DOES UNCERTAINTY DRIVE BUSINESS CYCLES? USING DISASTERS AS A NATURAL EXPERIMENT

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Abstract: A growing body of evidence suggests that uncertainty is counter cyclical, rising sharply in recessions and falling in booms. But what is the causal relationship? To identify this we construct cross country panel data on stock market levels and volatility as proxies for the first and second moments of business conditions. We then build a panel of indicators for natural disasters, terrorist attacks and unexpected political shocks, and use these to instrument our stock market proxies for first and second moment shocks. Using this approach in regressions for annual GDP growth we find that: (i) both the first and second moments are highly significant, and (iii) second moment shocks account for about 60% of explained variation in GDP growth and first moment shocks for about 40%. We also run a micro to macro simulation model with disaster shocks, to generate simulated data and test our empirical estimation strategy on the simulated data. We find in our simulated data that using exogenous disasters to instrument stock levels and volatility is effective, suggesting that using macro shocks to instrument stock market levels and returns can identify the impact different moment shocks on economic growth.

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1. Introduction

A rapidly growing literature is centered on investigating the relationship between uncertainty and business cycles. One stylized fact from this literature is that macro and micro uncertainty is strongly counter cyclical, rising steeply in recessions and falling in booms.[1] What is not clear, however, is to what extent this relationship is casual. Does uncertainty drive recessions, do recessions drive uncertainty, or does something else drive both, jointly? Since theoretical models of uncertainty and economic activity predict effects in both directions[2], identifying the direction of causation is ultimately an empirical question.

Identifying the direction of this relationship is difficult because most macro variables move together over the business cycle, without any obvious causal direction. In large part this is because, as Kocherlakota (2009) aptly noted, "*The difficulty in macroeconomics is that virtually every variable is endogenous*". As a result, the prior literature has either assumed the direction of causation, or relied on timing for identification in something like a Vector Auto Regression. This is problematic, however, because of the contemporaneous movement of macro variables and the forward looking nature of investment and hiring. Because of this, it is not surprising that a wide range of different results have been found using VAR regressions because of their sensitivity to subtle differences in auxiliary assumptions.[3]

In this paper we take what we believe is a more robust approach, which exploits the large number of exogenous shocks that occur in a panel of sixty countries since 1970. These exogenous shocks are natural disasters, terrorist attacks and political shocks (assassinations, coups, and revolutions). We use these shocks to instrument for changes in the level and volatility of stock-market returns as a way to separate the effects of our

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[1] See, for example, evidence of counter-cyclical volatility in: macro stock returns in the US in Schwert (1989) and Bloom (2009), and internationally in Engel and Rangel (2008); in firm-level stock returns in Cambell et al. (2001), Bloom, Bond and Van Reenen (2007) and Gilchrist et al (2009); in plant, firm, industry and aggregate output and productivity in Bloom, Floetotto, Jaimovich, Saporta and Terry (2011), Bachman and Bayer (2011), and Kehrig (2010); in price changes in Berger and Vavra (2010); and in consumption and income in Storesletten et al (2004) and Meghir and Pistaferri (2004). Other papers find that GDP and prices forecasts have a higher within-forecaster dispersion and cross-forecaster disagreement in recessions, for example, Bachman et al (2010), Popescu and Smets (2009) and Arslan et al (2011); and that the frequency of the word "uncertainty" close to the word "economy" rises steeply in recessions, for example Alexopolous and Cohen (2011).

[2] Models predicting impacts of uncertainty on economic activity include effects via: (a) risk aversion; (b) via the concavity of the production function (for example Oi (1961), Hartman (1976) and Abel (1983)); (c) real-options effects (for example Bernanke (1983), Bertola and Caballero (1994), Dixit and Pindyck (1996), Hassler (1996), Gilchrist and Williams (2005), Sim (2008)); and (d) via financial contracting frictions (for example, Arrellano et al. (2010), and Narita (2011)). There are also a range of models predicting effects of economic activity on uncertainty, for example on information collection in Van Nieuwerburgh and Veldkamp (2006), or on experimentation in Bachman and Moscarini (2011).

[3] For example, Bloom (2009), Christiano et al. (2010), Arslan et al. (2011), Fernandez-Villaverde (2011) and Alexopolous and Cohen (2011) report a large impact of uncertainty on recessions in their VARs, while Bachman and Bayer (2010) and Bachman et al. (2011) report the reverse (a large effect of recessions on uncertainty).

exogenous shocks into first- and second-moment components. The identifying assumption is that to the extent that some shocks – like natural disasters - leads primarily to a change in stock-market levels it is more of a first moment shock, and to the extent it leads more to a change in stock-market volatility it is more of a second moment shock.

To refine this analysis we 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, we would use the 322% increase in the count of the word "Japan" in five days after the March 11th, 2011 earthquake compared to the five days before to weight this shock. This ensures that only events that are unanticipated are included, since anticipated events generate steady increases in coverage rather than short-run jumps. Moreover the largest most newsworthy shocks will get the largest weight, which should be correlated with their economic impact. Figure 1 shows the average increase in newspaper coverage of the countries in which the shocks occurred for fifteen days before and after the shocks. This shows these events lead to a jump in newspaper coverage on the day of the event, and an increase of 61% over the five days after the event.

Using this strategy, we find a significant causal impact of both first and second moment effects on economic activity. In the quarter following a shock we estimate a one standard deviation reduction in stock-market levels (our first moment proxy) and increase in stock-market volatility (our second moment proxy) leads to a 2.0% and 2.8% respective reduction in GDP. In the year following a shock we estimate larger effects, with a one standard deviation reduction in stock market levels and rise in stock market volatility leading to falls in annual GDP growth of 3.2% and 6.8% respectively.

There are clearly some potential issues with this identification strategy. One of these is whether stock market volatility is a good indicator of second moment shocks to business conditions. As an alternative estimation approach we use exchange rate volatility to proxy for second moment shocks, and find very similar results. A second concern is whether these events are really shocks, or some of them are endogenous events. For example, maybe some revolutions were predicted in advance or natural disasters arising from human actions (like deforestation) could be foreseen. To address this we test our shock instruments directly and find while these have extremely high predictive power for future economic outcomes like stock returns and GDP growth, we cannot find any predictive power for these shocks using our stock returns and GDP growth date. Moreover, as shown in Figure 1, there is no increase in newspaper mentions of these countries in the days leading up to the day of the event, suggesting they were not anticipated (at least in the short-run). We also run the standard over-identification tests in our regressions and find no evidence to reject the instruments.

Third, our results are only valid to the extent that they identify the first and second moment impact of our shocks in the countries and years that they occur. This is a classic local average treatment effect (LATE) issue (see Imbens and Angrist, 2004), in that our identification is driven by the variation in our instrument. As a robustness test, we re-estimate our results using countries above and below the median income level as well as

with data before and after the median year, finding similar results. This suggests these results appear broadly representative for a least the median country in our sample.

Finally, our stock market levels and volatility indicators will be proxying for a range of channels of economic impact, for example the destruction of property after a natural disaster and the closure of the banking system after a revolution. We see these as all part of the first and second moment impacts of these shocks. But it is worth noting that in obtaining causal identification of the impact of first and second moment effects of exogenous shocks on the economy, we are conflating all these channels together.

In section 2 we describe the stock-market and natural and political shock data, in section 3 we describe the data and provide some descriptive VAR regressions, while in section 4 we estimate instrumental variable estimations. In section 5 we run a series of extension and robustness tests, and finally we conclude in section 6.

2. Model and Simulation (incomplete)

To investigate the ability for our empirical approach to identify the impact of uncertainty shocks using natural disasters, terrorist attacks and political disasters we build a simulation model. This helps to both clarify the underlying economic model we have and show that, at least in this set-up, our empirical approach is able to identify parameters of interest.

2a) Basic model

We set up a standard micro-macro model and include disaster shocks of varying types. It is based very heavily on Bloom (2009), which itself builds heavily on prior papers like Bertola and Caballero (1994), Dixit and Pindyck (1994), Abel and Eberly (1996) and Cooper and Haltiwanger (2006). So we only sketch key details here.

Each firm operates using a standard Cobb-Douglas production function for output (Y):

$$Y = A^{1-\alpha-\beta} K^{\alpha} L^{\beta}$$

where labor (L) and capital (K) face adjustment costs are the usual combination of convex (quadratic) and non-convex (fixed and partial irreversibility) adjustment costs. Business conditions (A) are given by a random walk with micro and macro (that is, firm and country level) components:

$$A = A_F * A_M$$

$$dA_{F,t} = \mu_F dt + \sigma_{F,t} dw \qquad dw_{F,t} = N(0,1)$$

$$dA_{M,t} = \mu_M dt + \sigma_{M,t} dw \qquad dw_{M,t} = N(0,1)$$

The uncertainty processes $\sigma_{F,t}$ and $\sigma_{M,t}$ evolve as 2-point Markov chains with the following transition matrix:

	σ^L	σ^H
σ^L	$35/36$	$1/36$
σ^H	.29	.71

where σ^H is defined such that it occurs, on average, once every 3 years and has a two month half-life when it does occur. Since in empirical data we find that micro and macro uncertainty move together over the business cycle we assume in the simulation that both are driven by a common uncertainty process σ_t.

2b) Simulated Disaster Shocks

As in our empirical data, we utilize four types of disaster shocks in our simulation. Each shock type affects the A_m process in a unique way through a bundle of first and second moment effects. These bundles are chosen to correspond roughly to those found in our empirical data.

The first shock type corresponds to natural disasters, and has a first moment ($w_{M,t}$) effect of -.5 standard deviations and a second moment ($\sigma_{F,t}$) effect of 0. The second shock type corresponds to political shocks and has a first moment effect of 0 and a second moment effect of 1 standard deviation. The third shock type approximates a revolution and has a first moment shock of -2 standard deviations and a second moment effect of 1 standard deviation. The final shock type approximates a terrorist attack with a first moment effect of -.5 standard deviations and a second moment effect of 1 standard deviation. These shocks are randomly drawn with a frequency of once per 20 years, so the typical 'country' is hit by one of these four types of shocks every 5 years on average (in our data, the average is 4.2 years between shocks).

2c) Generating Simulated Data

We assume our countries are small open economies with prices and wages fixed so we can run our simulation at the firm level and aggregate up. This is empirically reasonable as our median country is open with a mean trade/GDP ratio of 0.83.

We run our simulation weekly for 500 firms per 'country' for 10,000 'countries' for 20 years. From this weekly level, we generate three series of quarterly data for each country. The first is quarterly data on overall output summed across all firms and weeks. The second is stock return data taken from the return over the quarter from holding all firms. Finally we also generate stock volatility data from the 13 sets of weekly stock returns.

For empirical realism we also add noise to our stock returns data, with a baseline series of noise distributed i.i.d. with the same standard deviation as true returns. Thus, in an average week, half of returns on the stock-market index will be noise and half will reflect the underlying shocks to the aggregate country process. We do this to mimic two factors. First, the presence of noise in high-frequency stock-market data based on evidence from

papers by Shiller (1987) and suggesting that stock-markets are too volatile at high frequencies to be justified by fundamentals. Second, the fact that many firms are not publicly listed in the countries we cover, so that the stock market index will not perfectly represent the average returns to all firms in the economy.

2d) Results on the Simulated Data

In Table 1, we give results from our simulated economy with disaster shocks. We apply our empirical strategy to the simulated data: first utilizing OLS and then instrumenting for volatility and stock market returns with the four types of disaster shocks (natural, political, revolution, terrorist).

Columns (1) and (2) show our OLS results regressing GDP growth in our simulated data on our simulated stock market level and volatility of returns over the past year. We find larger coefficients at a yearly level in column (2) compared to the quarterly results in column (1), consistent with stronger associations estimated over a longer time period.

Columns (3) and (4) display our IV results utilizing our simulated data. In both the quarterly results and the annual results, we find higher point estimates than those in the corresponding OLS results. This is due to a combination of measurement error and endogeneity biasing our OLS results. The measurement error arises due to the assume noise in the stock-market returns, so that part of the levels and volatility movement is unrelated to fundamentals. The endogeneity arises because first moment shocks to aggregate business conditions A_M also generate positive stock-market volatility effects, and second moment shocks to uncertainty σ have positive levels effects through the Oi-Hartman-Abel effect[4]. As a result stock market levels and volatility measures conflate the offsetting impact of underlying first and second moment shocks, and so both sets of coefficients are biased towards zero under OLS.

In the first stage, we find that all types of shocks increase volatility of stock returns, despite not all types of shocks having an explicit volatility-enhancing component. This is because some effect of higher or lower returns mechanically leads to stock volatility, thereby inducing positive results. We find negative effects on returns for all shocks except for political shocks, where we find a significantly positive effect. Moreover, both IV regressions pass weak instruments and overidentification tests, suggesting that utilizing bundles of shocks and controlling only for first and second moment shocks are viable methods of obtaining the 'true' causal effect of uncertainty.

In Table 2 we examine to what extent in the simulation our set of disaster instruments provide identification for the impact of first and second moment shocks on growth. To do that in column (1) we again display our IV results for annual growth from column (1) of Table 1 as the baseline. In comparison in column (2) we present results for the estimation in which we instrument stock-market returns levels and volatility using the true

[4] This reflects the fact that with flexible factors of production a mean preserving spread in business conditions increases the expected marginal revenue product of the factors (see Oi (1961), Hartman (1972) and Abel (1983) for various formulations of the underlying idea).

underlying process for A_t and σ_t. While in real data we clearly cannot observe the true underlying first and second moment shock process (A_t and σ_t), in the simulation we can which enables us to compare the ability of the bundle of disaster shocks to proxy for these. Comparing between the estimates in the two columns we see that the point estimates on the stock-market levels and volatility measures are very similar across the two specifications. This highlights that fact that - at least in our simulation – using disaster shocks as proxies for the underlying first and second moment shocks is an effective estimation strategy.

3 Data

We use 60 countries in our analysis, selected as countries with more than $50 billion in nominal GDP in 2008 according to the World Bank ranking. We also required at least 5 years of daily stock returns data from a national index. While a number of countries have data beginning in the 1940s, most countries have relatively complete data starting only in the 1970s or later. Thus, we construct our sample from 1970 onwards in order to avoid early years with only a few countries with data in our panel. The data can be divided into shock data and economic data, which we now discuss in turn.

3a) Shock Data

To obtain the causal impact of first and second moment shocks on GDP growth we want to instrument using arguably exogenous shocks. This leads us to focus on exogenous natural disasters, terrorist attacks and political shocks, which are typically exogenous in the short-run. This approach has some clear precedent in the literature, such as the paper by Jones and Olken (2005) looking at successful assassinations of national leaders as an instrument for leadership change and Hoover and Perez (1994) who use oil-price shocks as instruments for aggregate productivity shocks. Furthermore, others have found strong effects of political 'shocks' on markets and asset prices, as in Zussman, Zussman, and Nielsen (2008).

As we discuss below, the exogeneity of many of these shocks is disputable in the long-run. For example, faster economic growth may increase the chances of a natural disaster through reduced forest cover but reduce the chances of a revolution by lowering poverty rates. To address this concern, we do three things.

First, we focus only on short-run impacts of shocks, looking at one quarter and one year impacts. At these short-run frequencies it is easier to argue shocks are exogenous. For example, while many commentators expected revolutions in the Middle East at some point over the next couple of decades, the start of the Arab Spring in December 2010 was unpredicted. Second, we weight shocks by the increase in media coverage 5 days after the event compared to 5 days before the event. This should remove anticipated shocks in that the media coverage running up to them would be smoothly increasing. For example, as Figure 2 shows to the media coverage in the one month around general elections shows no jump in the 5 days after the event compared to the 5 days before the event.[5] Third, we

[5] We also did similar analysis for the World Cup and Super Bowl also finding no jump in coverage around the event.

do a variety of robustness tests and tests of the exogeneity of our shocks and find the results reassuringly robust. For example as shown in Table A1 these shocks cannot be forecast in advance by stock market data, suggesting they are not anticipated by the market.

We now discuss the definitions of each of these three groups of shocks in turn, and note that all data-sets and do-files to replicate every result and regression are available online at www.stanford.edu\nbloom\bakerbloom.dta.

One initial issue is that the number of events covered by natural, political and terrorist disasters is extremely large, typically with several per day. So we need to apply a filter to focus only on major event. We also apply a filter to screen minor events from these databases of shocks. We include a shock only if it fulfills one of the following conditions (we show that our results are robust to modification of filters for both deaths and monetary damages):

1. More than 100 deaths
2. More than $1 billion in damage
3. A successful coup or regime change

Table 3 contains some summary statistics of our country sample, economic and shock variables. We have a total of about 6000 quarterly observations for the 60 countries with full GDP growth and stock returns data, with over 1000 shocks occurring over this period. Table A1 gives a full listing of all shocks in our sample, by country and year. Included for each shock, in parenthesis, are the quarter the shock occurred in, the ratio of news citations for the 5 days following the shock to the 5 days preceding it, and the type of shock (Natural Disaster, Political, Revolution, or Terrorism).

Natural Disasters: Our natural disaster data has been obtained from the Center for Research on the Epidemiology of Disasters (CRED) [6]. This dataset contains over 15,000 extreme weather events, droughts, earthquakes, epidemics, floods, extreme temperatures, insect infestations, avalanches, landslides, storms, volcanoes, fires, and hurricanes from 1960 to 2011. The dataset includes the categorized event, its date and location, the number of deaths, the total number of people affected by the event, and the estimated economic cost of the event. The CRED dataset also includes industrial and transportation accidents which we exclude in our analysis. We selected all natural disasters with at least 100 deaths or more than $1b damage to define as a shock.

Terrorist Attacks: To define terrorist events we use the Center for Systemic Peace (CSP): High Casualty Terrorist Bombing[7] list, which extends from 1993-2009 and includes all

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[6] See http://www.emdat.be/database CRED is a research center which links relief, rehabilitation, and development. They help to promote research and expertise on disasters, specializing in public health and epidemiology. Their EM-DAT database is an effort to provide a standardized and comprehensive list of large-scale disasters with the aim of helping researchers, policy-makers, and aid workers better respond to future events.

[7] See http://www.systemicpeace.org/inscr/inscr.htm The CSP is a research group affiliated with the Center for Global Policy at George Mason University. It focuses on research involving political violence in the global system, supporting research and analysis regarding problems of violence in societal development.

terrorist bombings which result in more than 15 deaths. This data includes the location and date of each event as well as the number of deaths and an indicator for the magnitude of the attack ranging from 1 to 6. As this data only extends from 1993-2009, we supplement it with a list of high death-toll terrorist attacks from Wikipedia.[8] This data includes attacks with greater than 30 deaths and the covers 1920-2011. We exclude terrorist attacks in Iraq (2003-2011) and Afghanistan (2001-2011), which were periods with US military presence. These locations and time periods contain an overwhelming number of 'terrorist attacks' and such attacks most likely do not induce any volatility in markets as they are generally anticipated on a quarterly basis.

Political Shocks: For political shocks, we utilize data from the Center for Systemic Peace (CSP): Integrated Network for Societal Conflict Research. To define political shocks we include all successful assassination attempts, coups, revolutions, and wars, from 1970-2009. Again, to supplement this measure, we utilize the list of coups and revolutions from Wikipedia for political shocks in 2010 and 2011.[9]

We include two types of political shocks. The first is composed of coup d'états and other regime changes. Coup d'états are defined as forceful or military action taken by an opposition group which results in the seizure of executive authority. This opposition group is already a member of the country's ruling elites, rather than say an underground opposition group. Typically these are coups brought by the military against left-wing governments.

Our second type of political shock denotes a revolutionary war or violent uprising. These are composed of events featuring violent conflict between a country's government and politically organized groups within that country who seek to replace the government or substantially change the governance of a given region. These groups were not previously part of the government or ruling elite. This category also does not include political violence stemming from ethnic grievances.

Within each category, by country and quarter, we give a value of one if a shock has occurred and a zero otherwise. This means that if a country has, for example, three earthquakes in one quarter, it still only receives a value of one. When using the shocks weighted by the increase in press citations we take the largest shock in that category in that quarter. The reason is to avoid double counting recurring but linked events within a quarter – such as an earthquake with multiple aftershocks.

3b) Economic data

Output data: Real GDP is obtained from the Global Financial Database for all but 15 countries. GDP data for Mexico, Venezuela, Chile, Greece, and Singapore was obtained from the IMF Statistics division. GDP data for Pakistan was obtained from the World Bank. Saudi Arabian GDP data was obtained from the World Development Indicators

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The CSP established the Integrated Network for Societal Conflict Research in order to coordinate and standardize data created and utilized by the CSP.

[8] http://en.wikipedia.org/wiki/List_of_battles_and_other_violent_events_by_death_toll#Terrorist_attacks

[9] http://en.wikipedia.org/wiki/List_of_coups_d%27%C3%A9tat_and_coup_attempts_since_2010

Database. GDP data for Bangladesh, Kenya, Kuwait, Serbia, and Vietnam was obtained from the World Economic Outlook database. Finally, GDP data is proxied for by Industrial Production for Poland, Romania, and Nigeria. Real GDP data is denominated in the local currency and its reference year varies. As we deal with percentage changes, the different denominations and base years of different countries does not matter.

We use yearly real GDP growth by quarter (GDP growth defined 4 quarters apart) as our primary dependent variable to remove seasonality and quarterly effects, and reduce the impact of high frequency measurement errors. In some specifications we also use quarterly GDP growth defined as growth in GDP between the current and preceding quarter.

Annual population data for all data was obtained from the Global Financial Database. Population data is taken from national estimates and represents annual December 31st population levels. Data on monthly Consumer Price Indexes is obtained for all countries from a variety of sources.

Stock market data: Data on stock indices was obtained from the Global Financial Database, using the broadest general stock market index available for each country. Wherever possible we used daily data, but for seven countries we used weekly or monthly data in the 1980s and early 1990s to construct stock returns and volatility indices when daily data was not available.[10] Our results are robust to the exclusion of observations taken from non-daily stock data and to excluding all observations from these countries. All stock indices in our analysis are normalized by the country level CPI data to obtain real returns.

In the empirical specifications, we generate yearly stock returns in each quarter, defined as the cumulative return over the proceeding four quarters, in order to match our yearly GDP growth rates. A measure of average yearly volatility is created by taking the average of quarterly standard deviation of stock daily returns over the last four quarters.

Exchange rate data: We also collect daily exchange rate data from the Global Financial Database whenever available, and use the volatility of this as an alternative measure of uncertainty.

3c) News Citations

Two natural concerns are that the shocks we utilize as instruments are either not unexpected or are relatively small in magnitude. In order to help alleviate both of these potential problems, we turn to a measure of unexpectedness and impact derived from news article mentions of the countries in question.

Using the Google News Archives, we construct an "attention" index surrounding each event. For each event we search the Google News Archives using the name of the country

[10] These countries are Saudi Arabia, Mexico, South Africa, Ireland, Russia, Turkey, and Venezuela.

the event occurred in. We then observe a 15 day period on either side of the day of each event, counting the number of articles written each day about the country. Figure 1 reports the average number of articles on the country surrounding the event, where each event's coverage has been normalized to 1 in the 15 days prior to the event.

We use this data to construct a measure of the jump in attention paid to the country subsequent to an event or disaster. This will help to distinguish events which were both unexpected and large enough in magnitude to plausibly affect national returns or volatility from those which were not. For example, if we observe a similar number of articles regarding the country before and after the event date, we can assume that either the event was predicted ahead and/or it was not that important. In contrast, observing a jump in articles just after the event makes it likely this was (at least in part) both unexpected and important enough to command news attention.

The way we define our jump in coverage index is to compute the percentage increase in the number of articles written in the 5 days after the event compared to the 5 days before the event. We choose this narrow 5-day window either side of the event to maximize our ability to detect discrete jumps in coverage (longer windows will also include gradual trends), and to minimize the chances of feedback from economic impacts of event onto our index. In the Appendix (*Scott - to do*), we show our results are robust to using narrower windows of 3-days either side of the event and wider windows of 15-days either side of the event. As an illustration of this approach if we see 15 articles written about a country in the 5 days prior to the event and 30 articles written about a country in the 5 days following an event, we would assign this event a weight of 1 as it reflects a 100% jump in citations.

4 The Impact of Uncertainty on Output

We display results from our primary specifications in Table 4. Columns (1)-(3) give results from Ordinary Least Squares (OLS) regressions of national GDP growth on stock market returns and volatility. We find significant positive effects of stock returns on growth and significant negative effects of stock market volatility on growth. Furthermore, we find a large increase in the measured effect when we move to the yearly OLS specification, exactly as in our simulation results, presumably due to the reduced influence of noise in our stock-market returns measures. Results are similar when we include time dummies, as in column (3). However, we worry about a high degree of endogeneity in these OLS results, so we proceed to our instrumental variable (IV) regressions.

Columns (4) and (5) show results from our quarterly and yearly IV regressions. Here we instrument for stock returns and volatility with our set of scaled disaster shocks. This set consists of four series: natural disasters, political shocks, revolutions, and terrorist attacks. Using this strategy, we find a significant causal impact of both first and second moment effects on economic activity. In the quarterly specification, we estimate a one standard deviation reduction in stock-market levels (our first moment proxy) and increase in stock-market volatility (our second moment proxy) leads to a 2.0% and 2.8% reduction

in GDP. In the yearly specification, we estimate larger effects, with a one standard deviation reduction in stock market levels and rise in stock market volatility leading to falls in annual GDP growth of 3.2% and 6.8% respectively.

In the first stage, we see largely sensible results. We find positive point estimates for all disasters on stock market volatility, with the greatest levels seen following political shocks and revolutions. We find negative effects of natural disasters and revolutions on stock market levels, but positive effects of political shocks on stock market levels. This stems from the nature of these shocks, where political shocks are generally right-wing military coups which often take power from left-wing or communist governments. Revolutions are generally left-wing or communist groups overthrowing military or right-wing governments. Finally, we find little impact of terrorist attacks, perhaps due to the fact that the majority of terrorist attacks have come in countries accustomed to such violence and thus they have less impact as single events.

Both IV specifications give point estimates much higher than those found in the corresponding OLS regressions. We posit that this could be due to a number of reasons. The first is endogeneity as in our simulation results, whereby positive first moment shocks can generate increased stock-market volatility and second-moment shocks can have first moment effects, so that under OLS the coefficients are downward biased on both the levels and volatility terms. The second is measurement error. Our stock market data is measuring actual market levels presumably with error due to incomplete stock market indices[11], as well as the presence of a great deal of noise in daily stock market data. Finally, an element of the Latent Average Treatment Effect (LATE) is surely present. Our disaster shock instruments are more prevalent among the poorer countries in our sample where the impact of volatility may be higher than in rich countries. A greater negative effect of volatility on growth is also seen in OLS regressions where we split between rich and poor halves of our data.

From these results, we can discern three primary points. The first is that we find both first and second moment shocks matter to growth and that excluding either will lead to misspecification bias. The second is that our findings show that the causal effect of uncertainty on growth is much higher than OLS estimates suggest due to factors such as measurement error and endogeneity, consistent with our simulation results. These higher values should be considered when calibrating other models of the effect of uncertainty. Finally, we find that our strategy passes the Sargan overidentification test, suggesting that controlling for the first two moments of business condition shocks (here, stock returns

[11] Stock market indices cover publicly quoted firms global activities while GDP figures cover all firms' domestic activities. These can differ for at least two reasons. The first is that many large companies have much of their operations abroad, so for that example firms like General Electric, British Petroleum and Nissan have more than 50% of their employees abroad but their full market capitalization is used in their domestic stock-market indices. Second, almost all small and medium companies, and even many large companies are privately held so that stock-market indices do not cover them. As a result stock-market indices and GDP figures will empirically align perfectly even in their coverage of economic activity. Beyond this other differences arise due from, for example, timing (Calendar year versus account years) and accounting rules (Census versus GAAP rules on capital equipment depreciation).

and stock volatility) is sufficient to capture the full effect of such shocks, again consistent with our simulation results.

5 Robustness and Extensions

Table 5 gives the results of a number of robustness exercises. Column (1) gives our baseline yearly IV regression which all of the robustness results are modifications of. Column (2) shows results when we exclude our media-citation weighting of the disaster shocks. We find largely similar and still significant results. In columns (3) and (4), we remove time and country fixed-effects and add population weighting, respectively. These leave our results essentially unchanged. In column (5) we utilize exchange rate levels and exchange rate volatility as alternate independent variables. We find negative effects of exchange rate volatility but no effect of exchange rate levels on growth. This may be due to the fact that exchange rate level 'returns' are harder to interpret than stock market returns.

Columns (6)-(9) give results from removing one of our instruments at a time. For instance, in column (6) we run our yearly IV specification using only political, revolution, and terror shocks. Over all four columns, we find very similar point estimates, though our power drops, especially when dropping political or revolution shocks. For these two columns, we lose significance on our findings, while maintaining equivalent point estimates.

6 Conclusions

A recent body of research has highlighted how uncertainty is counter cyclical, rising sharply in recessions and falling in booms. But what is the causal relationship? Does rising uncertainty drive recessions, or is uncertainty just an outcome of economic slowdowns?

In this paper, we perform two analyses designed to determine the direction of causality. First, we perform a simulation in which a modeled economy undergoes shocks to business conditions and test the effects of these shocks. Second, we construct cross country panel data on stock market levels and volatility as proxies for the first and second moments of business conditions. We then build a panel of indicators for natural disasters, terrorist attacks and political shocks, and weight them by the change in daily newspaper coverage they induce.

Using these shocks to instrument our stock market proxies for first and second moment shocks, we find that both first and second moment shocks are highly significant in driving business cycles, conforming well to our simulated results. We also find that IV estimates of the effects of uncertainty are much larger than OLS estimate, suggesting that measurement error and endogeneity are significant concerns in OLS analyses. Finally, we find that controlling for first and second moments is sufficient to determine true effects of shocks on growth.

Bibliography: (incomplete)

Abel, Andrew. (1983): "Optimal Investment Under Uncertainty," *American Economic Review*, 73, pp. 228-233.

Alexopoulos, M. and J. Cohen, 2009a. "Nothing to Fear but Fear itself? Exploring the effect of economic uncertainty", Manuscript, University of Toronto working paper.

Arrellano, Cristina, Bai, Yan and Kehoe, Patrick (2010): "Financial Markets and Fluctuations in Uncertainty," Federal Reserve Bank of Minneapolis Research Department Staff Report.

Arslan, Yavuz, Atabek, Ashhan and Sahinoz, Saygin (2011), "Expectation errors, uncertainty and economic activity", Bank of Turkey mimeo.

Bachmann, Ruediger, Elstner, S, and Sims, Erik (2011): "Uncertainty and Economic Activity: Evidence from Business Survey Data", NBER WP 16143.

Bachmann, Ruediger. and Christian. Bayer (2011): "Uncertain business cycles: really?", CESIFO-WP 2844.

Bachmann, Ruediger, Ricardo. Caballero and Eduardo. Engel (2010): "Aggregate Implications of Lumpy Investment: New Evidence and a DSGE Model", mimeo Yale University.

Bachmann, Ruediger., and Guissepe. Moscarini. (2011) "Business Cycles and Endogenous Uncertainty," Yale mimeo.

Berger, D., and J. Vavra (2010): "Dynamics of the U.S. Price Distribution," Yale mimeo

Bernanke, B. (1983): "Irreversibility, Uncertainty and Cyclical Investment," *Quarterly Journal of Economics*, 98, pp. 85–106.

Bertola, G., and R. Caballero. (1994): "Irreversibility and Aggregate Investment," *Review of Economic Studies*, 61, pp. 223–246.

Bloom, Nick. (2009): "The Impact of Uncertainty Shocks," *Econometrica,* 77, pp. 623-685.

Bloom, Nick., S. Bond, and J. Van Reenen (2007): "Uncertainty and Investment Dynamics," *Review of Economic Studies*, 74, pp. 391–415.

Bloom, N. M. Floetotto, N. Jaimovich, I. Saporta and S. Terry, (2011), "Really Uncertain Business Cycles," Mimeo, Stanford.

Bloom, N., and J. Van Reenen (2007): "Measuring and Explaining Management Practices Across Firms and Countries," *Quarterly Journal of Economics*, 122, pp. 1351–1408.

Campbell, J., Lettau, M., Malkiel B. and Xu, Y. (2001), "Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk", *Journal of Finance*, 56(1), 1-43.

Christiano, Lawrence, Motto and Rostagno. (2010): "Financial Factors in Business Cycles," mimeo Northwestern University.

Dixit, A. and R. Pindyck (1994): *Investment Under Uncertainty*. Princeton, NJ: Princeton University Press.

Engle, R.F. and Rangel, J.G. (2008), "The Spline-GARCH Model for Low-Frequency Volatility and Its Global Macroeconomic Causes", Review of Financial Studies, 21(3), 1187-1222.

Fernandez-Villaverde, Jesus, Pablo Guerron, Juan Rubio-Ramirez and Martin Uribe (2011), “Risk Matters: the real effects of volatility shocks”, forthcoming American Economic Review.

Gilchrist, S., J. Sim and E. Zakrajsek (2009). “Uncertainty, Credit Spreads and Aggregate Investment”, mimeo.

Gilchrist, S., and J. Williams. (2005): “Investment, Capacity and Uncertainty: A Putty–Clay Approach,” Review of Economic Dynamics, 8, 1–27.

Hamilton, J.D. and Lin, G. (1996), "*Stock Market Volatility and the Business Cycle*", Journal of Applied Econometrics, 11(5), 573-593.

Hassler, J. (1996): “Variations in Risk and Fluctuations in Demand—A Theoretical Model,” *Journal of Economic Dynamics and Control*, 20, 1115–1143.

Hoover, Kevin and Perez, Steven, (1994), “Post Hoc Ergo Propter Hoc one more: an evaluation of ‘Does Monetary Policy Matter’ in the spirit of James Tobin”, *Journal of Monetary Economics*, vol. 34, 89-99.

Imbens, Guido and Angrist, Joshua (1994), “Identification and estimation of local average treatment effects”, *Econometrica* 62, 467-475.

Jones, Ben and Olken, Ben (2005), “Do Leaders Matter? National Leadership and Growth since World War II”, *Quarterly Journal of Economics,* 120(3), 835-864.

Kehrig, M. (2010): “The Cyclicality of Productivity Dispersion”, mimeo Northwestern University.

Kjetil Storesletten, Christopher I. Telmer, and Amir Yaron. (2005): "Consumption and risk sharing over the life cycle" *Journal of Monetary Economics* 52, 1331-1358.

Kocherlakota, N. (2009): “Some thoughts on the state of macro”, Minneapolis Fed mimeo.

Meghir, C., and L. Pistaferri. (2004): “Income Variance Dynamics and Heterogeneity,” *Econometrica*, 72, 1–32.

Narita, F. (2010): “Hidden Actions, Risk-Taking and Uncertainty Shocks”, mimeo University of Minnesota.

Oi, Walter (1961), “The desirability of price stability under perfect competition”, *Econometrica* vol 29(1), pp 58-64.

Popescu, A. and F. Smets (2009). “Uncertainty, Risk-Taking and the Business Cycle”, mimeo.

Schwert, G. W. (1989): “Why Does Stock Market Volatility Change Over Time?” Journal of Finance 44, 1115-1153.

Shiller, R. (1987), “The volatility of stock market prices”, *Science*, volume 235, pp. 33-37.

Sim, J. (2006): “Uncertainty, Irreversible Investment and General Equilibrium,” Mimeo, Boston University.

Van Nieuwerburgh, Stijn and Veldkamp, Laura (2006), “Learning asymmetries in real business cycles” *Journal of Monetary Economics,* v53(4), p753-772.

Zussman, Asaf and Zussman, Noam and Nielsen, Morten (2008): “Asset Market Perspectives on the Israeli-Palestinian Conflict” Economica 75, 84-115.

APPENDIX A:

A1) Data cleaning:

Data on GDP growth, stock volatility, stock returns, and exchange rate volatility is windsorized at a 0.1% level. That is, the lowest and highest 0.1% of our values are constrained to be equal to the 0.1^{th}-percentile and 99.9^{th}-percentile, respectively. This is done to prevent extreme outliers from driving the results. Censoring the data (dropping the top and bottom 0.1%) yields similar results as shown in Table X1.

We also drop data when the stock market has been suspended for the quarter or data is missing. This affects 4 quarters of data in Mexico, Morocco, Saudi Arabia, and Pakistan. Additionally, we do not use values of 0 for exchange rate volatility, which affects 548 quarters due to fixed exchange rates.

A2) Google News Archive Searches

Google News' result algorithm produces articles in order of relevance and media outlet importance, so our results comprise a 31 day index of attention focused on the country from the international media. Google generally caps the number of citations at 100 per search request, but delivers these in order of importance – that is first reporting mentions in the New York Times, Wall Street Journal and other national news before reporting them in local news. Hence, our search results represent the distribution of the new reports focused in particular in the national media around the event.

Table A1: Economic variables cannot forecast disasters

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimation procedure	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Dependent variable (shock type):	Natural, Scaled by Media Cites	Political, Scaled by Media Cites	Revolution, Scaled by Media Cites	Terrorist, Scaled by Media Cites	Natural, Scaled by Media Cites	Political, Scaled by Media Cites	Revolution, Scaled by Media Cites	Terrorist, Scaled by Media Cites
Volatility of stock returns, last quarter	0.042	0.144	-0.000	0.010				
	(0.101)	(0.140)	(0.001)	(0.009)				
Level of stock returns, last quarter	0.008	0.034	0.002	0.001				
	(0.020)	(0.034)	(0.002)	(0.003)				
GDP growth, last quarter	-0.298	0.052	-0.007	0.051				
	(0.263)	(0.091)	(0.008)	(0.086)				
Volatility of stock returns, last year					0.032	-0.093	-0.009	0.027
					(0.138)	(0.061)	(0.009)	(0.023)
Level of stock returns, last year					0.020	0.001	0.002	-0.003
					(0.022)	(0.003)	(0.002)	(0.007)
GDP growth, last year					0.407	0.010	-0.006	-0.042
					(0.287)	(0.045)	(0.006)	(0.030)
F-test p-value	0.637	0.767	0.829	0.240	0.242	0.461	0.751	0.279
Observations	4982	4982	4982	4982	5737	5737	5737	5737

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Data is quarterly by country from 1970 until 2011. All columns include a full set of 59 country dummies and from column (3) onwards a full set of 164 year by quarter dummies. The F-test p-value is the probability value of the F-test of the three economic variables in each column.

Table 1: Simulation Results - Volatility, Returns and GDP Growth

	(1)	(2)	(3)	(4)
Estimation procedure	OLS	OLS	IV	IV
Dependent variable:	GDP Grth (Quarterly)	GDP Grth (Yearly)	GDP Grth (Quarterly)	GDP Grth (Yearly)
Volatility of stock returns, over last quarter	-0.020***		-0.107***	
Level of stock returns, over last quarter	0.160***		0.331***	
Volatility of stock returns, over past year		-0.048***		-0.138***
Level of stock returns, over past year		0.261***		0.640***
			IV 1st stage: Volatility (of Stock Returns)	
Natural Disasters, over past year			0.028***	0.017***
Political Shocks, over past year			0.101***	0.238***
Revolutions, over past year			0.176***	0.316***
Terrorist attacks, over past year			0.108***	0.248***
Instrument F-test			1290	221
			IV 1st stage: Level (of Stock Returns)	
Natural Disasters, over past year			-0.079***	-0.074***
Political Shocks, over past year			0.036***	0.053***
Revolutions, over past year			-0.143***	-0.108***
Terrorist attacks, over past year			-0.047***	-0.021***
Instrument F-test			5080	4292
Sargan test p-value			0.719	0.825
Observations	79000	75000	75000	75000
Year-Quarter dummies	Yes	Yes	Yes	Yes

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Standard errors are clustered by country. Quarterly GDP growth is current versus last quarter growth. Yearly GDP growth is current versus four quarters growth. Annual stock returns are averaged over last year, and annual volatility is calculated over the last year. Overid test is the Hansen test of overidentification restrictions.

Table 2: Simulation Results – IV Baseline and Utilizing True Shocks

	(1)	(2)
Dependent variable:	GDP Grth (Yearly)	GDP Grth (Yearly)
Volatility of stock returns, over past year	-0.138***	-0.143***
Level of stock returns, over past year	0.640***	0.644***
	IV 1st stage: Volatility (of Stock Returns)	
Natural Disasters, over past year	0.017***	
Political Shocks, over past year	0.238***	
Revolutions, over past year	0.316***	
Terrorist attacks, over past year	0.248***	
Shock		0.031***
Variance		4.064***
Instrument F-test	221	47,310
	IV 1st stage: Level (of Stock Returns)	
Natural Disasters, over past year	-0.074***	
Political Shocks, over past year	0.053***	
Revolutions, over past year	-0.108***	
Terrorist attacks, over past year	-0.021***	
Shock		0.828***
Variance		0.370***
Instrument F-test	4292	39,759
Sargan test p-value	0.825	n/a
Observations	75000	75000
Year-Quarter dummies	Yes	Yes

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Standard errors are clustered by country. Quarterly GDP growth is current versus last quarter growth. Yearly GDP growth is current versus four quarters growth. Annual stock returns are averaged over last year, and annual volatility is calculated over the last year. Overid test is the Hansen test of overidentification restrictions.

Table 3: Descriptive Statistics

All variables yearly unless noted	Obs.	Mean	Median	Std. Dev.	Min	Max
GDP Growth	6398	.036	.034	.052	-.335	.444
GDP Growth, Quarterly	5847	.009	.008	.024	-.219	.152
Stock Returns	6776	.042	.015	.35	-.536	.556
Stock Returns, Quarterly	6737	.010	.014	.160	-.773	.958
Log (Stock Ret. Volatility)	6550	-4.41	-4.46	.575	-6.07	-1.93
Log (Stock Ret. Volatility), Quarterly	6736	-4.45	-4.52	.636	-6.29	-1.93
Log (Exchange Rates, per $)	9787	.950	1.69	6.55	-50.7	9.87
Log(Exch. Rate Volatility)	8861	-5.52	-5.21	1.19	-14.8	-2.45
Natural Disasters	10020	.024	0	.153	0	1
Natural Disasters (scaled by media increase)	10020	.025	0	.367	0	25
Political Shocks	10020	.003	0	.054	0	1
Political Shocks (scaled by media increase)	10020	.011	0	.296	0	17.5
Revolution shock	10020	.001	0	.026	0	1
Revolutions (scaled by media increase)	10020	.001	0	.040	0	3.6
Terrorist attacks	10020	.001	0	.035	0	1
Terrorist attacks (scaled by media increase)	10020	.003	0	.129	0	9.7
GDP Per Capita (2005 $US, World Bank PPP)	10020	22,450	18,477	16,293	1335	78,559

Notes: All values are yearly averages unless noted otherwise. Data from 60 countries from 1970 to 2011. The natural disaster, political shocks and revolution instruments have been reported including the weighting for the increase in media coverage after a shock.

Table 4: Volatility, Returns and GDP Growth

	(1)	(2)	(3)	(4)	(5)
Estimation procedure	OLS	OLS	OLS	IV	IV
Dependent variable:	GDP Grth (Quarterly)	GDP Grth (Yearly)	GDP Grth (Yearly)	GDP Grth (Quarterly)	GDP Grth (Yearly)
Volatility of stock returns, over last quarter	-0.003***			-0.044***	
	(0.001)			(0.012)	
Level of stock returns, over last quarter	0.012***			0.127***	
	(0.004)			(0.029)	
Volatility of stock returns, over past year		-0.011***	-0.006**		-0.117***
		(0.003)	(0.003)		(0.032)
Level of stock returns, over past year		0.110***	0.098***		0.351**
		(0.018)	(0.020)		(0.163)
				IV 1st stage: Volatility (of Stock Returns)	
Natural Disasters, over past year				0.054	0.058
				(0.045)	(0.049)
Political Shocks, over past year				0.242**	0.376**
				(0.098)	(0.173)
Revolutions, over past year				1.25***	2.90***
				(0.183)	(0.185)
Terrorist attacks, over past year				0.020	0.047
				(0.037)	(0.101)
Instrument F-test				14.05	66.55
				IV 1st stage: Level (of Stock Returns)	
Natural Disasters, over past year				-0.004	.012
				(0.008)	(0.012)
Political Shocks, over past year				0.059***	0.080***
				(0.011)	(0.027)
Revolutions, over past year				-0.526***	-0.607***
				(0.042)	(0.048)
Terrorist attacks, over past year				-0.002	0.001
				(0.009)	(0.009)
Instrument F-test				45.47	41.13
Sargan test p-value				0.844	0.201
Observations	5163	6169	6169	5163	6169
Year-Quarter dummies	No	No	Yes	Yes	Yes

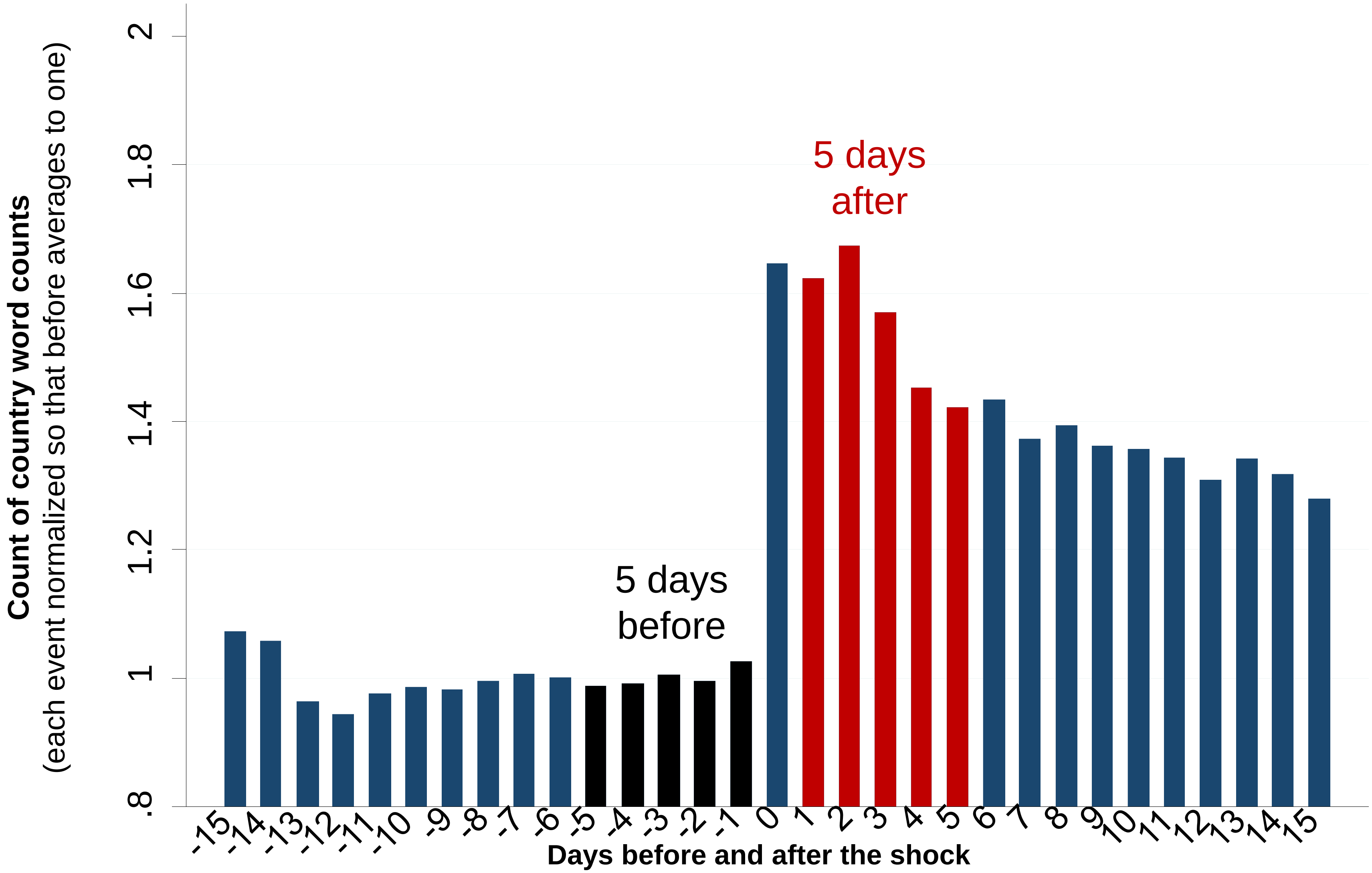
Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Data is quarterly by country from 1970 until 2011. Columns (1) to (3) estimated by OS and (4) to (6) by instrumental variables. Instruments are scaled by the increase in media mentions of the country in the 5-days after the shock compared to the 5-days before the shock. Sargan test is the over-identification test of instrument validity. All columns include a full set of 59 country dummies and from column (3) onwards a full set of 164 year by quarter dummies. For parsimony the first stage for Skewness of stock returns has not been shown (the F-test was 2.71). Volatility is in logs in the regression.

Table 5: Robustness of Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Specification	Baseline	No scaling by cites	No time or country dummies	Population weighted	Exchange rates	No natural disaster IV	No political shock IV	No revol IV	No terrorist attack IV
Volatility (of stock returns)	-0.116***	-0.093**	-0.069**	-0.117***		-0.115***	-0.129**	-0.115	-0.120***
	(0.034)	(0.039)	(0.027)	(0.031)		(0.035)	(0.055)	(0.094)	(0.033)
Level (of stock returns)	0.371***	0.366*	0.416***	0.334**		0.360***	0.294	0.363	0.353***
	(0.179)	(0.191)	(0.087)	(0.162)		(0.176)	(0.271)	(0.517)	(0.165)
Volatility (of exchnge rates)					-.070**				
					(.035)				
Level (of exchnge rates)					-.001				
					(.015)				
IV F-tests (vol and level)	69.15	69.79	103.46	61.43	3.51	88.18	85.41	2.25	88.79
	44.01	42.59	6730.3	37.59	10.72	54.70	54.50	3.32	54.70
Sargan p-valu	0.889	0.827	0.937	0.403	0.452	0.912	0.363	0.894	0.160
Observations	6169	6169	6169	6169	8059	6169	6169	6169	6169

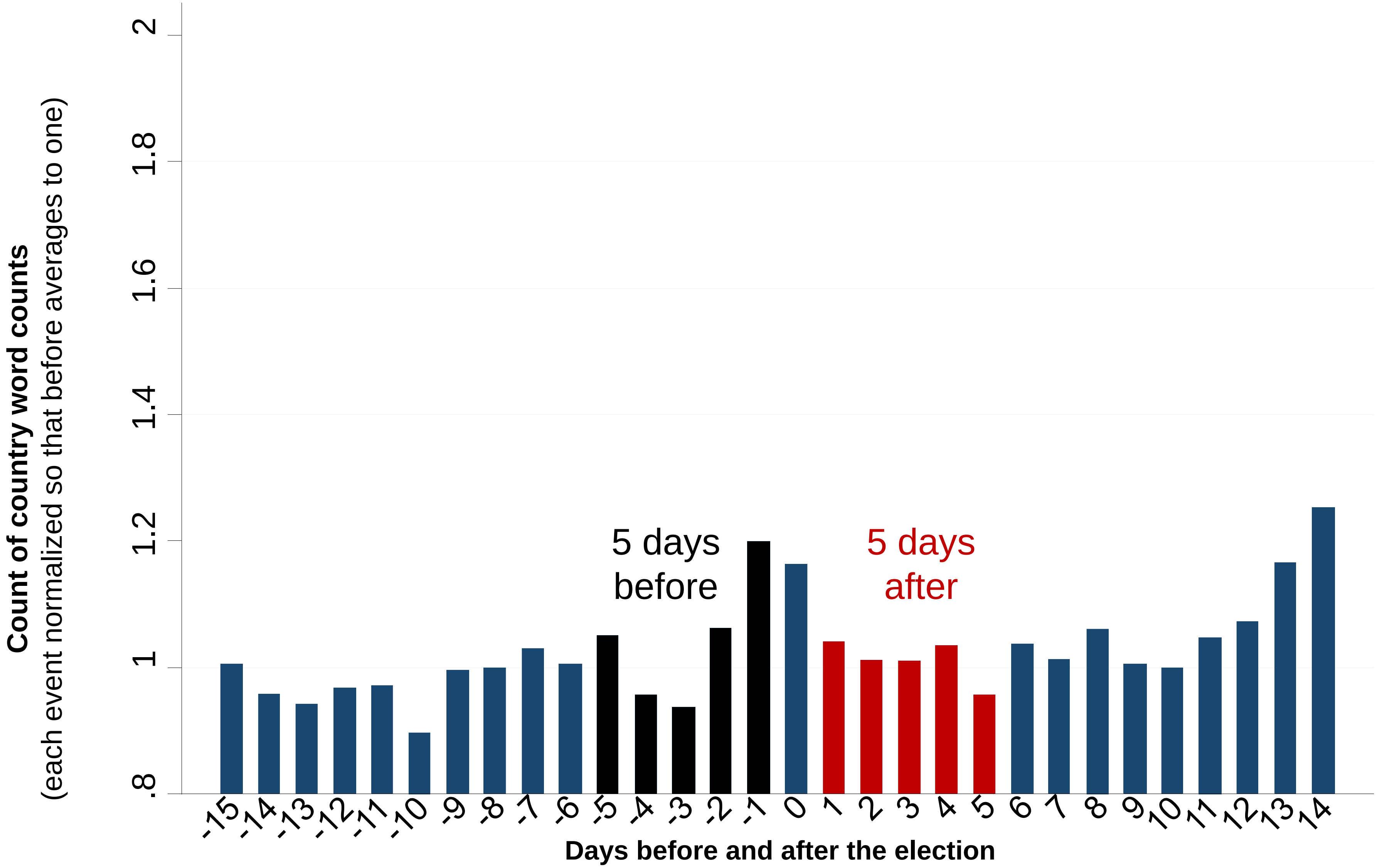
Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Data is quarterly by country from 1970 until 2011. All columns estimated by instrumental variables with a full set of quarter-by-year time dummies. Instruments are all multiplied by the increase in media mentions of the country in the 5-days after the shock compared to the 5-days before the shock, except for column (1) which is multiplied by the log of 1 + this number, and column (2) which is not multiplied at all (but the instruments are only used for jumps of 25% or more). All columns include a full set of 59 country dummies and 164 year by quarter dummies. Volatility is in logs in the regression.

Figure 1: Newspaper daily word counts for the affected country in the one month around the natural disaster, political or terrorist shock



Notes for the figure: Shows the daily count of the name of the impacted country in the two weeks before and after the shock, averaged over the 1794 shocks studied in the regression analysis. For graphing purposes the series for each event is normalized so that the 15 days before the shock has a mean of one. In the regressions events are weighted by the increase in cites in the 5 days after the event compared to the 5 days before to focus on the jump in cites in the narrow window around the event.

Figure 2: Newspaper daily word counts for the affected country in the one month around national elections



Notes for the figure: Shows the daily count of the name of the impacted country in the two weeks before and after the election, averaged over the 133 elections in the G20 countries our sample. The series for each event is normalized for graphing so that the 15 days before the election has a mean of one.