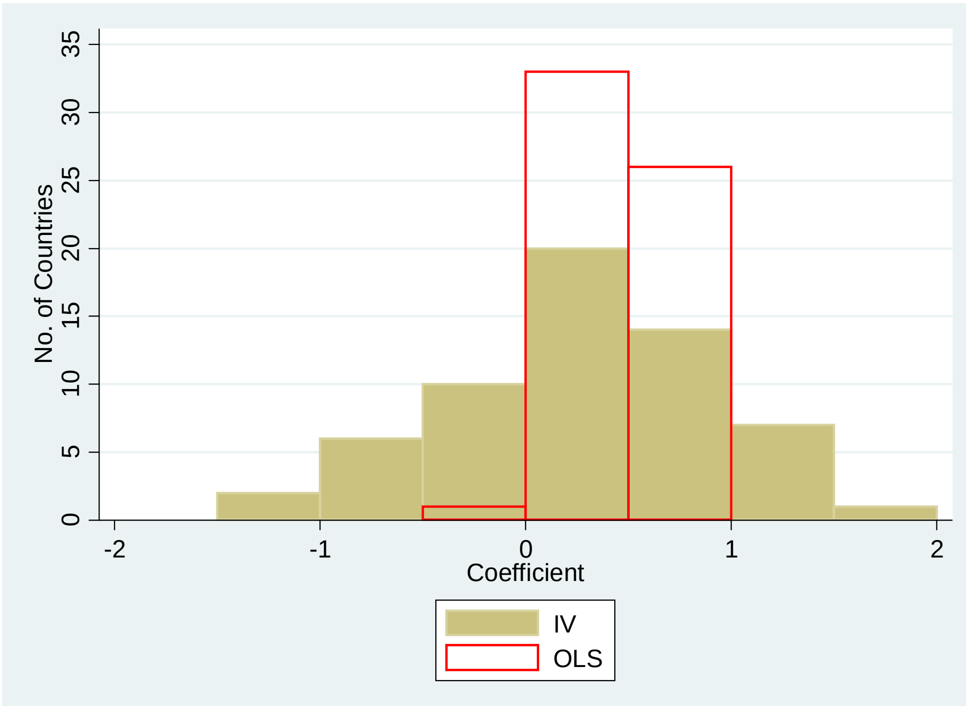
It must be reasonable to assume that the degree of spillover varies a lot from country to country. To compare sample countries' responsiveness to external shocks, I estimate the following equation for country $i = 1, 2, \cdots 60$ using least square and instrument variables regressions

$$\tilde{\sigma}_{it} = \alpha_i + \beta_i \tilde{\sigma}_{-it} + u_{it} \tag{5}$$

where $\tilde{\sigma}_{it}$ is domestic volatility and $\tilde{\sigma}_{-it}$ is external volatility for country i at time t. In this specification, β_i shows the degree of volatility spillover of country i. The OLS point estimates are strongly positive for all but three countries, Venezuela, Ecuador and Iran. For Iran, it is significantly negative. While the OLS point estimates are concentrated between zero and one, the dispersion in the IV point estimates are sizable, as in the Figure 4. By looking at the IV coefficients, I find that external volatility has a negative impact on domestic volatility for a number of countries, most of which are emerging economies. In particular, the coefficients are negative for every country in Latin America. In general, however, more than half of countries show the point estimates between zero and one, which is consistent with the results of the panel regressions. Indonesia, Germany, France and Korea are mostly responsive countries to external volatility.

Table 4 summarizes estimation results by calculating pooled mean group consistent estimators $\bar{\beta} = N^{-1} \sum \beta_i$ where N is number of countries and average t or $z - ratios$, $\bar{z} = \sqrt{N}^{-1} \sum z_i$ for sub-samples according to Pesaran et al (1999). The average OLS and IV point estimates for the full sample are 0.45 and 0.3 respectively. I find that advanced economies are much more sensitive to external volatility than emerging economies in terms of both OLS and IV estimates. In particular, the difference between the two groups is amplified when I apply IV estimation. The average point estimate $\bar{\beta}$ for advanced economies is 0.72, but that of the emerging economies is only 0.06. This may be due to several reasons. First, stock markets in advanced economies fluctuate a lot during crises in emerging economies such as 1994-5 economic crisis in Mexico and 1997-8 Asian financial crises. However, shocks in

Figure 4: Distribution of OLS and IV Coefficients



emerging economies do not affect the computed external volatility due to their small weights as trade partners by construction. Therefore, the point estimates may overstate advanced economies' responsiveness to explain observed international co-movements with given external volatility. Secondly, volatility of advanced economies has lower standard deviation than that of emerging economies. So, part of the gap between advanced and emerging economies is explained by the difference in their standard deviations of domestic volatility. In the third place, the gap may suggest the role of capital controls or market intervention devices in the emerging markets. For instance, circuit breakers halt the market operation temporarily when there is large change in stock prices. The price limits are usually set at a fixed per cent change. Circuit breakers are common both in advanced and emerging markets[8], but an equal fixed price limit rule does not mean an equal effect to volatility. For example, if stock index drops by 10 per cent a day and stays constant throughout a week, the volatility of the week is equivalent three standard deviations from mean in the advanced economies, but two

[8]From various sources, I find that at least 16 advanced and 17 emerging countries of my sample have circuit breakers in their stock markets.

Table 4: Effects of External Volatility by Regional Groups

	$\bar{\beta}_{OLS}$	$\bar{t}_{OLS}$	$\bar{\beta}_{IV}$	$\bar{z}_{IV}$	n
Advanced	0.68	126.6	0.72	31.7	21
Asia Pacific	0.66	42.0	0.49	8.68	4
Europe	0.67	110.5	0.80	28.56	15
North America	0.80	48.2	0.91	15.54	2
Emerging	0.33	63.0	0.06	3.67	39
Asia Pacific	0.38	41.9	0.39	8.47	12
Europe	0.47	49.0	0.23	4.16	10
Latin America	0.19	15.8	-0.74	-7.93	8
Middle East and Africa	0.22	16.2	0.12	0.96	9
Total	0.45	125.7	0.30	22.32	60

Note: All standard errors are robust.

standard deviations from mean in emerging economies. As a result, regulatory intervention becomes more often in emerging markets. Lastly, some negative point estimates from mostly Latin America lower the average response of emerging economies.

European and North American advanced countries are highly responsive to external volatility. This indicates the well established market integrations among these countries. Amongst emerging economies, Asia Pacific countries are most affected from external volatility whose average point estimate is 0.39. Emerging Europe is the next responsive group, as its coefficient is 0.23. Latin America shows a negative point estimate as mentioned. This is against economic intuition as well as inconsistent with the OLS result. That is, increase in external volatility actually lowers domestic volatility in these countries. Finally, Middle East and African emerging countries respond only a little to the external volatility and the point estimate is not significant. This can be related to the low stock market volatilities in this region. Estimation results of all individual countries are reported in the appendix.

3.5 Extensions and Robustness Checks

In this section, I evaluate the effects from U.S. volatility to other countries using the U.S. disaster series as instruments. That is, the following equation is estimated for countries

Table 5: Effects of the U.S. Volatility

	$\bar{\beta}_{OLS}$	$\bar{t}_{OLS}$	$\bar{\beta}_{IV}$	$\bar{z}_{IV}$	n
Advanced	0.61	93.97	0.95	22.08	20
Asia Pacific	0.54	30.27	0.66	8.88	4
Europe	0.62	84.72	1.03	18.66	15
North America	0.79	33.36	0.80	8.71	1
Emerging	0.26	47.84	0.16	4.25	39
Asia Pacific	0.27	30.52	0.41	7.29	12
Europe	0.39	36.08	0.19	3.30	10
Latin America	0.11	8.05	-0.26	-4.78	8
Middle East and Africa	0.23	18.71	0.16	1.45	9
Total	0.38	93.61	0.43	16.31	59

Note: All standard errors are robust.

$i = 1, 2, \cdots 59$ in two stage least square regressions.

$$\tilde{\sigma}_{it} = \alpha_i + \beta_i \tilde{\sigma}_{USt} + v_{it} \tag{6}$$

where U.S. volatility $\tilde{\sigma}_{USt}$ will be instrumented using natural disasters, terrorist attacks and accidents, because there is no identified political shocks or revolutions in the U.S. The results in the Table 5 are comparable to the Table 4. One standard deviation increase in the U.S. volatility raises the volatility of the other countries by 0.43 standard deviations on average. The spillover from the U.S. is greater in advanced economies than emerging economies. In addition, European advanced economies are mostly affected by the U.S. volatility. Among emerging economies, Asia Pacific region has greatest positive impact from the U.S. European emerging economies are also positively affected. Latin America shows negative impact of the U.S. volatility under IV estimation.

Table 6 contains the results using different specifications. Column (1) is the baseline in which external volatility is trade-weighed-average. In this method, the share of the U.S. in external volatility is 0.18 on average, while its maximum is 0.8 to Mexico and Canada and its minimum is 0.03 to Czech Republic and Luxemburg. To find how much the estimated volatility spillover is robust to the weights in external volatility, I consider GDP-weighted external volatility. A desirable alternative weight can be stock market capitalization, but

I choose GDP instead due to the limited data availability. From this method, the U.S. becomes the most important source of external shock to all other countries, as it explains 30 per cent of it. Column (2) shows similar with a lower point estimate to the baseline. In column (3), I use unweighted averages to compute external volatility in which a shock in Kenya or in Vietnam becomes as important as one in the U.S. or in Japan in terms of its effect on external volatility. Because this is an extreme assumption, it is hard to explain the higher point estimate. Still, the result is qualitatively consistent with other specifications. In column (4), external volatility is measured by the cross-country dispersion of returns. The set of instruments used in the baseline model results in an insignificant point estimate. Thus, an alternative combination of disasters is used for column (4). The point estimate is lower than any other specifications, but the result is largely consistent with the others. The first stage indicates that the cross-sectional dispersion rises during disaster shocks like other types of external volatility. The correlation coefficients amongst four measures of external volatility are reported in the Table 7. External volatilities as an average of volatility of foreign countries are strongly correlated. Cross-country dispersion in return is also positively correlated with the other measures of external volatility. Finally, the baseline specification is robust to the choice of instruments. In column (5) and (6) of the Table 6, revolutions or political shocks are omitted from the instruments, and the results are very similar to column (1).

4 Conclusion

Does stock market volatility in a country raise that in other countries? To answer this question, I conduct two types of empirical exercises. I fit a simple bivariate-VAR, which show a persistent positive response of domestic volatility to a shock in external volatility. In addition, I run a two stage least square regression of domestic volatility on external volatility to resolve the problem of an endogenous explanatory variable. Disaster shocks are used as the instrument for external volatility. I find that international spillovers do occur in stock markets. In particular, one standard deviation increase in external volatility raises domestic

Table 6: Robustness under Different Specifications

	(1) Baseline	(2) GDP-weighted	(3) Unweighted	(4) Cross-country dispersion	(5) No Revolutions	(6) No Political
External Volatility	0.392***	0.344***	0.615***	0.215**	0.391***	0.377***
	(0.101)	(0.092)	(0.145)	(0.092)	(0.101)	(0.097)
First Stage						
Natural Disasters	0.047***	0.053***	0.013	0.071***	0.047***	0.049***
	(0.014)	(0.009)	(0.009)	(0.009)	(0.014)	(0.014)
Terrorist Attacks	0.241***	0.277***	0.097***		0.241***	0.248***
	(0.016)	(0.012)	(0.010)		(0.016)	(0.016)
Revolutions	0.009	-0.161***	0.415***	1.008***		0.021
	(0.049)	(0.029)	(0.026)	(0.034)		(0.049)
Political Shocks	-0.141***	-0.12***	-0.087***		-0.141***	
	(0.009)	(0.006)	(0.007)		(0.009)	
Accidents	0.296***	0.32***	0.239***		0.296***	0.276***
	(0.013)	(0.011)	(0.010)		(0.013)	(0.013)
Weak identification F	131.27	357.62	127.87	165.605	376.69	335.28
Overidentification p-value	0.497	0.051	0.741	0.43	0.532	0.456
R-squared	0.258	0.239	0.244	0.08	0.258	0.255
Observations	86757	86757	86757	86757	86757	

1) * p<0.1 ** p<0.05 *** p<0.01

2) Robust standard errors are in parentheses and clustered by country

3) Cragg-Donald Wald F statistic provided for weak identification test.

4) P-value of Sargan-Hansen J statistic provided for overidentification test.
A rejection casts doubt on the validity of the instruments

Table 7: Correlations between Measures of Volatility

	Trade-weighted	GDP-weighted	Unweighted	Cross-country
Trade-weighted	1			
GDP-weighted	0.8669	1		
Unweighted	0.8242	0.8941	1	
Cross-country	0.3941	0.4135	0.5747	1

Note: Every correlation coefficient is significant at 0.1% level

volatility by 0.3 standard deviations. Moreover, I show that disaster shocks are valid and robust instrument for volatility. To the best of my awareness, this is the first work addressing the issue of endogeneity in international stock markets with instrument variables.

As future research, this work can be extended in a way to emphasize financial linkages. For instance, domestic return and volatility can be measured in the U.S. dollars about which global equity market investors might care. The result might be different if some countries experienced high inflation but not an equal depreciation in their local currencies. Similarly, external volatility can be computed in a way to explain patterns of capital flows by weighing origin countries of capital more. In addition, taking this approach in other asset markets could be an interesting work as an additional test of validity of the instruments. Lastly, the existing literature on the relation between volatility and real economic activity gives sensible charts available in estimating losses in asset prices, investment or GDP from external shocks.

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Appendix

Table 8: Weekly Stock Market Data of Advanced Countries

Country	Mean of Return	Std. Dev. of Return	Mean of Volatility	Std. Dev. of Volatility	Number of Observations
Australia	0.02	0.95	0.90	0.96	2191
Austria	1.49	1.15	0.95	1.22	1378
Belgium	1.97	1.01	0.92	1.17	1409
Canada	1.67	0.97	0.87	0.96	1879
Denmark	2.63	0.98	0.87	0.95	1721
Finland	2.23	1.61	1.59	1.87	1304
France	0.58	1.12	1.07	1.08	2180
Germany	1.31	1.18	1.20	1.24	2191
Italy	-1.01	1.35	1.23	1.26	2034
Japan	0.21	1.13	1.17	1.33	2177
Luxemburg	3.17	1.09	0.93	1.20	1406
Netherlands	2.56	1.23	1.24	1.36	1513
New Zealand	-1.17	0.88	0.78	0.83	2167
Norway	4.64	1.27	1.26	1.38	1513
Portugal	0.53	1.37	1.00	1.32	1356
Singapore	2.59	1.34	1.09	1.32	2190
Spain	-0.73	1.19	1.00	1.18	2104
Sweden	4.42	1.23	1.22	1.27	1669
Switzerland	3.36	1.28	1.30	1.34	1305
United Kingdom	0.69	1.11	1.03	1.08	2191
United States	1.00	1.00	1.00	1.00	2190

Notes: Every variable except for number of obervations is normalized by the level of the U.S. The mean and standard deviation of retun and volatility for the U.S. are 0.0004, 0.0233, 0.01 and 0.007 respectively.

Table 9: Weekly Stock Market Data of Emerging Countries

Country	Mean of Return	Std. Dev. of Return	Mean of Volatility	Std. Dev. of Volatility	Number of Observations
Argentina	-0.79	2.61	2.31	2.76	2185
Bangladesh	1.50	1.53	1.06	1.60	1124
Brazil	6.53	2.72	2.70	2.79	1670
Chile	6.24	1.27	0.97	1.28	1931
China	-2.06	2.24	1.96	2.22	993
Colombia	3.40	1.44	1.17	1.43	1039
Czech Republic	-0.44	1.48	1.33	1.52	936
Ecuador	-8.51	1.32	0.73	1.73	935
Egypt	4.27	1.73	1.42	1.67	982
Greece	-1.58	1.78	1.61	1.64	1213
Hong Kong	2.43	1.60	1.51	1.64	1625
Hungary	1.70	1.64	1.55	1.81	1094
India	3.62	1.59	1.40	1.48	1659
Indonesia	0.47	1.58	1.19	1.79	1486
Iran	2.71	0.76	0.51	0.77	862
Ireland	0.93	1.28	1.17	1.39	1301
Israel	4.05	1.45	1.34	1.30	1251
Kenya	-3.37	1.16	0.74	1.04	1086
Korea	2.16	1.50	1.43	1.59	2170
Kuwait	1.37	0.95	0.80	0.91	707
Malaysia	1.68	1.34	1.15	1.54	1663
Mexico	7.80	1.76	1.63	1.76	1392
Morocco	4.10	0.84	0.64	0.81	883
Nigeria	0.66	1.10	0.65	0.99	1151
Pakistan	2.24	1.59	1.30	1.43	1171
Peru	9.63	1.90	1.52	1.96	1148
Philippines	3.81	1.76	1.52	1.65	1355
Poland	4.63	2.02	1.62	1.82	1039
Romania	-2.99	1.94	1.75	2.07	724
Russia	5.85	2.63	2.03	2.42	916
Saudi Arabia	2.38	1.24	1.18	1.25	1337
South Africa	1.89	1.47	1.22	1.80	900
Taiwan	3.05	1.73	1.63	1.73	2160
Thailand	1.20	1.53	1.25	1.54	1914
Tunisia	4.05	0.69	0.50	0.62	726
Turkey	-0.07	2.74	2.66	2.65	1243
Ukraine	1.35	2.19	1.71	2.18	706
Venezuela	-0.67	1.79	1.40	1.75	930
Vietnam	-1.87	2.06	1.53	1.77	561

Notes: Every variable except for number of obervations is normalized by the level of the U.S. The mean and standard deviation of retun and volatility for the U.S. are 0.0004, 0.0233, 0.01 and 0.007 respectively.

Table 10: Effects of External Volatility in Advanced Countries

Region	Country	OLS Coeff.	t-ratio	IV Coeff.	z-ratio	Sargan p-value	Weak id F stat
Asia Pacific	Australia	0.68	18.16	0.20	1.88	0.39	17.98
	Japan	0.65	16.07	0.76	6.12	0.01	10.73
	New Zealand	0.57	15.51	0.46	2.8	0.00	7.60
	Singapore	0.74	34.27	0.54	6.57	0.10	11.92
Europe	Austria	0.58	12.77	0.36	2.59	0.20	5.24
	Belgium	0.51	11.17	0.76	3.94	0.00	2.94
	Denmark	0.73	22.53	0.83	10.81	0.01	13.00
	Finland	0.55	19.27	1.17	6.32	0.00	3.79
	France	0.84	42.41	1.36	17.37	0.00	9.14
	Germany	0.79	35.89	1.40	13.79	0.47	10.15
	Italy	0.56	31.43	0.00	0.04	0.05	14.84
	Luxemburg	0.32	6.99	0.85	3.76	0.00	2.96
	Netherlands	0.79	38.71	0.74	12.89	0.00	8.89
	Norway	0.72	21.26	0.25	2.50	0.01	6.99
	Portugal	0.62	28.73	0.49	4.71	0.01	3.14
	Spain	0.81	53.15	1.38	10.84	0.01	7.91
	Sweden	0.80	32.41	1.14	11.71	0.26	9.70
	Switzerland	0.73	31.19	1.08	7.71	0.08	2.83
	United Kingdom	0.68	40.04	0.17	1.61	0.00	2.96
North America	Canada	0.79	34.33	0.96	13.13	0.75	9.43
	United States	0.81	33.90	0.86	8.84	0.00	12.47

Notes: All standard errors are robust.

Table 11: Effects of External Volatility in Emerging Countries

Region	Country	OLS Coeff.	t-ratio	IV Coeff.	z-ratio	Sargan p-value	Weak id F stat
Asia	Bangladesh	0.04	2.43	0.10	0.56	0.00	7.35
Pacific	China	0.22	9.60	0.22	0.48	0.64	3.23
	Hong Kong	0.57	16.16	0.06	0.25	0.21	6.54
	India	0.46	11.41	0.67	4.88	0.39	11.58
	Indonesia	0.47	12.75	1.71	4.85	0.81	3.99
	Korea	0.55	16.74	1.21	10.49	0.49	17.01
	Malaysia	0.48	10.73	0.00	-0.03	0.01	7.74
	Pakistan	0.11	2.45	0.17	0.98	0.21	2.91
	Philippines	0.44	15.64	-0.49	-2.11	0.25	3.94
	Taiwan	0.36	16.10	0.14	1.80	0.00	14.06
	Thailand	0.53	19.47	0.92	7.47	0.00	10.89
	Vietnam	0.36	11.79	-0.05	-0.31	0.19	20.58
Europe	Czech Republic	0.71	12.65	0.46	3.25	0.00	6.83
	Greece	0.47	19.23	0.05	0.34	0.24	12.08
	Hungary	0.56	16.78	0.25	2.31	0.00	15.18
	Ireland	0.75	30.47	0.46	4.08	0.36	3.53
	Poland	0.30	10.72	0.05	0.39	0.00	18.52
	Romania	0.39	12.74	0.14	0.70	0.02	3.74
	Russia	0.50	11.59	0.22	0.91	0.18	3.15
	Turkey	0.31	12.78	-0.05	-0.29	0.03	5.08
	Ukraine	0.45	15.64	0.98	2.90	0.26	3.45
Latin	Argentina	0.15	6.42	-0.55	-4.06	0.00	23.89
America	Brazil	0.26	9.95	-0.67	-2.78	0.07	5.12
	Chile	0.10	3.81	-0.94	-5.05	0.03	13.55
	Colombia	0.21	4.72	-0.53	-1.97	0.13	3.03
	Ecuador	0.01	0.49	-1.00	-2.18	0.34	2.05
	Mexico	0.42	10.13	-0.36	-2.11	0.01	9.96
	Peru	0.34	7.80	-1.39	-2.22	0.01	2.75
	Venezuela	0.04	1.36	-0.50	-2.07	0.00	17.34
Middle East	Egypt	0.42	10.60	0.86	3.06	0.64	4.48
and Africa	Iran	-0.10	-4.05	0.94	1.49	0.07	2.28
	Israel	0.31	12.26	-0.24	-1.44	0.29	4.78
	Keyna	0.28	5.92	-0.35	-2.04	0.09	5.16
	Kuwait	0.24	7.73	0.89	2.62	0.28	2.08
	Morocco	0.15	4.76	-0.44	-1.65	0.02	3.70
	Nigeria	0.25	7.94	0.36	2.66	0.06	8.93
	Saudi Arabia	0.21	3.71	-0.11	-0.61	0.06	3.32
	South Africa	0.41	8.87	-0.81	-1.17	0.27	1.18
	Tunisia	0.12	3.14	-0.21	-1.48	0.11	6.21

Notes: All standard errors are robust.