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# Economic Policy Uncertainty and Stock Market Volatility: A Causality Check

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# Economic Policy Uncertainty and Stock Market Volatility: A Causality Check

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**Abstract**

Using causal graphs, this paper develops a simple check to uncover the direction of the causal link between economic policy uncertainty and stock market volatility. The check is applied to monthly data for 22 countries. The results imply that uncertainty is an instantaneous cause of stock market volatility. Estimates suggest that stock market volatility increases by 0.15% to 0.85% after a 1% increase in economic policy uncertainty.

Keywords: Causal inference; Causal graph; Economic policy uncertainty; Stock market volatility

JEL codes: C12, D80, E66, G10

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**Non-Technical Summary**

Empirical modeling that involves economic policy uncertainty (EPU) indices and measures of stock market volatility often requires an assumption about the causal relationship between these two variables. Using causal graphs, this paper develops a simple check to uncover the direction of the causal link between EPU and stock market volatility.

The check considers the causal links between domestic EPU, external EPU, and stock market volatility. The check is applied to monthly data for 22 countries. The empirical results suggest that domestic EPU and external EPU are both instantaneous causes of stock market volatility.

A further graphical analysis shows that the check is informative and robust against certain types of omitted variables. Estimates from a simple econometric model that is consistent with the results of the check suggest that a 1% increase in unexpected EPU leads to an increase in stock market volatility in a range of 0.15% to 0.85%.

# 1 Introduction

Economic policy uncertainty (EPU) and financial market volatility tend to move together. But does EPU cause volatility, or is EPU a result of volatile financial markets? Which assumption is more appropriate in empirical modeling that involves both variables?[1] EPU may create uncertainty about future cash flows and discount factors and thereby increase financial market volatility (Pástor and Veronesi, 2012). But volatile financial markets could also be a source of EPU (Ajmi et al., 2015; Antonakakis et al., 2013).[2]

Using causal graphs and d-separation (Pearl, 1995, 2009; Peters et al., 2017), this paper develops a simple check to uncover the causal relationship between EPU, as measured by monthly EPU indices (Baker et al., 2016), and stock market volatility. The check is applied to 22 countries. The results suggest that EPU is an instantaneous cause of stock market volatility. An additional graphical analysis shows that the check is informative and robust against certain types of omitted variables.

A simple econometric model suggests that an unexpected 1% increase in domestic EPU increases stock market volatility by 0.15% to 0.85%. An unexpected 1% increase in US EPU increases stock market volatility in other countries by 0.3% to 0.6%.

# 2 Preliminaries

Causal graphs express causal relationships between variables. In a causal graph the variables are the nodes, edges indicate links between the nodes, and arrowheads indicate the causal direction of the links. A path is a sequence of nodes connected by edges (ignoring arrowheads).

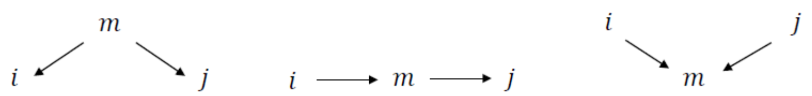


Figure 1: Basic causal configurations.

Figure 1 shows three causal graphs for random variables $i$, $j$, and $m$. The graphs are directed

[1]The fast growing literature about uncertainty, business cycle fluctuations and financial markets includes Berger et al. (2020), Bloom (2009), Boutchkova et al. (2012), Jurado et al. (2015), Krol (2014), Liu and Zhang (2015), and Ludvigson et al. (forthcoming), among others. On causality in economics and econometrics, see Hoover (2001) and Hoover (2008).

[2]Another, rather unlikely possibility is that volatility and EPU are entirely unrelated and determined by a third variable.

acyclic graphs (DAGs) because all links have directions and there are no cyclical paths. What happens if $m$ is held constant in these basic causal configurations?

In the fork, $i \leftarrow m \rightarrow j$, the variable $m$ causes $i$ and $j$, and conditioning on $m$ blocks the path between $i$ and $j$. In the chain, $i \rightarrow m \rightarrow j$, the variable $m$ mediates the effect of $i$ on $j$. Again, conditioning on $m$ blocks the path between $i$ and $j$. Ignoring $m$ keeps the path open. In the third configuration, $i \rightarrow m \leftarrow j$, the variable $m$ is a collider - a joint outcome of $i$ and $j$. Here, conditioning on $m$ unblocks the path between $i$ and $j$ because holding $m$ constant introduces a selection bias that creates correlation between $i$ and $j$. The path remains blocked if $m$ is ignored.

*D-separation* identifies independence relations in causal graphs and translates them into probabilistic independence relations.[3] A path between nodes $A$ and $B$ in a DAG G can be d-separated (blocked) by a set of nodes $C$ in two ways. The path either contains a chain, $i \longrightarrow m \longrightarrow j$, or a fork, $i \longleftarrow m \longrightarrow j$, and $m$ is in $C$. Or, the path contains a collider, $i \longrightarrow m \longleftarrow j$, and $m$ (or any of its descendants) is *not* in $C$ (Pearl (2009), Theorem 1.2.3).

If a set $C$ blocks all paths between $A$ and $B$ in a DAG G, then $A$ and $B$ are d-separated by $C$, denoted as $(A \perp\!\!\!\perp B \mid C)_G$. Then $A$ is independent of $B$ conditional on $C$, denoted as $(A \perp\!\!\!\perp B \mid C)_P$, in every distribution $P$ that is compatible with the DAG G.[4] If $A$ and $B$ are not d-separated by $C$, then they are dependent conditional on $C$ in at least one distribution $P$ compatible with the DAG G (Pearl (2009), Theorem 1.2.4).

As a result, d-separation can be applied to a causal graph to identify testable empirical implications of the implied causal model. Moreover, the configurations in Figure 1 help to uncover causal links between variables.

# 3 Causality check

The check assumes that domestic EPU, external EPU, and past stock market volatility are structural causes of stock market volatility. Other causes of stock market volatility are assumed to be unsystematic (Gerlach et al., 2006).

The DAG in Figure 2 shows the assumed links between domestic EPU ($x$), external EPU ($ex$) and stock market volatility ($y$). EPU in month $m-1$ can affect EPU and volatility in month $m$. Past volatility can also affect current volatility. External EPU can affect volatility directly and indirectly via spillovers to domestic EPU (Klößner and Sekkel, 2014). The US

[3] D stands for "directional".

[4] A distribution is (Markov) compatible with a DAG G if it admits a factorization that is implied by G.

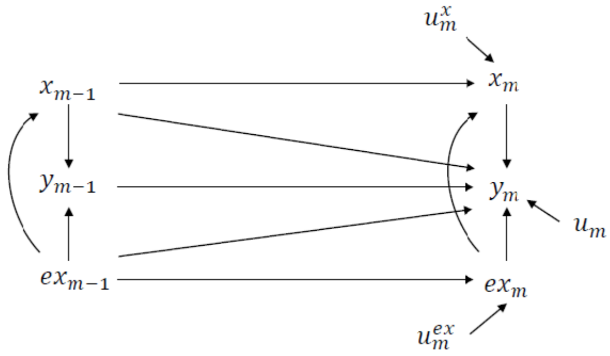


Figure 2: Domestic EPU ($x$) and external EPU ($ex$) cause stock market volatility ($y$).

EPU is the external EPU for the other countries due to the global economic importance of the USA. European EPU is the external EPU for the USA. The variables $u_m^x$, $u_m^{ex}$, and $u_m$ indicate mutually independent unsystematic causes of domestic EPU, external EPU, and stock market volatility.[5]

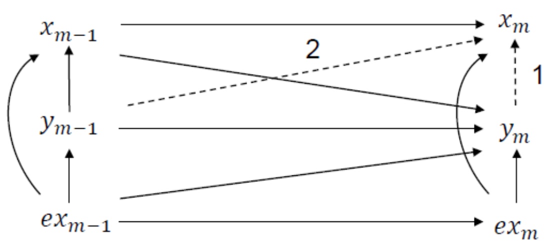


Figure 3: Stock market volatility ($y$) causes domestic EPU ($x$).

The check empirically examines a *local* property of the DAG in Figure 2, namely whether $y_m$ is a collider along the path $(y_{m-1}, y_m, x_m)$. If $y_m$ is found to be a collider, then domestic EPU is a contemporaneous cause of stock market volatility. Otherwise, stock market volatility causes domestic EPU.

The first step of the check examines whether $y_{m-1}$ and $y_m$ are d-connected when $x_{m-1}$ and $ex_{m-1}$ are held constant. The second step examines whether $y_{m-1}$ and $x_m$ are d-connected if $y_m$ can vary and $x_{m-1}$ and $ex_{m-1}$ are held constant.

If $y_{m-1}$ is d-connected with $y_m$ and $x_m$ as in Figure 3, then $y_m$ or (and) $y_{m-1}$ are causes of $x_m$. Either $y_m$ causes $x_m$ as in link (1), or $y_{m-1}$ causes $x_m$ as in link (2), or both links exist.

[5]To avoid clutter, unsystematic causes are suppressed from now on.

However, if $y_{m-1}$ is only d-connected with $y_m$, but *not* with $x_m$, then $y_m$ is a collider as in Figure 2 and $x_m$ is a cause of $y_m$.

For simplicity, let us assume linear relationships and multivariate normally distributed variables. Then (conditional) uncorrelatedness implies (conditional) independence and the check can be based on two auxiliary regressions.[6]

The first regression,

$$y_m = b_0 + b_1 y_{m-1} + b_2 x_{m-1} + b_3 ex_{m-1} + r_m, \tag{1}$$

examines whether $y_{m-1}$ and $y_m$ are d-connected. Conditioning on $x_{m-1}$ and $ex_{m-1}$ isolates the link from $y_{m-1}$ to $y_m$, and $y_{m-1}$ is d-connected with $y_m$ if $b_1 \neq 0$.

The second regression,

$$x_m = c_0 + c_1 y_{m-1} + c_2 x_{m-1} + c_3 ex_{m-1} + r_m, \tag{2}$$

examines whether $y_{m-1}$ and $x_m$ are d-connected conditional on $x_{m-1}$ and $ex_{m-1}$. As $y_m$ can vary it does not appear in Equation 2.

If $b_1 \neq 0$ and $c_1 \neq 0$, then $y_{m-1}$ is d-connected with $y_m$ and $x_m$. Stock market volatility is then a cause of domestic EPU. Note that $c_1 \neq 0$ does not rule out domestic EPU as a cause of stock market volatility. Arrow (1) in Figure 3 could point from $x_m$ to $y_m$ and $c_1 \neq 0$ because of a direct link (2) from $y_{m-1}$ to $x_m$.

In contrast, if $b_1 \neq 0$ and $c_1 = 0$, then $y_{m-1}$ and $x_m$ are d-separated and $y_m$ is a collider. This implies that domestic EPU is an instantaneous cause of stock market volatility. In addition, $c_1 = 0$ also implies that there are no other unblocked links between $y_{m-1}$ and $x_m$.

An analogous check can be carried out for external EPU. The second regression becomes

$$ex_m = d_0 + d_1 y_{m-1} + d_2 x_{m-1} + d_3 ex_{m-1} + r_m, \tag{3}$$

and $b_1 \neq 0$ and $d_1 = 0$ implies that external EPU is an instantaneous cause of volatility because $y_m$ is a collider along the path $(y_{m-1}, y_m, ex_m)$.

In order to exclude pathological cases in which $c_1 = 0$ or $d_1 = 0$ occurs due to special (or "tuned") parameter constellations, we need a "stability" or "faithfulness" condition. Faithfulness implies that the independence relations embedded in the probability distribution generated by a causal model are stable and match with the independence relations implied by the DAG (Peters et al. (2017), chap. 6, Pearl (2009), chap. 2).

[6] More general assumptions require more sophisticated conditional independence tests, but the steps of the check remain the same.

## 4 Data

The data cover Australia, Brazil, Canada, Chile, China, Croatia, France, Germany, Greece, India, Ireland, Italy, Japan, Mexico, Netherlands, Russia, Singapore, South Korea, Spain, Sweden, United Kingdom, and the USA. The sample period is March 2003 to February 2020.

EPU is measured by monthly EPU indices which are based on keyword searches in a county's most important newspapers.[7] The European EPU index covers France, Germany, Italy, Spain and the UK and is based on two newspapers per country.

Stock market volatility is calculated for a county's leading stock index. The daily index values $I_t$ come from the Macrobond database. The daily index returns $r_t = 100(ln(I_t) - ln(I_{t-1}))$ are first regressed on $r_{t-1}$ to remove any predictability in the first moment of the returns. Then volatility is computed from the absolute values $|e_i|$ of the regression residuals as

$$\sigma_m = a\sqrt{\frac{\pi}{2}}\sum_{i=1}^{D_m}\frac{|e_i|}{D_m}, \tag{4}$$

where $D_m$ denotes the number of trading days in month $m$, $a = \sqrt{252}$ converts daily volatility into annualized volatility, and $\sqrt{\pi/2}$ accounts for using absolute values to obtain a measure of volatility that is more robust to extreme observations (Schwert, 1989; Ederington and Guan, 2005).

## 5 Empirical results

In the check EPU and volatility enter in logarithms to ensure that the variables are always positive. The transformation also removes most of the skewness in the distribution of the original data and yields data that are much closer to the normal distribution. There are 204 observations available for each country.

Table 1 reports the estimates for $b_1$, $c_1$, and $d_1$ in (1), (2) and (3) and p-values for t-tests for zero coefficients. The coefficient $b_1$ is, Greece aside, always large and highly statistically significant. In contrast, $c_1$ and $d_1$ are typically close to zero and almost never statistically significant at usual levels. Hence, past stock market volatility is almost always found to be d-separated from domestic and external EPU. This suggests that domestic and external EPU are both instantaneous causes of stock market volatility. If we also allow the possibility that EPU

[7] For the USA the keywords are: "economic" or "economy", "uncertain" or "uncertainty" and at least one of the terms "congress", "deficit", "Federal Reserve", "legislation" or "White House". Baker et al. (2016) provide details about the country-specific EPU indices, which are available at http://www.policyuncertainty.com/.

Table 1: Results of the causality check

| country | $b_1$ | pv | $c_1$ | pv | $d_1$ | pv | pv-Fd | pv-Fex |
|---|---|---|---|---|---|---|---|---|
| Australia | 0.74 | 0.00 | 0.12 | 0.05 | 0.00 | 0.95 | 0.87 | 0.69 |
| Brazil | 0.51 | 0.00 | 0.01 | 0.93 | -0.03 | 0.45 | 0.68 | 0.35 |
| Canada | 0.69 | 0.00 | -0.02 | 0.65 | 0.04 | 0.12 | 0.07 | 0.97 |
| Chile | 0.48 | 0.00 | 0.08 | 0.18 | 0.04 | 0.20 | 0.14 | 0.25 |
| China | 0.74 | 0.00 | 0.02 | 0.82 | 0.02 | 0.43 | 0.04 | 0.71 |
| Croatia | 0.63 | 0.00 | -0.37 | 0.00 | -0.04 | 0.20 | 0.12 | 0.19 |
| France | 0.57 | 0.00 | -0.07 | 0.26 | 0.03 | 0.30 | 0.29 | 0.54 |
| Germany | 0.61 | 0.00 | -0.04 | 0.52 | 0.01 | 0.87 | 0.46 | 0.83 |
| Greece | 0.17 | 0.03 | 0.03 | 0.37 | 0.00 | 0.92 | 0.60 | 0.22 |
| Hong Kong | 0.73 | 0.00 | -0.02 | 0.79 | 0.05 | 0.10 | 0.88 | 0.47 |
| India | 0.65 | 0.00 | 0.05 | 0.38 | -0.01 | 0.72 | 0.33 | 0.29 |
| Ireland | 0.73 | 0.00 | 0.05 | 0.53 | 0.05 | 0.11 | 0.38 | 0.66 |
| Italy | 0.55 | 0.00 | 0.06 | 0.34 | 0.02 | 0.72 | 0.52 | 0.88 |
| Japan | 0.57 | 0.00 | 0.01 | 0.80 | -0.07 | 0.02 | 0.30 | 0.06 |
| Mexico | 0.62 | 0.00 | 0.04 | 0.64 | 0.02 | 0.58 | 0.75 | 0.96 |
| Netherlands | 0.59 | 0.00 | 0.07 | 0.32 | 0.02 | 0.50 | 0.53 | 0.89 |
| Russia | 0.65 | 0.00 | -0.05 | 0.51 | 0.01 | 0.70 | 0.04 | 0.92 |
| Singapore | 0.72 | 0.00 | -0.02 | 0.58 | 0.02 | 0.45 | 0.48 | 0.85 |
| South Korea | 0.70 | 0.00 | -0.04 | 0.40 | -0.00 | 0.94 | 0.85 | 0.96 |
| Spain | 0.63 | 0.00 | 0.03 | 0.70 | 0.05 | 0.12 | 0.72 | 0.63 |
| Sweden | 0.65 | 0.00 | -0.03 | 0.36 | 0.03 | 0.36 | 0.25 | 0.85 |
| United Kingdom | 0.55 | 0.00 | 0.01 | 0.81 | 0.05 | 0.11 | 0.35 | 0.99 |
| United States | 0.57 | 0.00 | 0.04 | 0.12 | -0.01 | 0.83 | 0.85 | 0.73 |

Notes: Columns $b_1$, $c_1$, and $d_1$ report estimates for the corresponding coefficients in regressions (1), (2), and (3). Columns denoted as pv report p-values for t-tests for zero coefficients. The columns pv-Fx and pv-Fex show p-values for F tests of $y_{m-1} = y_{m-2} = y_{m-3} = y_{m-4} = 0$ in regressions (2) and (3) that include $x_{m-1}$ and $ex_{m-1}$ and four lags of $y_m$.

and volatility are actually unrelated and determined by a third variable, then we can conclude that stock market volatility does not cause EPU.

## 6 Robustness

The causal assumptions behind the check may appear restrictive. However, omitted variables (e.g. another external EPU) and omitted lags of included variables do not necessarily invalid the check. On the contrary, these possible omissions increase the information content of the check, as omitted variables lead to $c_1 \neq 0$ or (and) $d_1 \neq 0$ in certain cases. The check can also easily be refined by including additional variables.

Figure 4 shows a DAG for $b_1 \neq 0$, $c_1 = 0$, and $d_1 = 0$ when a structural cause $z$ of $y$ is omitted. The variables $x_{m-1}$ and $ex_{m-1}$ are shown in bold to indicate that they are held constant. Blocked paths and paths that are already implied not to exist before omitted variables are taken into account are suppressed for clarity.

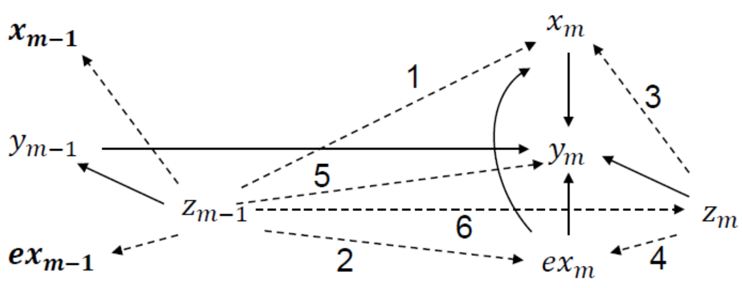


Figure 4: Omitted structural variable.

If $z_m$ causes $y_m$ without links like (1), (2), (5), or (6), then the check is unaffected as there are no new open paths between $y_{m-1}$ and $y_m$, $x_m$, or $ex_m$, even if $z_m$ causes $x_m$ or $ex_m$ as in links (3) and (4). Link (5) only affects $b_1$ in regression (1) which is unproblematic, except when $b_1$ is therefore close to zero.

Link (6) could affect $b_1$ via the path $y_{m-1} \leftarrow z_{m-1} \rightarrow z_m \rightarrow y_m$. But $c_1 = 0$ and $d_1 = 0$ implies that there are no unblocked paths between $y_{m-1}$ and $x_m$ or $ex_m$. Hence, links (1) and (2) can be ruled out immediately, and links (3) and (4) can also be ruled out if a link (6) exists. In contrast, $c_1 \neq 0$ and (or) $d_1 \neq 0$ would indicate that such links are present. The check could then be refined by including $z_m$.

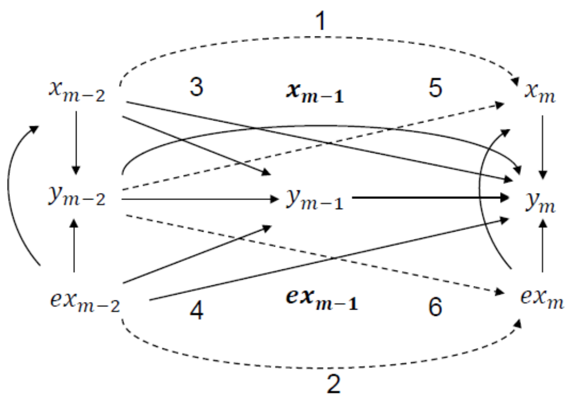


Figure 5: Omitted lags.

Figure 5 shows a DAG for $b_1 \neq 0$, $c_1 = 0$ and $d_1 = 0$ when $x_{m-2}$, $ex_{m-2}$, and $y_{m-2}$ are omitted. Now links (1), (2), (5), and (6) would imply $c_1 \neq 0$ and $d_1 \neq 0$. A direct link from $y_{m-2}$ to $y_m$, and links (3) and (4) would only affect $b_1$.

The finding $c_1 = 0$ and $d_1 = 0$ implies the absence of links (1), (2),(5) and (6). Hence, including $x_{m-2}$, $ex_{m-2}$, and $y_{m-2}$ in the auxiliary regressions should not change our conclusion. Indeed, the pattern $b_1 \neq 0$, $c_1 = 0$, and $d_1 = 0$ also emerges when $x_{m-2}$, $ex_{m-2}$, and $y_{m-2}$ are included.[8]

We can also include more lags of $y_m$ in the auxiliary regressions to account for more distant effects of volatility on EPU. The two rightmost columns in Table 1 report p-values for an F test of the restriction $y_{m-1} = y_{m-2} = y_{m-3} = y_{m-4} = 0$ in regressions (2) and (3) that include $x_{m-1}$ and $ex_{m-1}$ and four lags of $y_m$. The rather large p-values suggest that past volatility has no effect on EPU.

## 7 Impact of EPU on stock market volatility

This section provides estimates of the impact of EPU on stock market volatility using a simple econometric model,

$$y_m = \alpha_0 + \beta_0 x_m + \gamma_0 ex_m + \beta_1 x_{m-1} + \gamma_1 ex_{m-1} + \rho_1 y_{m-1} + ... + \rho_4 y_{m-4} + u_m, \qquad (5)$$

that is consistent with the findings of the causality check. All variables enter again in logarithms. The model contains four lags of $y_m$ to obtain a dynamically well specified model with uncorrelated residuals.

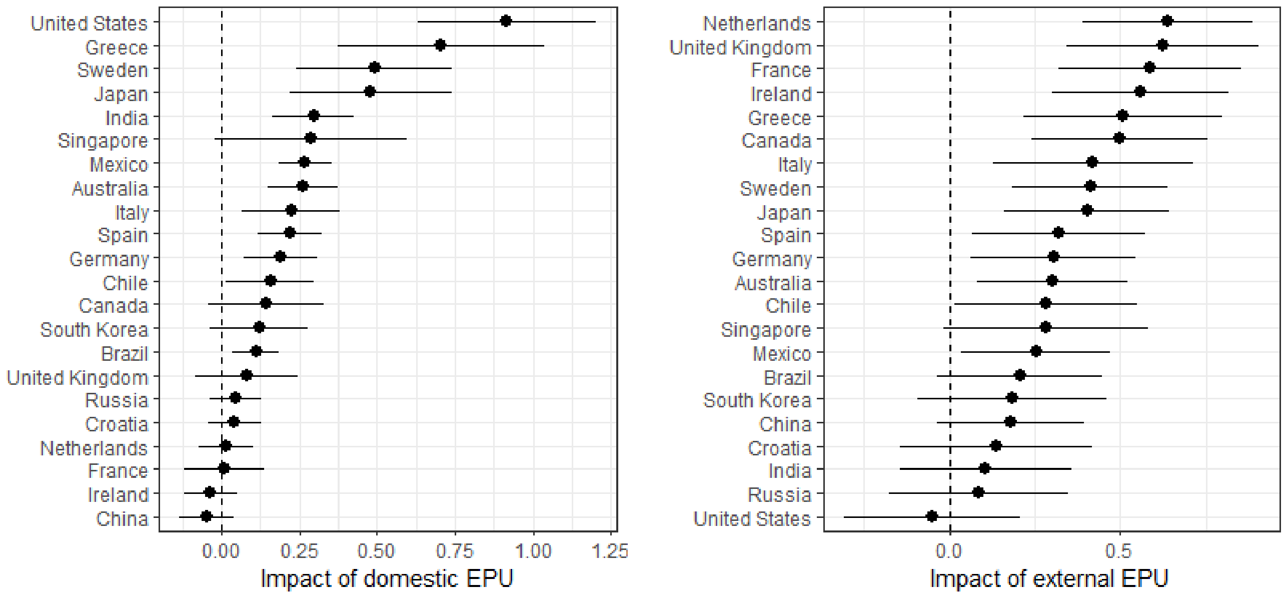


Figure 6: Impact of unexpected domestic and external EPU on stock market volatility.

Note that $\beta_0$ and $\gamma_0$ measure the impact of unexpected EPU. Keeping $x_{m-1}$ and $ex_m$ constant

[8]Results available upon request.

eliminates their effects on $x_m$, and keeping $ex_{m-1}$ constant eliminates its effect on $ex_m$. The variation left in $x_m$ and $ex_m$ thus reflects unexpected EPU.

Figure 6 shows the country-specific estimates for $\beta_0$ and $\gamma_0$ together with 90% confidence intervals based on robust standard errors.[9] As can be seen, unexpected EPU affects stock market volatility in many cases. The estimates for $\beta_0$ imply that a 1% change in domestic EPU typically increases stock market volatility by 0.15% to 0.30%. US stock market volatility increases even by 0.85%. The estimates for $\gamma_0$ imply that a 1% change in external EPU increases stock market volatility by 0.3% to 0.6% in most countries.

# 8 Conclusions

A graph-based causality check, developed in this paper, was applied to monthly data for 22 countries to uncover the direction of the causal link between EPU and stock market volatility. The results imply that EPU is an instantaneous cause of stock market volatility. Assuming that EPU is a cause of stock market volatility appears to be sensible in empirical modeling with monthly data.

[9]Full results and specification tests available upon request.

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