Economic Policy Uncertainty Spillovers in Small Open Economies: the Case of Hong Kong

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Abstract

This paper studies the extent to which economic policy uncertainty shocks in major economies affects real economic activity in small open economies. We use Hong Kong as a case study. Following Baker, Bloom and Davis (2016), we construct a newspaper-based economic policy uncertainty index for Hong Kong for the period 1998 to 2016. We estimate international spillovers of uncertainty and find large spillovers of uncertainty from major economies to Hong Kong. Furthermore, using a structural VAR approach, we show that a rise in domestic economic policy uncertainty leads to tight financial conditions, and lower investment and vacancy posting, which dampens domestic output growth.

Keywords: Policy uncertainty, spillovers, crisis transmission.
JEL classification: E32, F42, F44.

1. Introduction

Heightened uncertainty is believed to be a key reason contributing to the weakness in global economic growth in recent years. In particular, a series of geopolitical and economic shocks, such as the Euroepan sovereign debt crisis and the Brexit referendum, are perceived to have raised economic policy uncertainty with repercussions on private domestic demand in many economies. One natural question for international macroeconomists and policymakers around the world is whether and to what extent economic policy uncertainty shocks originating in one country affect economic policy uncertainty and ultimately the business cycle in another country. In particular, the international transmission of economic policy uncertainty shocks may have large impacts on small-open economies with free capital mobility, sizable openness and a large financial sector. A large external sector and free capital mobility means that the economy is strongly affected by the external environment. The size of the financial sector matters because recent studies find that uncertainty shocks can affect financial conditions and hence the real economy (Gilchrist et al., 2014; Caldara et al., 2016).

We choose Hong Kong as a case study because its openness to trade and financial flows is among the highest in the world. For instance, in the year 2011-2015, Hong Kong's imports and exports added up to about 440% of GDP, and its trading and logistics industries accounted for around 20% of total employment. Hong Kong is also an international financial hub. During the same period, the ratio of average gross

foreign assets to GDP was about 1400%.[2] With such a high degree of openness, the impact of uncertainty spillovers estimated using Hong Kong data can be viewed as the upper bound of the impact of external uncertainty shocks on a small open economy.

Our empirical analysis comprises three steps. First, we compile an economic policy uncertainty index for Hong Kong for the period 1998M4-2017M4 using the Baker et al. (2016) method to count the number of related news articles. This method has several advantages. It captures a wide range of uncertainty in a timely manner. The measure is of high frequency and can go back for decades. Our constructed measure can be compared with economic policy indices for other countries constructed by Baker et al. (2016) as well. The resulting index is intuitive and signals high uncertainty during major past economic and political events. We compare our economic policy uncertainty index with another proxy of uncertainty based on realized stock market volatility and find that our index has stronger predictive power for real GDP growth.

In the second step, we examine to what degree uncertainty shocks in Hong Kong are 'imported' from the rest of the world. The Hong Kong economy is sensitive to economic developments in the US, and highly connected to other major economies such as the European Union, Mainland China and Japan. Following Diebold and Yilmaz (2009, 2014), we adopt a non-structural network-connectedness approach to study cross-country spillovers of economic policy uncertainty from these major economies to Hong Kong. To account for the small-open-economy nature of Hong Kong, we restrict

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[2] Data on trade openness are sourced from the Census and Statistics Department of Hong Kong Special Administration Region. Data on gross external assets and liabilities come from International Financial Statistics.

uncertainty spillovers from Hong Kong to the rest of the world to be zero. We find that over 40% of Hong Kong's economic policy uncertainty stems from its major trading partners. This figure is much larger than what is found in Klößner and Sekkel (2014) who study a network of G7 countries. Our finding suggests that uncertainty spillovers are more important for financially-integrated small open economies.

The third step of the analysis investigates the impact of economic policy uncertainty on macro-financial conditions. We estimate a Structural Vector Autoregressive (SVAR) model using our constructed economic policy uncertainty index together with maroeconomic and financial variables of Hong Kong. We employ a standard Cholesky approach to identify an unanticipated shock to economic policy uncertainty. Our impulse response analysis shows that a one standard deviation increase in the uncertainty index results in a 1% fall in real output growth in 2-3 quarters. The shock works through financial, employment and investment channels.

The rest of the paper is organized as follows. Section 2 discusses the related literature. Section 3 describes the methodology we use to compile the economic policy uncertainty index for Hong Kong, followed by an assessment of its perfomance in predicting real GDP growth. Section 4 conducts an inward spillover analysis of uncertainty. Section 5 estimates a VAR model to assess the macro-financial impact of uncertainty on the Hong Kong economy. Section 6 concludes.

2. Related Literature

Our paper is related to the newspaper text search literature. Following the influential paper by Gentzkow and Shapiro (2010) which uses text search methods to study media slant, Baker, Bloom and Davis (2016) and Alexopoulos and Cohen (2015) use similar methods to extract uncertainty measures from newspapers. Lam (2017) is the first to apply text search methods to newspapers in Hong Kong, focusing on political influences on newspaper advertisement behaviour. To the best of our knowledge, we are the first to construct a newspaper-based measure for economic policy uncertainty in Hong Kong.

Our paper is related to the literature on the international transmission of uncertainty shocks. On the theoretical side, Fernández-Villaverde et al. (2011) and Benigno et al. (2012) model uncertainty as stochastic volatility shocks and show that external uncertainty shocks are a key driver of business cycle volatilities in small open economies. Luk (2017) constructs a two-country model and shows that shocks in cross-sectional dispersions in productivity can transmit from a center economy to a small open ecnomy through global banks and cross-border lending. The empirical literature typically uses VAR models to study the international transmission of uncertainty shocks. A growing literature studies how uncertainty shocks orignating in the US transmit to the UK (Mumtaz and Theodoridis, 2015), Canada (Caggiano et al., 2017a) and Europe (Colombo, 2013). Similar to our research, Klößner and Sekkel (2014) use a network approach to study multi-country spillovers of uncertainty. We make additional identifying assumptions on the direction of spillovers to capture the small-open-economy nature of Hong Kong.

A third strand of literature studies the real effects of uncertainty shocks. Theoretical work points to investment, employment and financial channels. Bernanke (1983),

Dixit and Pindyck (1994) and Bloom (2009) show that uncertainty can delay economic activities due to the real option value of 'wait and see' generated by the presence of adjustment costs or irreversibility. Leduc and Liu (2016) and Guglielminetti (2016) outline another option-value channel through which a rise in uncertainty increases labor market search frictions and reduces vacancy posting. Finally, uncertainty also affects the economy through financial channels (Caldara et. al., 2016; Christiano et al., 2014; Gilchrist et al., 2014; Arellano, Bai and Kehoe, 2016). Turning to the empirical literature, Bloom et al. (2016), Caggiano et al. (2017b), Colombo (2013) and Moore (2017) use a SVAR approach to estimate the real economic impacts of uncertainty shocks using newspaper-based uncertainty data. The literature mainly studies the US economy except for Moore (2017) which looks at Australia. In this paper, we study a financially-integrated small open economy and take financial factors into account by incorporating a financial condition index into a SVAR model.

3.   Measuring Economic Policy Uncertainty in Hong Kong

This section discusses the compilation of our economic policy uncertainty index for Hong Kong. Since there is no newspaper-based economic policy uncertainty index for Hong Kong available, we compile the index following the Baker et al. (2016) methodology. Put simply, the method involves counting the frequency of news articles that contain terms relating to uncertainty. We use the *Wisers Information Portal*, a digital archive of Chinese news media in Hong Kong, to search for relevant Chinese words in the following ten major local Chinese newspapers: *Wen Wei Po, Sing Pao, Ming Pao, Oriental Daily, Hong Kong Economic Journal, Sing Tao Daily, Hong Kong Economic Times, Apple Daily, Hong*

Kong Commercial Daily, and *Tai Kung Pao*.[3] The dataset begins in April 1998, and so our index starts from the same time.

Our set of relevant Chinese words (with translation into English) is summarized in Table A1 in Appendix A. They are classified into four categories: (1) *'Domestic (or variant)'*; (2) *'Economy (or variant)'*; (3) *'Uncertainty (or variant)'*; and, (4) at least one of the following terms: *'Policy (or variant)'*, *'Public'*, *'Expenditure (or variant)'*, *'Investment'*, *'Budget'*, *'Fiscal'*, *'SAR Government'*, *'Politics'*, *'Chief Executive'*, *'Interest'*, *'Reform'*, *'Optimize'*, *'Deficit'*, *'Tax'*, *'Regulation (or variant)'*, *'Hong Kong Monetary Authority'*, *'Reserves'*, or *'Linked Exchange Rate System'*. Criteria (1) – (3) contain the key words on uncertainty in Hong Kong, while criterion (4) captures key words on major local policy issues.[4]

To control for the change in the volume of news articles across newspapers and time, we scale the number of articles meeting criteria (1) – (4) *in each month* by those that meet only criteria (1) and (2) (i.e. the base group of articles that are related to the Hong Kong economy only) *for the same month*.[5] We then standardize the scaled series to a unit standard deviation, followed by

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[3] We do not include *Tin Tin Daily, Hong Kong Daily News* and *The Sun* which ceased publication in 2000, 2015 and 2016 respectively. We do not include free newspapers including *Metro Daily, Sky Post, Headline Daily*, AM730 and *The Standard*. The economic policy uncertainty index is robust to the inclusion of the local English newspaper *South China Morning Post.*

[4] While dropping criterion (4) in the news search criteria would not materially affect the pattern of our economic policy uncertainty index as well as the results of our subsequent analysis, we prefer to retain it on the basis that (a) it can help ensure the relevancy of the news to Hong Kong; and (b) it makes our index readily comparable with other country's indices constructed by Baker et al. (2016).

[5] The compilation of our index differs from Baker et al. (2016) in the choice of the base of normalization. While Baker et al. (2016) normalize counts by the total number of all kind of articles (including sports, lifestyle etc), we normalize counts by the total number of articles on the economy only, as we believe that changing volume of unrelated articles (e.g. sports, lifestyle) due to social taste or editorial preference may introduce irrelevant fluctuation in the uncertainty index.

an averaging of the resulting monthly series across the ten newspapers. We then normalize the index to have a mean of 100 for the period of April 1998 to December 2009, and seasonally adjust the index.

Figure 1 plots our economic policy uncertainty index, with key economic or political events highlighted to help with interpretation. As shown, fluctuations in our uncertainty index are broadly consistent with economic intuition, showing spikes during major global events such as the Asian Financial Crisis in 1997-98, the 9/11 terrorist attack in 2001, the US subprime crisis in 2007, the bankruptcy of Lehman Brothers in 2008, the downgrading of US sovereign credit rating in 2011, and the deepening of the European sovereign debt crisis in the same year. Our index also appears to be sensitive to local events, such as the outbreak of SARS in 2003, discussions about the implementation of goods and services tax in 2006, and the weakening of the local economic environment in early 2016.

Figure 1: Economic policy uncertainty index for Hong Kong

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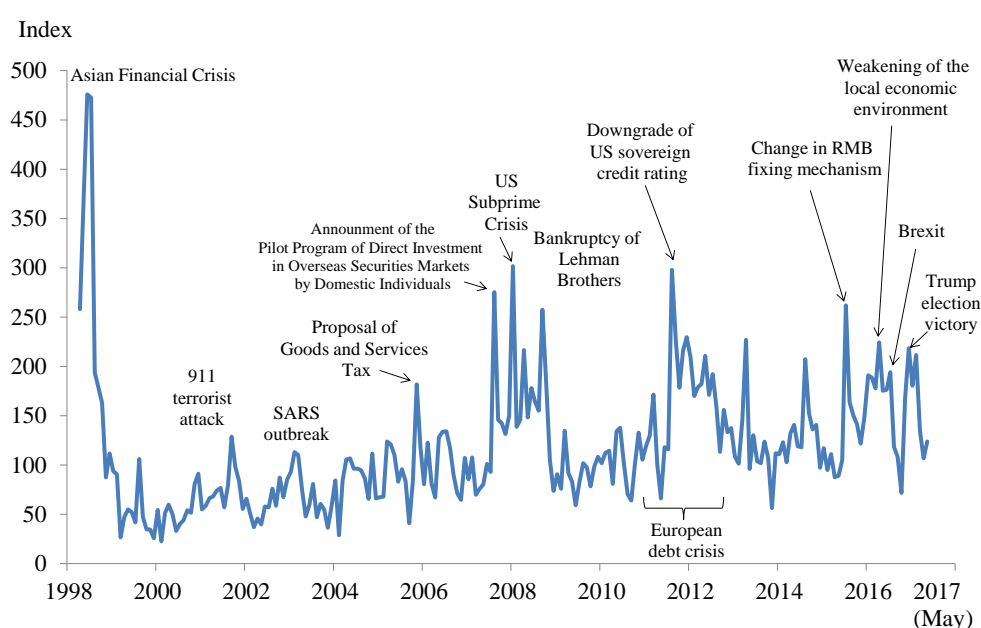
Source: Authors' estimates

We conduct three validity checks against our newspaper-based measure. First, our selection of newspapers does not account for the credibility of the newspapers. It is possible that newspapers with low credibility may distort our index. To investigate this issue, we recalculate the index with the five most credible newspapers in our sample only. The credibility ranking is based on a Public Evaluation on Media Credibility Survey conducted by The Chinese University of Hong Kong in various years.[6] Appendix B plots this credibility-adjusted index along with our baseline index. They move together closely, with a correlation of 0.94.

Second, our newspapers do not take into account for readership. To the extent that the newspapers themselves are a transmission mechanism for uncertainty shocks, newspapers with a larger readership can be expected to have a larger effect on the business cycle. We construct another index which uses only data in the *Oriental Daily* and *Apple Daily,* which together account for about 75% of total readership.[7] The resulting readership-adjusted index is plotted in Appendix B. Although this index is more volatile, the peaks match those of the baseline index, and the correlation with our baseline index is 0.74. These findings suggest that our baseline index is robust to alternative specifications.

In the third exercise, we compare our economic policy uncertainty index with a measure of stock market volatility, which is another proxy of uncertainty commonly used in the literature. This paper chooses not to measure uncertainty by stock market

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[6] See the survey results of Public Evaluation on Media Credibility
http://www.com.cuhk.edu.hk/ccpos/en/research/Credibility_Survey%20Results_2016_ENG.pdf.
[7] See 2014 data from AC Nielsen Media Index Report. See also Table 1 of Lam (2017).

volatility, as this volatility can be influenced by factors such as risk aversions in addition to uncertainty (Bekaert et al., 2013). That said, uncertainty can affect risk premium and hence asset pricing (Kostka and van Roye, 2017), and so major fluctuations in our economic policy uncertainty index should be reflected in higher stock market volatility. As shown in Figure 2, despite occasional divergences (say, during the European debt crisis), our index largely spikes at around the same time as the realized volatility of the Hang Seng Index, especially during the Asian Financial Crisis, the Global Financial Crisis, downgrading of US sovereign credit rating, and the European sovereign debt crisis. On the other hand, our newspaper-based uncertainty index captures less financially related uncertainty that is not captured by stock market volatility, such as the proposal of goods and service tax in late 2005. The correlation between these two indices is 0.25.

Figure 2: Economic policy uncertainty index and realized HSI volatility index
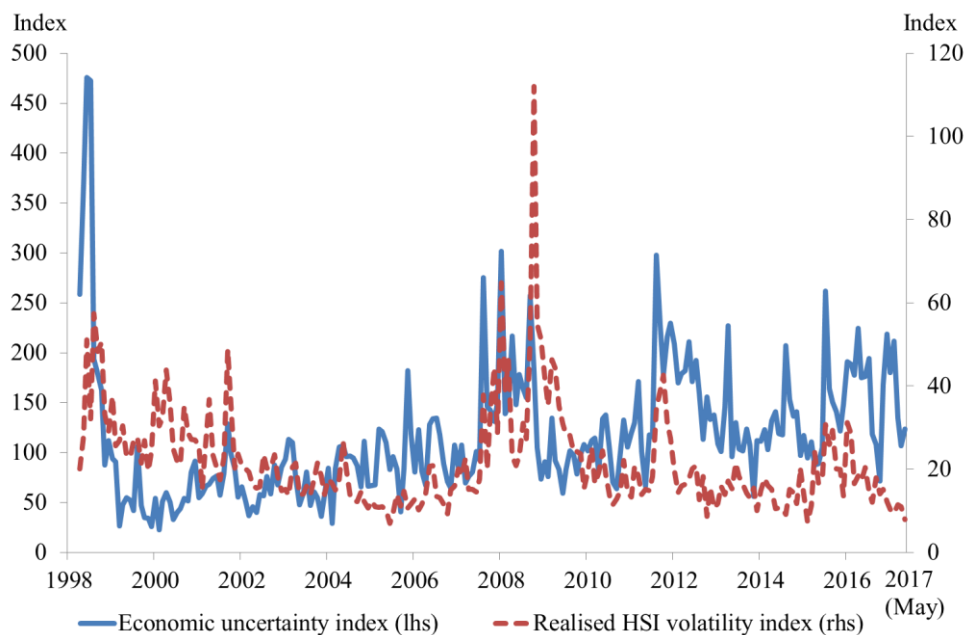
Sources: CEIC and authors' estimates

As a further test, we compare the in-sample forecasting power of our uncertainty index for real GDP growth against that of the stock market volatility. Following Caldara et al. (2016), we use the simple uni-variate forecasting model below:

$$\Delta_h Y_{t+h} = \alpha + \sum_{i=1}^{h} \beta_i \Delta Y_{t-i} + \gamma_1 Uncert_t + \omega_t,$$

where $\Delta_h Y_{t+h} = \frac{400}{h+1} \ln\left(\frac{Y_{t+h}}{Y_{t-1}}\right)$ is the *h*-quarters ahead annualized quarterly growth of real, and $Uncert_t$ is either our economic policy uncertainty index (EPU) or the realized Hang Seng Index Volatility ($HSI\ vol.$), converted into quarterly frequency by averaging the monthly series. We estimate the model using ordinary least squares and use the full sample period starting from 1998Q2 for our estimation.

Table 1 shows the coefficient estimates of the forecasting model, with the t-statistics reported in brackets. A statistically significant coefficient suggests that the variable can help to predict real GDP growth. As shown in column 1 and 2, our economic policy uncertainty index (EPU) is highly significant at the one-quarter ahead (*h=1*) horizon, while the Hang Seng Index volatility ($HSI\ vol.$) is not. Similar findings also hold at the two-quarter ahead (*h=2*) horizon, as shown in column 5 and 6 of Table 1. Our uncertainty index compares favourably against one based on the volatility of the Hang Seng Index in predicting real GDP growth.

To check for robustness, we add the financial condition index (FCI) to the forecasting model as a control variable (see Chan et al., 2016).[8] The weight of each component

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[8] Appendix C outlines the construction of the financial condition index.

variable in the financial condition index is determined by its impact on real GDP growth, and a fall in the index corresponds to a tightening of local financial conditions. Chan et al. (2016) show that this index helps to predict real GDP growth.[9] Controlling for such index in the forecasting model therefore allows us to examine the marginal information content of our index. Column 3 and 4 of Table 1 show that our index is highly significant at the one-quarter ahead ($h=1$) horizon, while the Hang Seng Index volatility is not. Column 7 and 8 report similar findings at the two-quarter ahead horizon.

Altogether, our analysis indicates that our economic policy uncertainty index is intuitive and has relatively good forecasting power of real GDP growth than other commonly-used proxies of economic uncertainty.

Table 1: Coefficient estimates of the forecasting model

	1-quarter ahead ($h = 1$)				2-quarter ahead ($h = 2$)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EPU	-0.03***		-0.02***		-0.03***		-0.03**	
	[-3.41]		[-2.83]		[-3.08]		[-1.91]	
HSI vol.		0.02		0.02		0.04		0.04
		[0.63]		[0.45]		[1.13]		[1.01]
FCI			2.35***	2.72***			1.73***	2.12***
			[4.33]	[4.57]			[3.87]	[5.21]
Adj. R^2	0.27	0.09	0.48	0.39	0.27	0.06	0.41	0.30

Note: The t-statistics reported in brackets are based on the heteroskedasticity- and autocorrelation-consistent asymptotic covariance matrix computed according to Newey and West (1987) with the automatic lag selection method of Newey and West (1994): * p < 0.10; ** p < 0.05; and *** p < 0.01.

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[9] We discuss the construction of the financial condition index in the Appendix.

4.   Spillovers of Uncertainty

We can use our economic policy uncertainty index to study uncertainty spillovers from the rest of the world to Hong Kong. As a small open economy, the economic policy uncertainty shocks facing Hong Kong inevitably stem in part from the external environment. Moreover, Hong Kong has trade and financial linkages with multiple major economies, so it is likely that Hong Kong imports economic policy uncertainty through these linkages. In the following we study spillovers from the US, Europe, Mainland China and Japan to Hong Kong, making use of the uncertainty indices created by Baker et al. (2016).[10] We obtain monthly data over a sample period between April 1998 and December 2016.

Table 2 presents the correlation matrix for the policy uncertainty indices in our sample. Three key observations can be made. First, all pairwise correlations are positive (and statistically significant). Second, the pairwise correlation between the US and Europe is high, at 65%, in line with Colombo (2013)'s empirical findings.[11] Third, the pairwise correlation between Hong Kong and its major trading partners are positive but not high, between 26% and 47%.[12] This suggests that Hong Kong's uncertainty is influenced by

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[10] The policy uncertainty measures are downloadable from http://www.policyuncertainty.org.

[11] The pairwise correlation between Europe and Mainland China (75%) is the highest in the table. As we explain below, this may be related to the data quality of the uncertainty index for China.

[12] It is surprising that the pairwise correlation between the US and Hong Kong is only 26%. The two series diverge on four occasions. First, in 2008-09, HK experienced the Asian financial crisis but the US did not, so EPU was high in HK and low in US. Second, in the early 2000s, the US experienced the dot-com bubble, but the crisis in Hong Kong was relatively minor. EPU was relatively low in HK and high in US. Third, in 2008-10, Hong Kong's economy was relatively strong due to strong Mainland Chinese growth and a domestic housing market boom, but US EPU was high in the aftermath of the global financial crisis. Fourth, in 2014 onwards, the EPU in HK was relatively high, which perhaps is related to local economic and political conditions.

economic policy uncertainty from multiple countries. For this reason, we include countries other than the US for the spillover analysis, departing from Caggiano et al. (2017a) and Mumtaz and Theodoridis (2015).

Table 2: Correlation matrix

	EU	US	CN	JP	HK
Europe (EU)	1.00				
United States (US)	0.65	1.00			
Mainland China (CN)	0.75	0.46	1.00		
Japan (JP)	0.50	0.52	0.38	1.00	
Hong Kong (HK)	0.37	0.26	0.37	0.47	1.00

Source: Authors' estimates

Note: this table shows the correlation matrix among all economic policy uncertainty indices in 1998M4-2016M12. All correlations are significantly different from zero at the 1 per cent level.

To identify the major driver of Hong Kong's economic uncertainty, we follow Diebold and Yilmaz (2009) and Klößner and Sekkel (2014)'s network approach to conduct a spillover analysis of uncertainty. Using the uncertainty indices above, we construct a connectedness table based on the shares of forecast error variance in various locations due to uncertiainties arising elsewhere.

Specifically, we use the methodology of Diebold and Yilmaz (2009) and estimate a VAR model with p lags as follows:

$$Y_t = \emptyset_1 Y_{t-1} + \cdots + \emptyset_p Y_{t-p} + \epsilon_t \,,$$

where ϵ_t is an i.i.d. shock, and $\emptyset_1, \ldots \emptyset_p$ are the coefficient matrix of the lag terms, and Y_t is a vector of economic policy uncertainty indices of Hong Kong and its major trading partners. With stationarity, the VAR has a moving average representation of $Y_t = \epsilon_t + A_1 \epsilon_{t-1} + A_2 \epsilon_{t-2} + \cdots$. Let Σ_ϵ be the covariance matrix of ϵ_t, the h-step ahead forecast error covariance matrix is given by $\Sigma_{\epsilon,h} = \sum_{h=0}^{h-1} A_h \Sigma_\epsilon A_h'$. Using the lower-triangular Cholesky factor L of the Σ_ϵ matrix (i.e. $LL' = \Sigma_\epsilon$), we can write $\Sigma_{\epsilon,h} = \sum_{h=0}^{h-1}(A_h L)(A_h L)'$. Then, $\sum_{h=0}^{h-1}(A_h L)_{ij}^2$ can be considered as the contribution of shocks to variable j to variables i's forecast error variance, which is a key measure in our analysis. In accordance with the indication of AIC, we set the lag length of the VAR model to $p = 4$ and conduct 12-month-ahead forecasts.

Based on the economic size of Hong Kong's major trading partners, we order the uncertainty index of the US or Europe either first or second in the VAR, followed by either the uncertainty index of Mainland China or Japan. In any case, Hong Kong's uncertainty index was ordered last, with its lag terms being restricted to zero in other economies' equations, on the assumption that Hong Kong's uncertainty does not spill over to other economies.

Table 3A shows the estimated spillovers of uncertainty from the 'source' economy in each column to the 'recipient' economy in each row. We report the estimates of spillovers across all four permutations of the system, so as to make our conclusion less susceptible to the ordering of variables. To understand this table, take

for example the (1, 2) entry of 21.7 which means that the US uncertainty index contributes 21.7% of the 12-month-ahead forecast error variance to the European uncertainty index. The last column labelled 'from others' sums up all foreign contributions to a given country's uncertainty index. The next to last row labelled 'contribution to others' reports the sum of a country's contribution to other countries' uncertainty indices. Given our VAR specification, Hong Kong's uncertainty index does not contribute to other countries' forecast error variance, and so the entry for Hong Kong is restricted to be 0. Finally, the last row labelled 'net' is the difference between 'contribution to others' and 'from others', which has a natural interpretation of the 'net export' of uncertainty to other countries.

The results in Table 3A are summarized as follows. First, self-contribution is typically large (over 50%). Second, the US and Europe are large net exporters of economic uncertainty, which reflects the size and centrality of these economies. Third, economic uncertainty in other countries contributes 42.9% to the forecast error variance of Hong Kong's uncertainty index, with uncertainty from Europe and the US playing a leading role, possibly reflecting the series of economic and political events that these economies have experienced in recent years. Notice that Hong Kong's net import of uncertainty from its major trading partners is much larger than found in Klößner and Sekkel (2014) for six developed countries (±15%). This finding suggests that international spillovers of uncertainty may be particularly important for small open economies with a high degree of openness.

One counterintuitive result in Table 3A is that the influence of Mainland China on itself is unreasonably low (49.1%). This is unreasonable because Mainland China has restrictions on private cross-border capital flows which should limit the degree of

international uncertainty spillovers. We suspect the low self-contribution may be related to the fact that Mainland China's economic policy uncertainty index is compiled based on only one non-local English newspaper (the *South China Morning Post*, published in Hong Kong), which may capture journalists' perceptions of the uncertainty in the global environment rather than in Mainland China. We conduct a robustness check by replacing the Mainland China's economic policy uncertainty index by the realised Shanghai Stock Exchange Composite Volatility. Table 3B shows the results with this change. The influence of Mainland China on itself is now more than 90%, which is in line with our intuition, and estimates among other economies do not change materially. In any case, our results indicate that Hong Kong's economic policy uncertainty receives notable spillovers.

Table 3A: Spillovers of uncertainty with Mainland China economic policy uncertainty index

	EU	US	CN	JP	HK	From others
Europe (EU)	69.4	21.7	6.0	3.0	0.0	30.6
United States (US)	15.3	81.2	1.3	2.3	0.0	18.8
Mainland China (CN)	38.4	11.6	49.1	1.0	0.0	50.9
Japan (JP)	12.2	18.7	4.8	64.5	0.0	35.6
Hong Kong (HK)	16.3	11.6	6.9	8.2	57.2	42.9
Contribution to others	82.1	63.5	18.8	14.4	0.0	
Net	51.5	44.7	-32.1	-21.2	-42.9	

Table 3B: Spillovers of uncertainty with realised Shanghai Stock Exchange Composite Volatility

	EU	US	CN	JP	HK	From others
Europe (EU)	73.2	22.7	0.4	3.8	0.0	26.8
United States (US)	15.1	81.6	0.8	2.5	0.0	18.4
Mainland China (CN)	3.7	2.3	92.6	1.5	0.0	7.5
Japan (JP)	13.0	19.6	3.4	64.1	0.0	36.0
Hong Kong (HK)	16.0	12.4	5.8	6.5	59.4	40.7
Contribution to others	47.7	56.9	10.4	14.3	0.0	
Net	20.9	38.6	2.9	-21.7	-40.7	

Source: Authors' estimates

Note: EU and the US would either be ordered first or second in the VAR, while CN and JP either third or fourth. The columns show the fraction of the forecast-error variance that the 'source' economy exports to other economies, based on the average of the estimates across four permutations of the ordering. Similarly, the rows indicate the fraction of the forecast-error variance that the 'recipient' economy imports from other economies.

Our findings therefore suggest that the external economic environment, in addition to trade and financial channels, can also lead to spillovers to Hong Kong by affecting economic policy uncertainty. The next logical question is whether a shock to economic policy uncertainty has quantitatively significant effects to real and financial variables in Hong Kong. This is investigated in the next section.

5. Macro-Financial Effect of Uncertainty

In this section, we analyze the real effects of economic policy uncertainty shocks. We adopt a Structural Vector Autoregressive (SVAR) model. A representation of the SVAR is:

$$B_0 X_t = c + B_1 X_{t-1} + B_2 X_{t-2} + \cdots + B_p X_{t-p} + \epsilon_t$$

where c is a vector of constants, $B_0, B_1, \ldots B_p$ are coefficient matrices, and ϵ_t is a vector of structural innovations. The vector X_t contains the following endogenous variables: (1) economic policy uncertainty index (*EPU*); (2) financial condition index (*FCI*); (3) growth in posting of private sector vacancy (*vag*); (4) real private investment growth *(inv)* and (5) real GDP growth (*y*). The financial, labor market and investment variables are included to capture the different transmission channels of uncertainty shocks. All growth rates are measured on a year-on-year basis.[13] We estimate the VAR model using quarterly data from 1998Q3 – 2016Q4 (because most of the real variables are only available in quarterly frequency). We set the lag length of the VAR model to one, as our sample size limits the degrees of freedom in our estimation.[14]

In our baseline specification, we use a standard Cholesky decomposition to recover the orthogonal shocks, with the ordering of the variables given above. The use of the Cholesky decomposition to identify uncertainty shocks is common in the literature (see Baker et al., 2016; Gilchrist et al., 2014; Colombo, 2013; Moore, 2017). However, there is no consensus regarding the ordering of economic policy

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[13] Data on the real GDP, real private investment and private vacancy are sourced from the Census and Statistics Department of Hong Kong Special Administrative Region. Data on the world GDP are estimated by the authors.

[14] SIC chooses a lag length of 1, but AIC chooses a lag length of 5.

uncertainty. For instance, Baker et al. (2016) and Gilchrist et al. (2014) order economic policy uncertainty first while Colombo (2013) and Moore (2017) order it last. We choose to order it first because the spillover analysis in the previous section suggests that innovations in uncertainty shocks are to a large extent externally driven and so do not respond to contemporaneous shocks in domestic variables immediately.

Figure 4 shows the impulse responses to a one standard deviation increase in the economic policy uncertainty index. Our impulse responses reveal a large and statistically significant drop in real GDP growth of about 1%, two to three quarters after the shock, returning to its the pre-shock level after one year. This effect is quantitatively similar to that found in Baker et al. (2016) (They find industrial production drops 1.1% at a maximum). Higher economic uncertainty leads to significantly tighter financial conditions on impact, followed by a dampening of private investment and private vacancy posting after a few quarters. The fall in all three variables is statistically significant, suggesting that all three transmission channels are at work.

Figure 4. Impulse responses to one standard deviation innovation in the economic policy uncertainty index

Response to Cholesky One S.D. Innovations
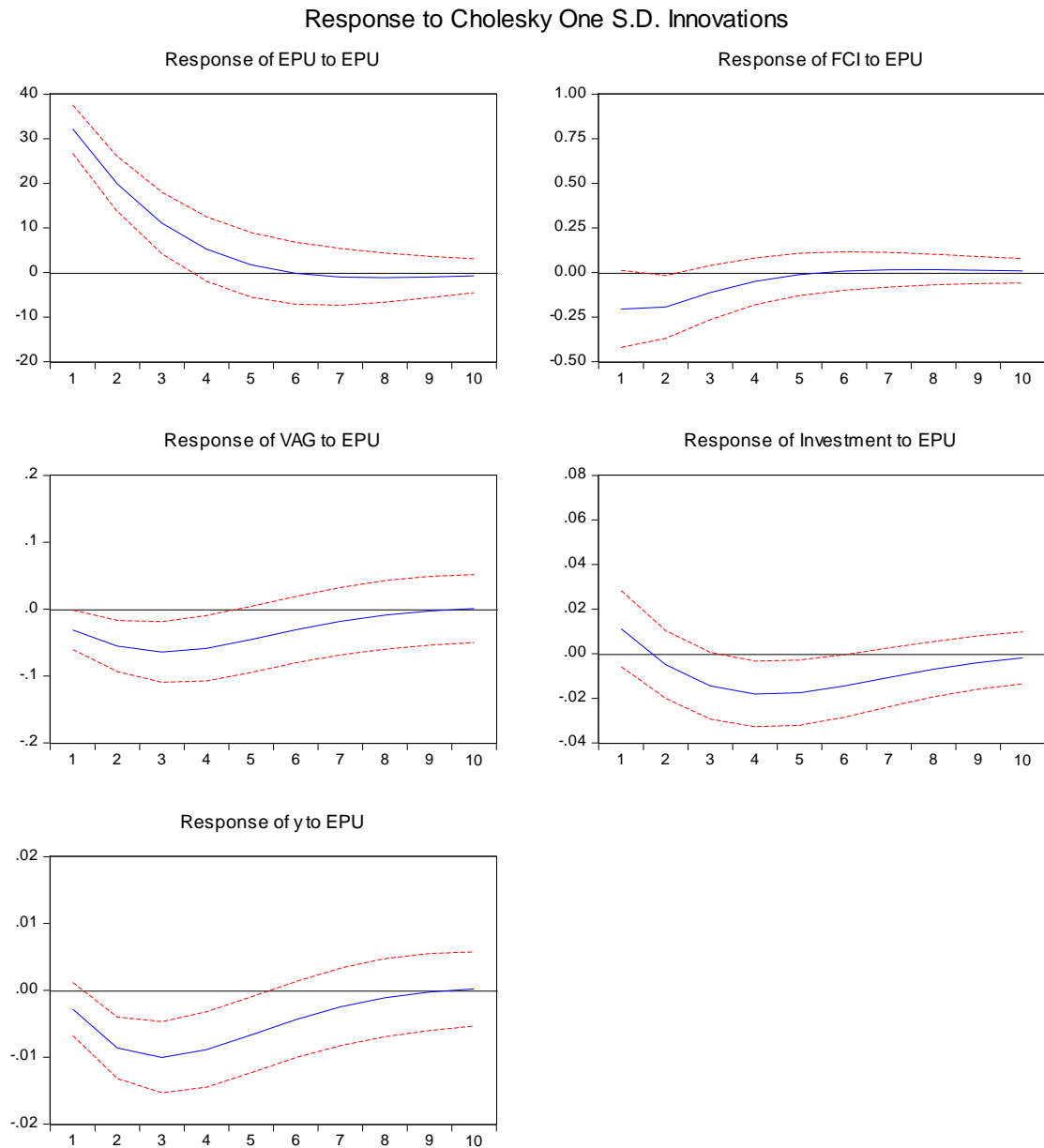
Source: Author's estimates.

Note: The solid lines denote the median IRFs. The dashed red lines denote 5% and 95% error bands, estimated using Monte Carlo simulation (with 100 simulations). Each period is a quarter.

We conduct a number of checks to ensure that our results are robust to alternative specifications. First, to avoid any dependence on the ordering of variables in the VAR model, we conduct our impulse response analysis using the generalized impulse response function (see Pesaran and Shin, 1998). Second, we use sign restrictions as an alternative identification scheme. We identify an uncertainty shock as one that increases uncertainty and decreases all other variables on impact. Third, we also consider a specification in which uncertainty shocks are ordered last. Fourth, to control for the influence from the external environment, we include world GDP growth (as measured by the growth in trade-weighted real GDP of Hong Kong's major trading partners) as an exogenous variable in the VAR. Fifth, we replace the financial condition index (*FCI*) with the average three-month return of the Hang Seng Index *(RHSI)*, which is more transparent.

Figure 5. Hong Kong real GDP growth response to an EPU shock, with alternative specifications and identification assumptions
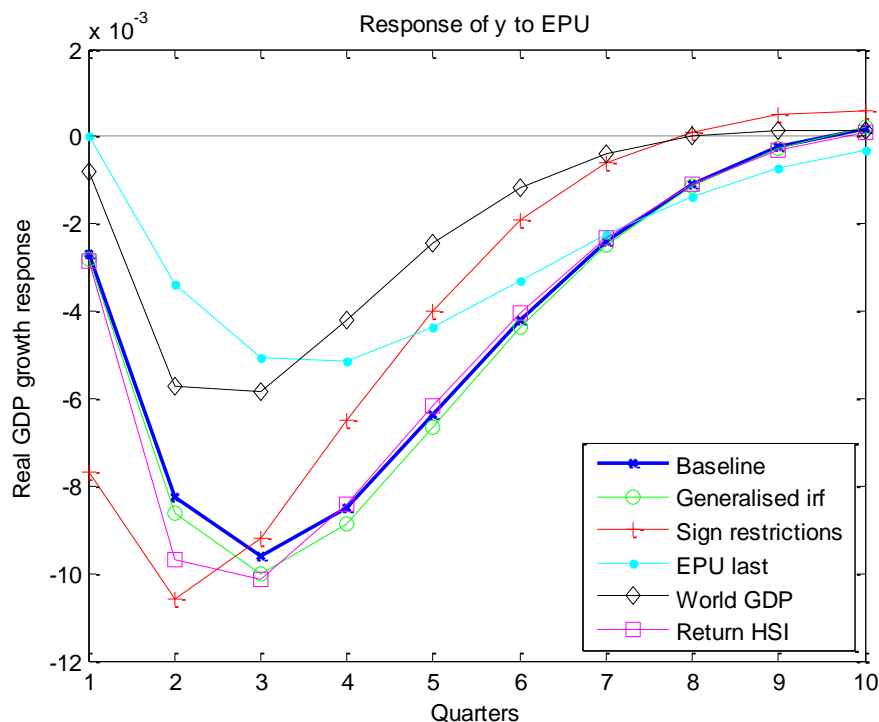
Source: Author's estimates.

Figure 5 reports the impulse response of real GDP growth to a one standard deviation shock to the economic policy uncertainty index. Under alternative specifications the fall in economic activity is still quite similar to the baseline, with a maximum fall ranging between 0.5-1%. Appendix D provides details of these robustness checks and shows that the fall in economic activity under all alternative assumptions is statistically significant. We conclude that our findings are robust to alternative assumptions.

6. Conclusions

In this paper, we used Hong Kong as an example to study the impact of uncertainty shocks from major economies on financially-integrated small-open economies. We constructed a newspaper-based economic policy uncertainty index for Hong Kong. Using the index, we show that there are sizable spillovers of economic policy uncertainty from the major economies to Hong Kong, and that a shock to uncertainty has a negative impact on real output growth rate in Hong Kong. In light of these findings, there is a need for a small open economy like Hong Kong to track economic policy uncertainty closely as it constitutes another key channel of international spillovers, in addition to the more standard effects through trade and financial channels.

Appendix A: Chinese terms for compiling economic policy uncertainty index

Table A1: Relevant Chinese terms (with translations to English) for compiling the economic policy uncertainty index

Criteria	English	Chinese
(1) Region	Domestic/Hong Kong	本地/本港/香港
(2) Economic	Economic/Economy/Financial	經濟/金融
(3) Uncertainty	Uncertainty/Uncertain/Unclear/ Unstable/Volatile/Unpredictable	不確定/不明確/不明朗/ 未明/不穩/波動/ 難料/難以預料/難以預測/ 難以預計/難以估計
(4) Policy terms	Policy/measures	政策/措施/施政
	Public	公共
	Expenditure/spending	支出/開支
	Investment	投資
	Budget	預算
	Fiscal	財政
	SAR government	當局/政府/ 特別行政區/特區
	Politics	政治
	Chief Executive	行政長官/特首
	Interest	利率/利息/息口
	Reform	改革
	Optimize/refine	優化
	Deficit	赤字
	Tax	稅
	Regulation/rules	規管/規例/規則
	Hong Kong Monetary Authority	金融管理局/金管局
	Reserves	儲備
	The Linked Exchange Rate System	聯繫匯率

Source: Authors' definition

Appendix B: Robustness of newspaper-based EPU indices

We check our baseline newspaper-based EPU index with two alternatives newspaper-based indices. The first alternative uses the 5 most credible newspapers in our sample to construct a credibility-adjusted index. The second alternative uses the two newspapers with the highest readership to construct a readership-adjusted index. Figure A1 compares the time plots of these alternative indices with the baseline.

Figure A1: Comparison of newspaper-based EPU indices
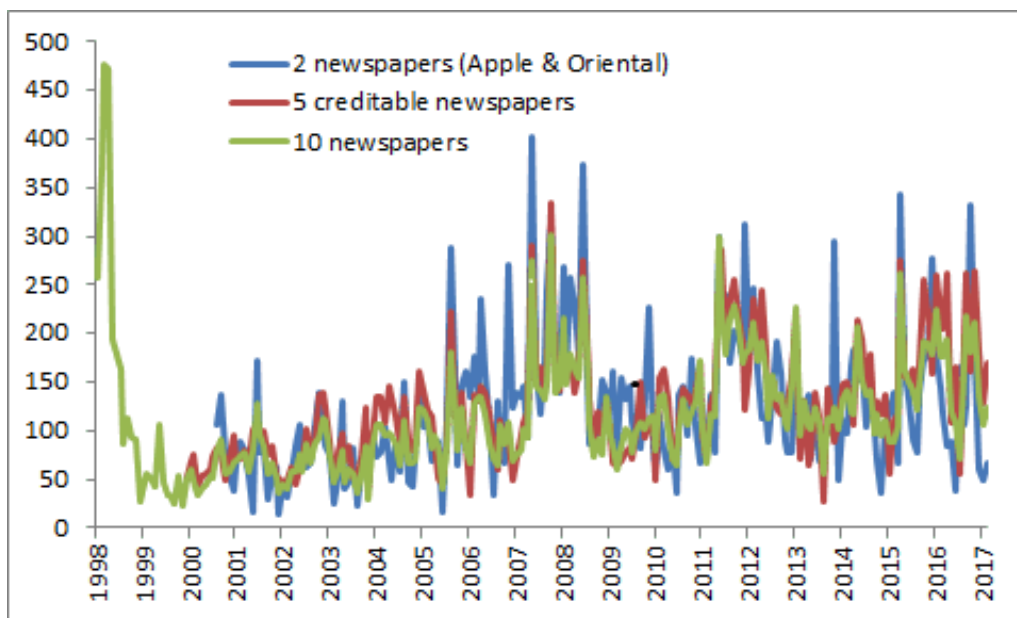
Source: Authors' estimates

Appendix C: Construction of the financial condition index (FCI)

In this Appendix, we outline the construction of the financial condition index used in our estimation. (Chan et al. (2016) provide the full detail of the construction and analysis of the financial condition index.) The methodology follows IMF (2015) and Osorio et al. (2011), and is based on a VAR model. We estimate the following VAR model:

$$X_t = A_0 + \sum_{i=1}^{2} A_i X_{t-i} + \sum_{i=1}^{2} B_i Y_{t-i}^* + \epsilon_t$$

where X_t is a vector of variables including Hong Kong's quarter-on-quarter real GDP growth, CPI inflation, and a list of financial variables: 3-month Hong Kong Interbank Offer Rate (HIBOR) (in quarterly changes), residential property prices (in quarter-on-quarter growth rate), the Hang Seng Index (in quarter-on-quarter growth rate), volatility of the Hang Seng Index, Hong Kong dollar real effect exchange rate (in quarter-on-quarter growth rate), Hong Kong dollar domestic loans (in quarter-on-quarter growth rate), and the spread of the 3-month HIBOR over the yield of the 3-month Exchange Fund Bill. Y_t^* is the weighted GDP of Hong Kong's trading partners.

The financial index is constructed as:

$$FCI_t = \sum_{j=1}^{n} w_j (x_{j,t} - \bar{x}_j)$$

The financial index FCI_t is the weighted sum of deviation of a financial variable $x_{j,t}$ from its sample average $\bar{x}_j$. The weight w_j for financial variable j is given by the accumulated responses of real GDP growth within four quarters to a one-unit shock to the financial variable. The generalized impulse response function (Persaran and Shin,

1998) is used to measure the impact on real GDP growth from each financial variables to avoid any dependence of the estimated weighted on the ordering of the variables in the VAR. Given this definition, a fall in FCI_t is a tightening in financial condition. The resulting time series of FCI_t is shown in Figure A2. The index drops significantly in 1998Q3 and 2008Q3, corresponding to the Asian financial crisis and and the global financial crisis. Overall, the index makes intuitive sense.

**Figure A2: Financial condition index**
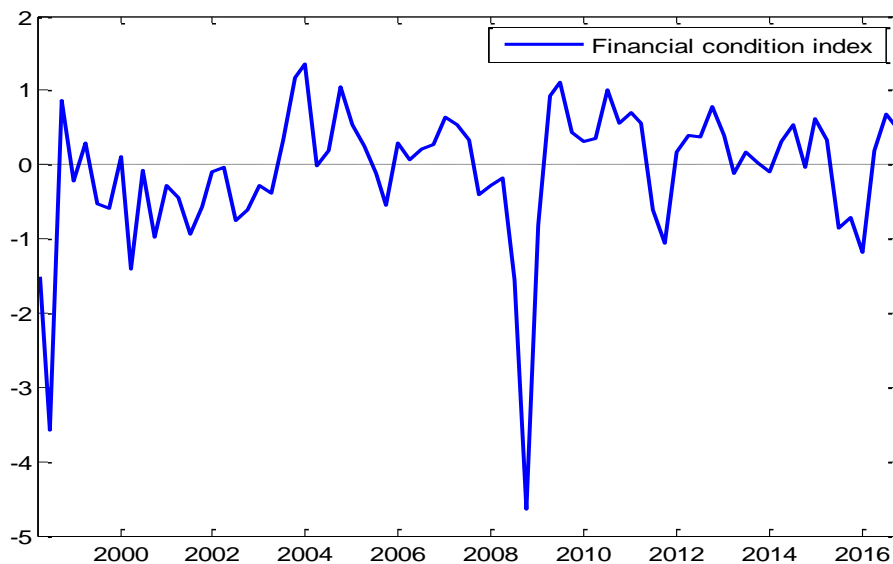
Source: Authors' estimates

Appendix D: Robustness in SVAR estimation of the macro-financial effect of uncertainty

In this Appendix, we report the detailed results of our impulse responses of a shock to an economic policy uncertainty shocks under different identification strategies and specifications discussed in Section 5 of the paper.

Figure A3: Generalized impulse responses to one standard deviation innovation in the economic policy uncertainty index

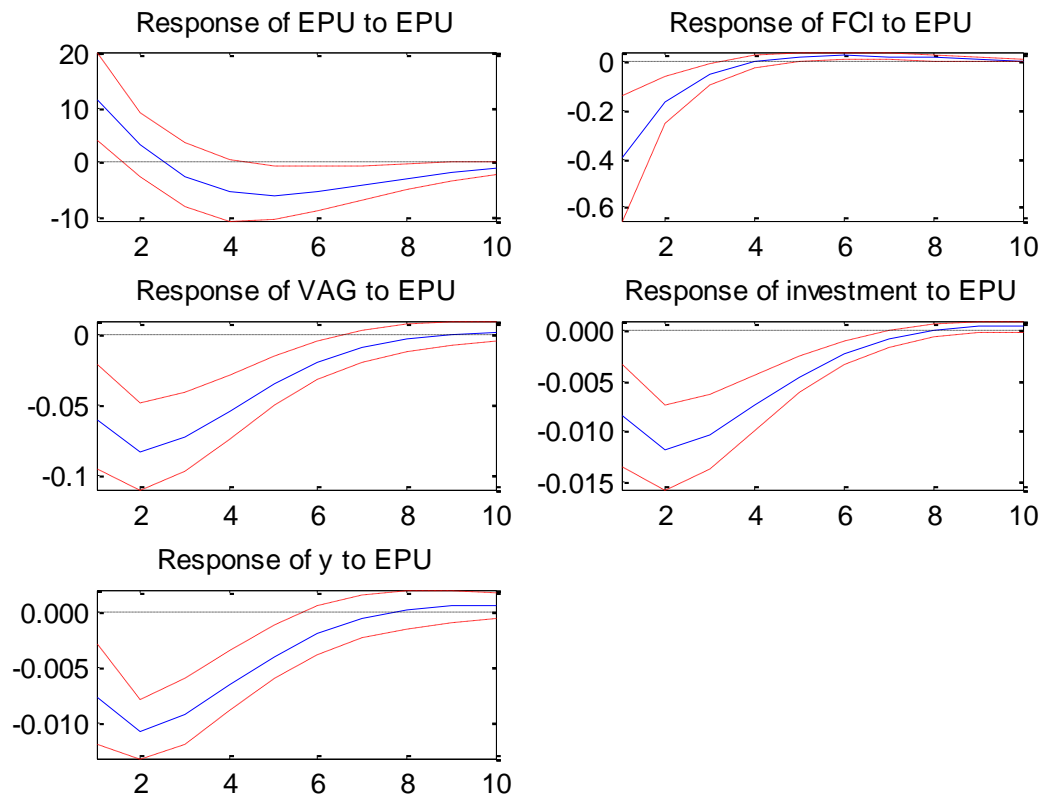Response to Generalized One S.D. Innovations
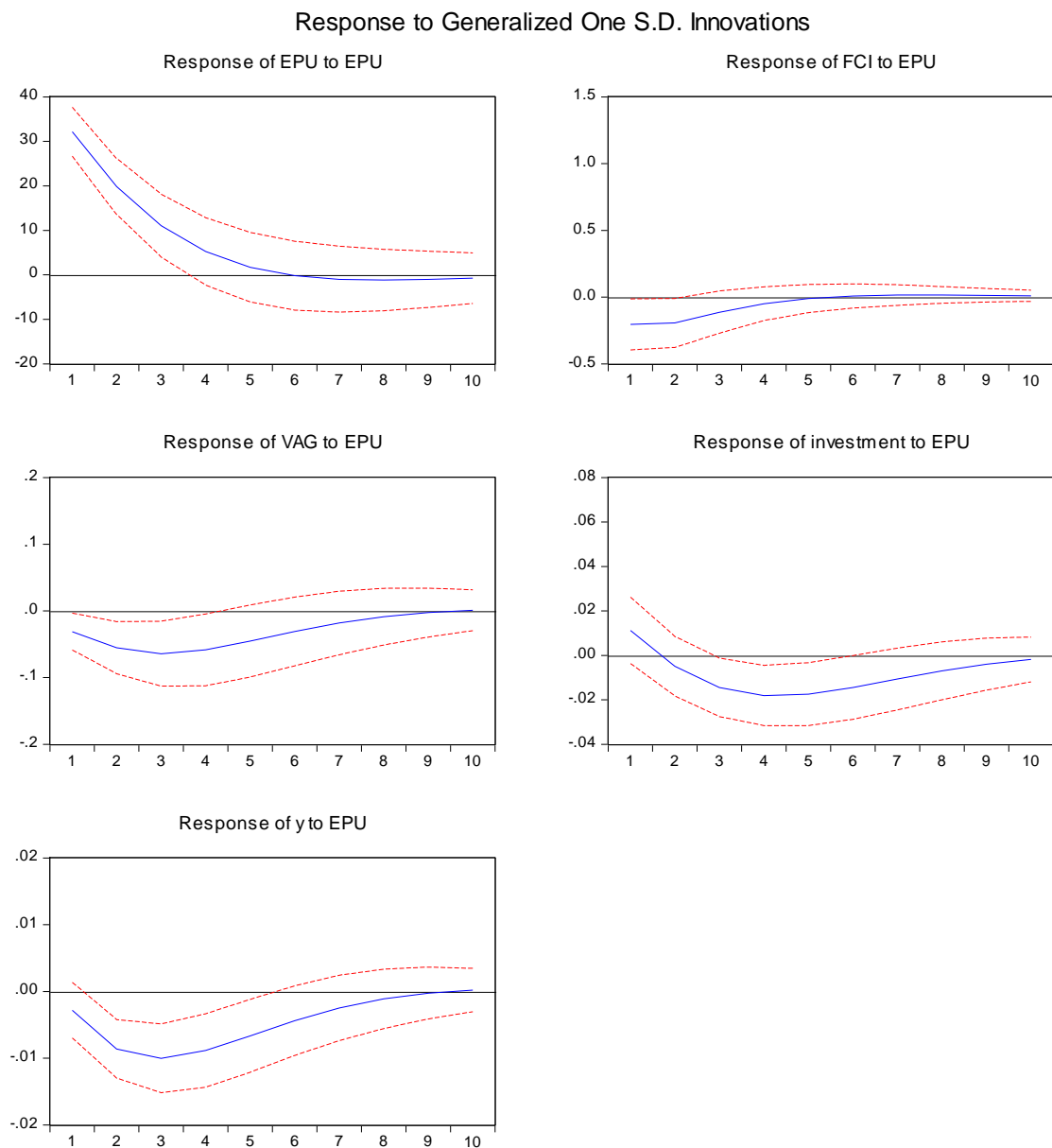
Source: Author's estimates.

Note: The solid lines denote the median IRFs. The dashed red lines denote 5% and 95% error bands, estimated using Monte Carlo simulation (with 100 simulations). Each period is a quarter.

Figure A4: Impulse responses to one standard deviation innovation in the economic policy uncertainty index, uncertainty shock identified by sign restrictions
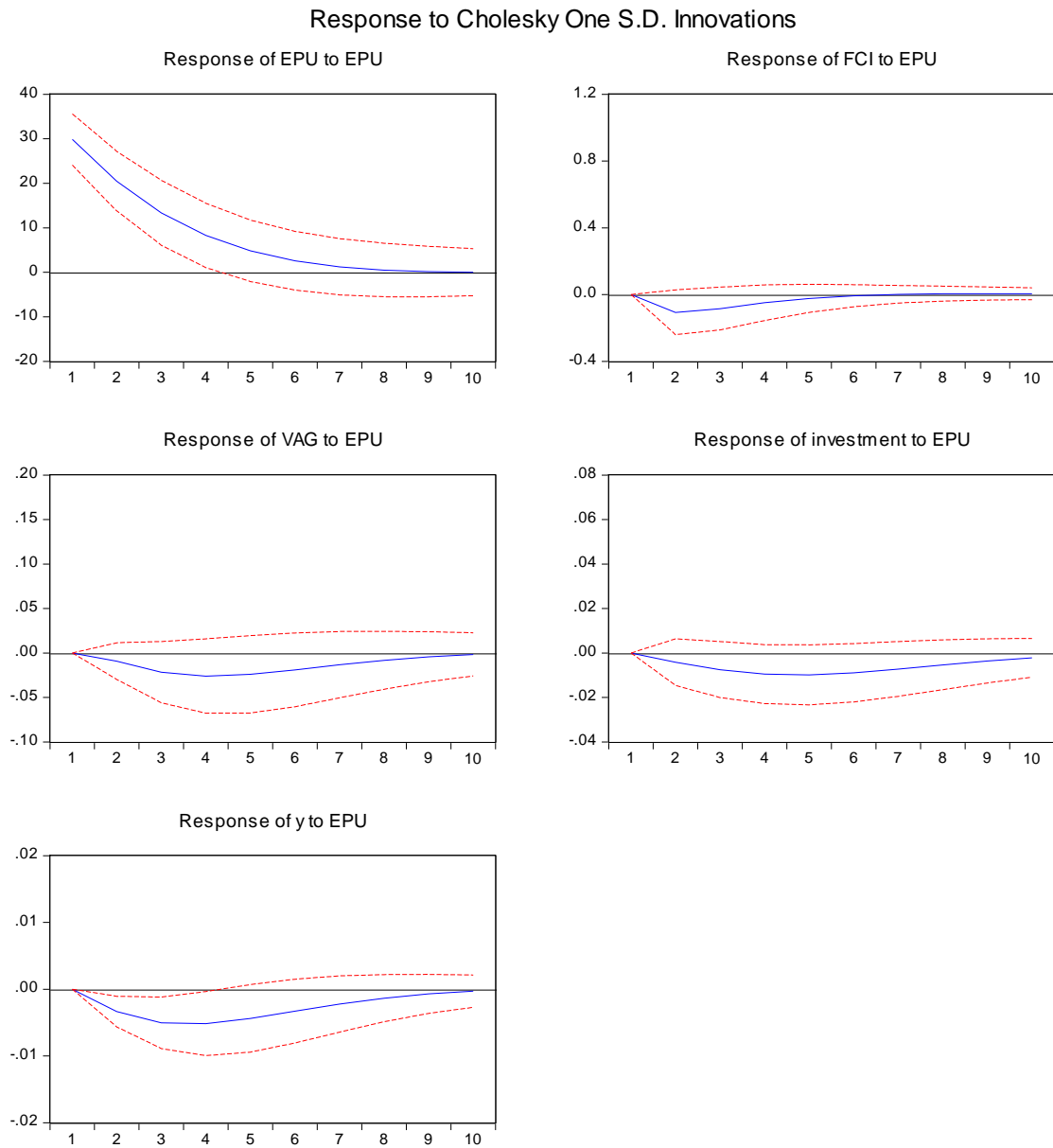

Source: Author's estimates.

Note: The solid lines denote the median IRFs. The dashed red lines denote 16% and 84% error bands, estimated using Monte Carlo simulation (with 10000 simulations). Each period is a quarter.

Figure A5: Impulse responses to one standard deviation innovation in the economic policy uncertainty index, with the shock identified using Cholesky decomposition and EPU ordered in the last position
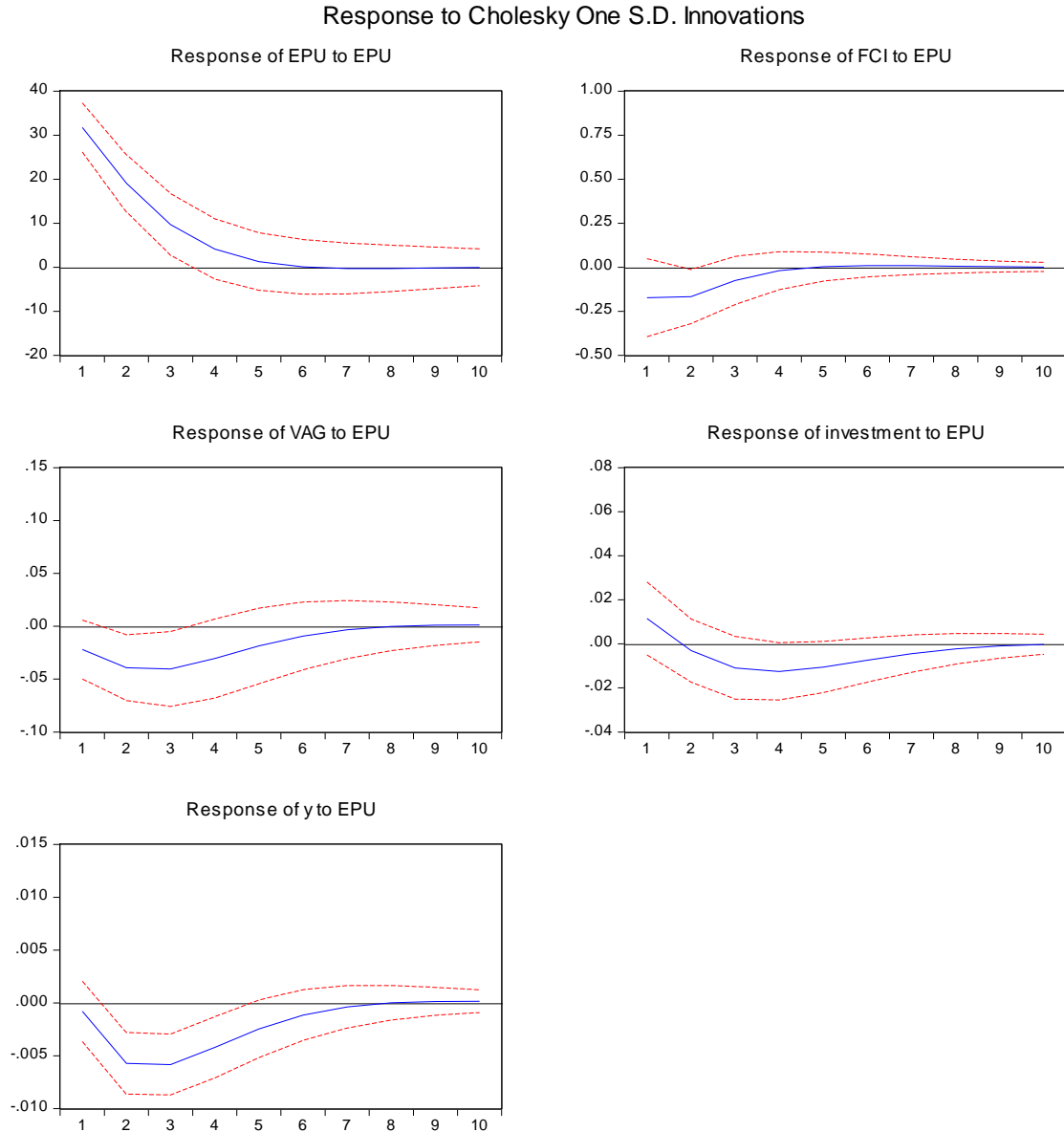

Response to Cholesky One S.D. Innovations

Source: Author's estimates.

Note: The solid lines denote the median IRFs. The dashed red lines denote 5% and 95% error bands, estimated using Monte Carlo simulation (with 100 simulations). Each period is a quarter.

Figure A6: Impulse responses to one standard deviation innovation in the economic policy uncertainty index with trade-weighted real GDP of Hong Kong's major trading partners as control

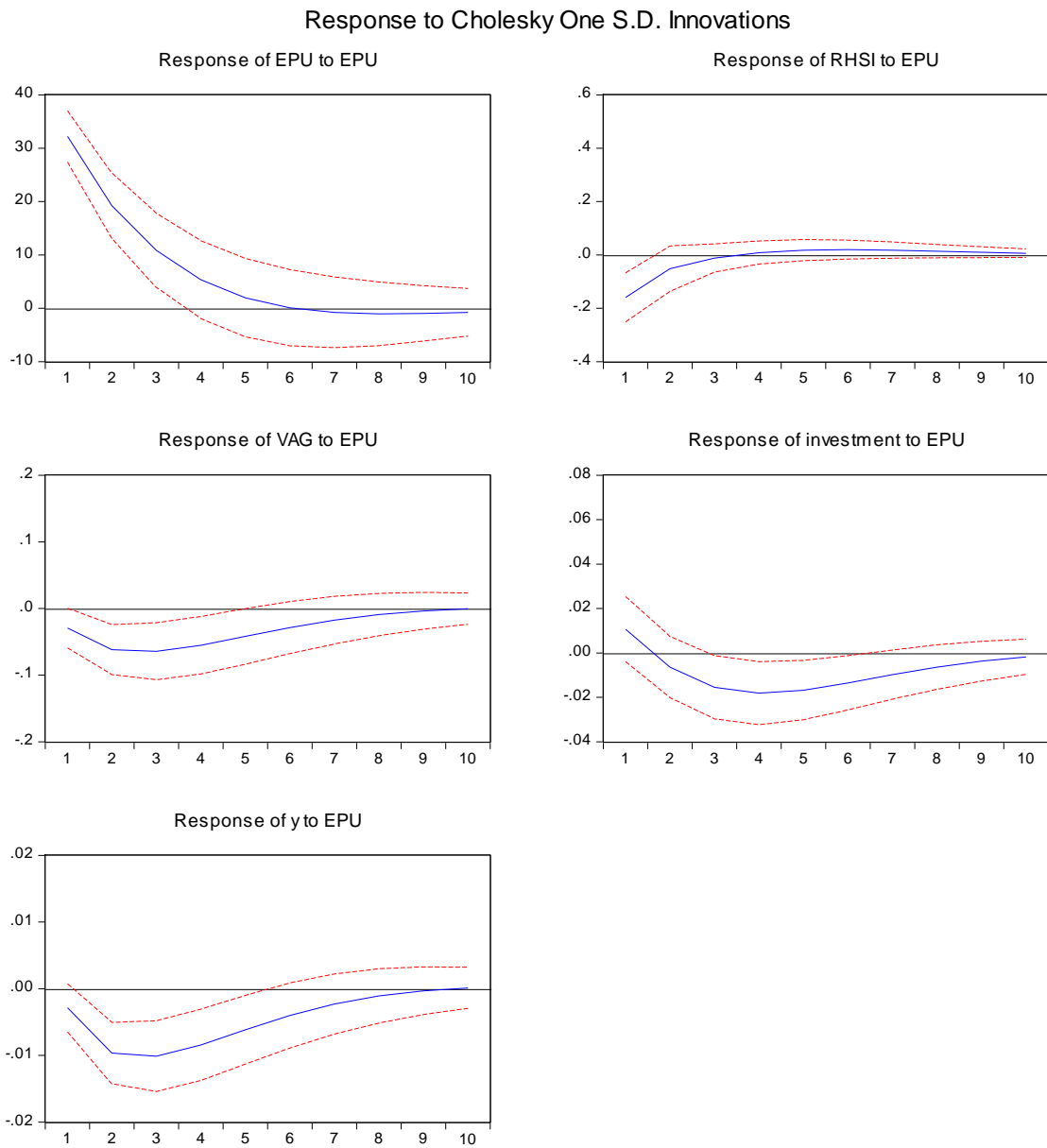Response to Cholesky One S.D. Innovations

Source: Author's estimates.

Note: The solid lines denote the median IRFs. The dashed red lines denote 5% and 95% error bands, estimated using Monte Carlo simulation (with 100 simulations). Each period is a quarter.

Figure A7: Impulse responses to one standard deviation innovation in the economic policy uncertainty index with RHSI

Response to Cholesky One S.D. Innovations

Response of EPU to EPU

Response of RHSI to EPU

Response of VAG to EPU

Response of investment to EPU

Response of y to EPU

Source: Author's estimates.

Note: The solid lines denote the median IRFs. The dashed red lines denote 5% and 95% error bands, estimated using Monte Carlo simulation (with 100 simulations). Each period is a quarter.

References

1. Alexopoulos, M. & Cohen, J. (2015). The Power of Print: Uncertainty Shocks: Markets and the Economy. *International Review of Economics and Finance*, 40, 8-28.

2. Arellano, C., Bai, Y. & Kehoe, P. J. (2016) Financial Frictions and Fluctuations in Volatility. NBER Working Paper No. 22990. Cambridge, MA: National Bureau of Economic Research.

3. Baker, S. R., Bloom, N. & Davis, S. J. (2016). Measuring Economic Policy Uncertainty, *Quarterly Journal of Economics*, 131(4), 1593-1636.

4. Bekaert, G., Hoerova, M. & Duca, M. L. (2013). Risk, Uncertainty and Monetary Policy. *Journal of Monetary Economics*,. 60(7), 771-788.

5. Benigno, G., Benigno, P. & Nisticò, S. (2011). Risk, Monetary Policy and the Exchange Rate. *NBER Macroeconomics Annual*, 26, 247-309.

6. Bernanke, B. S. (1983). Irreversibility, Uncertainty and Cyclical Investment, *Quarterly Journal of Economics*, 98(1), 85-106.

7. Bloom, N. (2009). The Impact of Uncertainty Shock, *Econometrica*, 77(3), 623-85.

8. Caggiano, G., Castelnuovo, E. & Figueres, J. M. (2017a). Economic Policy Uncertainty Spillovers in Booms and Busts. Melbourne Institute Working Paper No. 13/17.

9. Caggiano, G., Castelnuovo, E. & Figueres, J. M. (2017b). Econoimc Policy Uncertainty and Unemployment in the United States: A Nonlinear Approach. *Economics Letters*, 151(C), 31-34.

10. Caldara, D., Fuentes-Albero, C., Gilchrist, S. & Zakrajšek, E. (2016). The Macroeconomic Impact of Financial and Uncertainty Shocks. *European Economic Review*, 88, 185-207.

11. Chan, S, Wu, T., Wong, K. & Cheng, M. (2016)., Financial Conditions Indexes for Hong Kong. HKMA Research Memorandum 09/2016.

12. Christiano, L, J., Motto, R. & Rostagno, M. (2014). Risk Shocks. *American Economic Review*, 104(1), 27-65.

13. Colombo, V. (2013). Economic Policy Uncertainty in the US: Does It Matter for the Euro Area?. *Economic Letters*, 121(1), 39-42.

14. Diebold, F. X. & Yilmaz, K. (2009). Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets. *Economic Journal*, 119, 158-171.

15. Diebold, F. X. & Yılmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, 182(1), 119-134.

16. Dixit, A. K. & Pindyck, R. S. (1994). Investment under Uncertainty. Princeton, NJ: Princeton University Press.

17. Fernández-Villaverde, J., Guerrón-Quintana, P., Rubio-Ramírez, J. F. & Uribe, M. (2011). Risk Matters: The Real Effects of Volatility Shocks. *American Economic Review*, 101(6), 2530-61.

18. Gentzkow, M. & Shapiro, J. M. (2010). What Drives Media Slant? Evidence from US Daily Newspapers. *Econometrica*, 78(1), 35-71.

19. Gilchrist, S., Sim, J. W. & Zakrajšek, E. (2014). Uncertainty, Financial Frictions, and Investment Dynamics. NBER Working Paper No. 20038.

20. Guglielminetti, E. (2016). The Labour Market Channel of Macroeconomic Uncertainty. Bank of Italy Temi di Discussione Working Paper No. 1068.

21. International Monetary Fund (2015). Regional Economic Outlook: Asia and Pacific, April 2015.

22. Klößner, S. & Sekkel, R. (2014). International Spillovers of Policy Uncertainty. *Economics Letters*, 124(3), 508-512.

23. Kostka, T. & van Roye, B. (2017). Assessing the Decoupling of Economic Policy Uncertainty and Financial Conditions. European Central Bank Financial Stability Review May 2017.

24. Lam, O. (2017). Advertising Capture: Evidences from Hong Kong. Working Paper. San Diego: University of California.

25. Leduc, S. & Liu, Z. (2016). Uncertainty Shocks are Aggregate Demand Shocks. *Journal of Monetary Economics*, 82, 20-35.

26. Luk, P. (2017). Global Banks, International Business Cycles and Moentary Policy. Hong Kong Baptist University Working Paper.

27. Moore, A. (2017). Measuring Economic Uncertainty and its Effect. *Economic Record*.

28. Mumtaz, H. & Theodoridis, K. (2015). The International Transmission of Volatility Shocks: An Empirical Analysis. *Journal of European Economic Association*, 13(3), 512-33.

29. Newey, W. K. & West, K. D. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation-Consistent Covariance Matrix. *Econometrica*, 55(3), 703–708.

30. Newey, W. K. & Wetst, K. D. (1995). Automatic Lag Selection in Covariance Matrix Estimation. *Review of Economic Studies*, 61(4): 631-53.

31. Osorio, C., Unsal, F. D. & Pongsaparn, R. (2011). A Quantitative Assessment of Financial Conditions in Asia. IMF Working Paper 11/170.

32. Pesaran, H. H. & Shin, Y. (1998). Generalized Impulse Response Analysis in Linear Multivariate Models. *Economics Letters*, 58(1), 17-29.