Quantitative Finance and Economics

QFE, 3(2): 412–424.
DOI: 10.3934/QFE.2019.2.412
Received: 10 April 2019
Accepted: 07 June 2019
Published: 18 June 2019

http://www.aimspress.com/journal/QFE

Research article

On the effects of policy uncertainty on stock prices: an asymmetric analysis

Mohsen Bahmani-Oskooee[1,*] and Sujata Saha[2]

[1] The Center for Research on International Economics and Department of Economics, The University of Wisconsin-Milwaukee, Milwaukee, USA
[2] Department of Economics, Wabash College, Crawfordsville, USA

* **Correspondence:** Email: bahmani@uwm.edu.

Abstract: Assessing the impact of policy uncertainty on any macroeconomic variables has recently gained momentum. One recent study that considered its impact on stock returns found that an increase in uncertainty has adverse short-run but not long-run effects. In this study, we show that once the nonlinear adjustment of policy uncertainty is introduced into the same multivariable model, policy uncertainty not only has short-run effects but also long-run effects. Furthermore, in most instances the short-run and long-run effects are asymmetric.

Keywords: policy uncertainty; stock prices; asymmetry; nonlinear ARDL

JEL Codes: G10, G38

1. Introduction

Since introduction of the measure of policy uncertainty by Baker et al. (2016), the impact of policy uncertainty on macro variables have gained momentum. While Baker et al. (2016) demonstrated its adverse effects on economic activity, Wang et al. (2014) assessed the response of corporate investment to the new uncertainty measure. On the other hand, Pastor and Veronesi (2013), Ko and Lee (2015), and Brogaard and Detzel (2015) investigated response of risk premium and market returns to uncertainty. Other macro variables which are said to be affected by policy uncertainty include oil prices which was subject of an analysis by Kang and Ratti (2013) as well as Bahmani-Oskooee et al. (2018a).

Additionally, while Bahmani-Oskooee et al. (2016) assessed the impact of policy uncertainty on the demand for money in the U.S., Bahmani-Oskooee and Ghodsi (2017) investigated the response of house prices in each state of the U.S.

The new policy uncertainty measure is now constructed on a monthly basis by the Policy Uncertainty Group for countries other than the U.S.[1] It is an index based on the volume of news associated with any uncertainty. Recently, Bahmani-Oskooee and Saha (2019) assessed the short- run and long-run effects of the policy uncertainty measure on stock returns in Canada, Japan, Korea, U.S., and U.K. These were the five countries for which a multivariate model could be estimated since monthly data were available for all the variables for these countries. Their main finding was that in all countries, increased uncertainty has adverse short-run effects but not long-run effects on stock prices. The main assumption included in Bahmani-Oskooee and Saha's (2019) study as well as other studies is that they have assumed that the effects of policy uncertainty on macro variables are symmetric. The symmetry assumption implies that if an x% increase in uncertainty hurts a variable by y%, an x% decrease in uncertainty will boost that variable by y%. However, this may not be the case since investors' reaction could be different to an increase in policy uncertainty as compared to a decline in uncertainty. If due to an x% increase in uncertainty investors shift their assets from stock to safer assets by y%, an x% decline in uncertainty may induce them to shift their portfolio into stock market by less than y%, if they expect decreased uncertainty to be short-lived, hence asymmetric effects. Similar arguments were recently made by Bahmani-Oskooee and Maki-Nayeri (2019) who assessed the asymmetric effects of policy uncertainty on domestic investment.

Therefore, the main purpose of this paper is to extend Bahmani-Oskooee and Saha's (2019) study from symmetric analysis to an asymmetric analysis of policy uncertainty on stock prices for the same five countries. To that end, we introduce the model and the methodology in Section II that is followed by the results in Section III. A summary is provided in Section IV and data definition and sources are cited in an Appendix.

2. The models and methodology

The model adopted here closely follows the model by Bahmani-Oskooee and Saha (2019), who followed the literature and used the following specification:[2]

$$LnSP_t = a + bLnEX_t + cLnIPI_t + dLnCPI_t + eLnM_t + fLnPU_t + \varepsilon_t \tag{1}$$

where SP denotes the stock prices, EX is the nominal effective exchange rate, IPI is a measure of output proxied by Index of Industrial Production (IPI), CPI is the Consumer Price Index as a measure of the price level, M is a measure of nominal money supply, and finally PU is the measure of policy uncertainty.

[1] For more details on constructing this index visit: www.policyuncertainty.com.

[2] The same model is used by Boonyanam (2014) and Moore and Wang (2014) with no policy uncertainty measure. Other variants of the model without policy uncertainty measure is also used by Granger et al. (2000), Ansari and Kolari (2001), Nieh and Lee (2001), Phylaktis and Ravazzolo (2005), Yau and Nieh (2006), Pan et al. (2007), Richards et al. (2009), Liu and Tu (2011), Tsai (2012), Lin (2012), Tsagkanos et al. (2013), Groenewold et al. (2013), and Bahmani-Oskooee and Saha (2016).

Specification (1) is a long run model and coefficient estimates are long-run estimates. Once the long run estimates are obtained, an estimate of *b* is expected to be negative or positive depending upon if firms associated with the specific stock are export or import oriented. Since an increase in economic activity measured by IPI is expected to increase the demand for stocks, an estimate of *c* is expected to be positive. An estimate of *d* is also expected to be negative or positive depending on whether inflation hurts firm costs and profit margin or if stocks are considered a hedge against inflation in the long run.[3] An estimate of *e* is also expected to be positive or negative, depending whether increase in money supply leads to lower interest rates and economic growth or inflation. Finally, if increase in uncertainty is to hurt the markets, we expect an estimate of *f* to be negative.

As mentioned above, specification (1) is a long-run model and in order to assess the short-run effects of right-hand side variables, we must incorporate the short-run dynamics. Bahmani-Oskooee and Saha (2019) followed Pesaran et al.'s (2001) ARDL (Auto Regressive Distributed Lag) bounds testing approach and considered the following error-correction model:

$$\Delta LnSP_t = \alpha + \sum_{i=1}^{n1} \beta_i \Delta LnSP_{t-i} + \sum_{i=0}^{n2} \delta_i \Delta LnEX_{t-i} + \sum_{k=0}^{n3} \varphi_i \Delta LnIPI_{t-i} + \sum_{i=0}^{n4} \theta_i \Delta LnCPI_{t-i}$$
$$+ \sum_{i=0}^{n5} \pi_i \Delta LnM_{t-i} + \sum_{i=0}^{n6} \omega_i \Delta LnPU_{t-i} + \lambda_1 LnSP_{t-1} + \lambda_2 LnEX_{t-1} + \qquad (2)$$
$$+ \lambda_3 LnIPI_{t-1} + \lambda_4 LnCPI_{t-1} + \lambda_5 LnM_{t-1} + \lambda_6 LnPU_{t-1} + \mu_t$$

In (2), the short-run effects of each variable is judged by the coefficient estimates attached to the first-differenced variables and the long-run effects by the estimates of λ_2–λ_6 normalized on λ_1.[4] However, for the long-run estimates to be meaningful, cointegration must be established. Pesaran et al. (2001) propose two tests: the F test to establish joint significance of lagged level variables in (2) and the t-test to establish significance of λ_1 which must be negative.[5] They demonstrate that the distribution of both tests are non-standard, hence they tabulate new critical values which also account for degree of integration of all the variables in a given model. Their upper bound critical values should be used to establish cointegration. These values are valid, even if some variables are I(0) and some I(1) and this is one of the main advantage of this approach since almost all macro variables are either I(0) or I(1).[6]

Shin et al. (2014) modified Pesaran et al.'s (2001) approach so that it could be used to assess asymmetric effects of any variable of concern. Since our concern is to assess asymmetric effects of

---

[3] See Fama (1981) for the negative effects and Anari and Kolari (2001) for the positive effects.

[4] Note that once normalization is done we will have $\frac{\hat{\lambda}_2}{-\hat{\lambda}_1} = \hat{b},\ \frac{\hat{\lambda}_3}{-\hat{\lambda}_1} = \hat{c},\ \frac{\hat{\lambda}_4}{-\hat{\lambda}_1} = \hat{d},\ \frac{\hat{\lambda}_5}{-\hat{\lambda}_1} = \hat{e},\ and\ \frac{\hat{\lambda}_6}{-\hat{\lambda}_1} = \hat{f}.$

[5] Note that the estimate of λ_1 in (2) is the same as estimate of coefficient attached to lagged error-correction term in Engle and Granger (1987) error-correction specification. For empirical demonstration of this, see Bahmani-Oskooee (2019) and Bahmani-Oskooee and Ghodsi (2019).

[6] Another advantage of this approach is that since short-run adjustment process is included in estimating the long-run effects, any feedback effects among variables are allowed to exert themselves which help reduce multicolinearity or endogeniety (Pesaran et al. 2001).

policy uncertainty measure, *PU*, we take the following steps. First, we form *ΔLnPU* which includes positive as well as negative changes. Second, we separate increases in uncertainty from declines and form two new time-series variable as follows:

$$POS_t = \sum_{j=1}^{t} \max(\Delta LnPU_j, 0), \quad NEG_t = \sum_{j=1}^{t} \min(\Delta LnPU_j, 0) \tag{3}$$

Where POS_t is the partial sum of the positive changes and reflects only increased uncertainty and NEG_t is the partial sum of negative changes in uncertainty and reflects only the decline in uncertainty. Next, we move back to the error-correction model (2) and replace the *LnPU* variable by the two partial sum variables to arrive at:

$$\begin{aligned}\Delta LnSP_t = \alpha &+ \sum_{i=1}^{n1} \beta_i \Delta LnSP_{t-i} + \sum_{i=0}^{n2} \delta_i \Delta LnEX_{t-i} + \sum_{i=0}^{n3} \varphi_i \Delta LnIPI_{t-i} + \sum_{i=0}^{n4} \theta_i \Delta LnCPI_{t-i} \\ &+ \sum_{i=0}^{n5} \pi_i \Delta LnM_{t-i} + \sum_{i=0}^{n6} \omega_i^{+} \Delta POS_{t-i} + \sum_{i=0}^{n7} \omega_i^{-} \Delta NEG_{t-i} + \lambda_1 LnSP_{t-1} + \lambda_2 LnEX_{t-1} + \\ &+ \lambda_3 LnIPI_{t-1} + \lambda_4 LnCPI_{t-1} + \lambda_5 LnM_{t-1} + \lambda_6^{+} POS_{t-1} + \lambda_6^{-} NEG_{t-1} + \mu_t\end{aligned} \tag{4}$$

Since the construction of the partial sum variables introduces nonlinear adjustment of policy uncertainty variable into our specification, Shin et al. (2014) refer models such as (4) as nonlinear ARDL model whereas, (2) is commonly referred to as the linear ARDL model. However, both models are subject to the same estimation, interpretation, and diagnostic tests.[7] Once (4) is estimated, a few asymmetric assumptions could be tested. First, short-run effects of policy uncertainty will be asymmetric if at any given lag order, *i*, $\hat{\omega}_i^{+} \neq \hat{\omega}_i^{-}$. However, if the Wald-test rejects the null hypothesis of $\sum \hat{\omega}_i^{+} = \sum \hat{\omega}_i^{-}$, short-run cumulative or impact asymmetry will be established. Second, short-run adjustment process will be asymmetric if ΔPOS and ΔNEG take a different lag order, i.e., if n6 ≠ n7. Finally, long-run effects of policy uncertainty on stock prices will be asymmetric if we reject the null hypothesis of $\frac{\hat{\lambda}_6^{+}}{-\hat{\lambda}_1} = \frac{\hat{\lambda}_6^{-}}{-\hat{\lambda}_1}$. Again, the Wald test will be used for this purpose.[8]

3. The results

Since the linear model (2) has already been estimated by Bahmani-Oskooee and Saha (2019) for Canada, Japan, Korea, U.K., and the U.S. using monthly data, we restrict ourselves to estimating only the nonlinear model (4) and compare our findings to theirs. We have updated the data and used monthly data over the period January 1985–October 2018. Following their approach we impose a

[7] Shin et al. (2014) even argue that the critical value of the F test should stay at the same high level when we move from (2) to (4) even if (4) has one more variable.

[8] For some other application of these and other nonlinear models see Apergis and Miller (2006), Wimanda (2014), McFarlane et al. (2014), Gogas and Pragidis (2015), Durmaz (2015), Baghestani and Kherfi (2015), Al-Shayeb and Hatemi-J (2016), Lima et al. (2016), Nusair (2017), Aftab et al. (2017), Arize et al. (2017), Gregoriou (2017), Bahmani-Oskooee and Kanitpong (2018), Olaniyi (2019), and Istiak and Alam (2019).

maximum of eight lags on each first-differenced variable and use Akaike Information Criterion to select the optimum number of lags. In any case, if there was evidence of serial correlation, following Bahmani-Oskooee and Fariditavana (2019) we added additional lags of dependent variable to reduce autocorrelation. Using required critical values reported in the notes to each table, we identify significant statistics by * at the 10% level and ** at the 5% level. The results are reported in five tables, one for each country.

From the short-run estimates in Panel A of each table, we gather that either *ΔPOS* or *ΔNEG* variable carry at least one significant coefficient in every optimum model, implying that changes in policy uncertainty has short-run effects on stock prices in all the five countries. This was also the case in the linear model. However, the new results reveal that except in the case of Japan, short-run effects are asymmetric since at the same lag order, the estimate attached to the *ΔPOS* variable is different than the one attached to the *ΔNEG* variable. Thus, in the four remaining countries, short-run effects of changes in policy uncertainty are asymmetric. However, sum of the coefficients attached to the ΔPOS variable is different than the sum attached to the *ΔNEG* variable only in the results for the U.S., since the Wald test reported as Wald-S in Panel C of each table is significant only in Table 5 for the U.S. In sum, while the short-run effects of policy uncertainty are asymmetric in four countries, evidence of cumulative or impact asymmetric effects is discovered only in one country (the U.S.).

Short-run effects of policy uncertainty last into the long-run significant effects in all countries. In all the countries, either the *POS* variable or the *NEG* variable carry a significant coefficient that is reported in Panel B of each table. These long-run effects are meaningful since cointegration is supported in all five countries either by the F or by the t-test, reported in Panel C. This was not the case in Bahmani-Oskooee and Saha (2019), who failed to find significant long-run effects of policy uncertainty on stock returns in any of the five countries, except Canada. These new significant long-run effects must be attributed to the nonlinear adjustment of policy uncertainty. Furthermore, the long-run effects are asymmetric in the results for Canada and the U.K., since the Wald test reported as Wald-L in Panel C is significant in these two cases, rejecting the equality of normalized coefficients attached to the POS and NEG variables.

In each table we have also reported additional diagnostic statistics. To test for serial correlation, the Lagrange Multiplier (LM) statistic is reported in Panel C and since it is insignificant in all models, there is no evidence of serial correlation. Ramsey's RESET test is also reported to check for misspecification. It is insignificant in three models and significant in two models. We have also applied the CUSUM and CUSUMSQ tests to the residuals of each optimum model to establish stability of estimated short-run and long-run coefficients. The stable coefficients are indicated by "S" and the unstable ones by "U". As can be seen, all estimates are stable.

Table 1. Full information estimate of the nonlinear ARDL model for Canada.

Panel A: short-run coefficient estimates									
Lag order	0	1	2	3	4	5	6	7	8
Δ*LnSP*									
	0.50								
Δ*LnEX*	(3.65)**								
	0.21	0.47							
Δ*LnIPI*	(0.93)	(2.17)**							
	0.76	0.03	−0.67	−0.31	−1.56				
Δ*LnCPI*	(1.30)	(0.06)	(1.15)	(0.53)	(2.72)**				
Δ*LnM*	0.001								
	(0.93)								
	−0.06								
Δ*POS*	(5.30)**								
	−0.007	−0.02	0.03						
Δ*NEG*	(0.56)	(1.39)	(2.18)**						

Panel B: long-run coefficient estimates						
Constant	*LnEX*	*LnIPI*	*LnCPI*	*LnM*	*POS*	*NEG*
12.94	0.41	0.09	−1.84	0.01	−0.18	−0.25
(0.83)	(1.34)	(0.12)	(1.86)*	(0.03)	(2.27)**	(3.08)**

Panel C: Diagnostics							
F	t-test	LM	RESET	$\bar{R}^2$	CUSUM (CUSUMQ)	Wald-L	Wald-S
2.57	−0.08	0.02	12.15**	0.19	S (S)	3.77*	1.33
	(4.25)**						

Notes: a. Numbers inside the parentheses are absolute value of t-ratios. *, ** indicate significance at the 10% and 5% levels respectively.

b. The upper bound critical value of the F-test for cointegration when there are five exogenous variables is 3.35 (3.79) at the 10% (5%) level of significance. These come from Pesaran et al. (2001, Table CI, Case III, p. 300).

c. The critical value for significance of ECM_{t-1} is −4.04 (−4.38) at the 10% (5%) level when k = 6. These come from Pesaran et al. (2001, Table CII, Case III, p. 303).

d. LM is the Lagrange Multiplier statistic to test for autocorrelation. It is distributed as χ^2 with 1 degree of freedom. The critical value is 2.70 (3.84) at the 10% (5%) significance level. e. RESET is Ramsey's test for misspecification. It is distributed as χ^2 with one degree of freedom. The critical value is 2.70 (3.84) at the 10% (5%) significance level.

f. Both Wald tests are also distributed as χ^2 with one degree of freedom. The critical value is 2.70 (3.84) at the 10% (5%) significance level.

Table 2. Full information estimate of the nonlinear ARDL model for Japan.

Panel A: short-run coefficient estimates

Lag order	0	1	2	3	4	5	6	7	8
Δ*LnSP*									
	−0.01								
Δ*LnEX*	(0.39)								
	0.04	0.36	−0.32						
Δ*LnIPI*	(0.22)	(2.17)**	(1.88)*						
	−0.65								
Δ*LnCPI*	(2.62)**								
Δ*LnM*	−2.71								
	(1.73)*								
	−0.002								
Δ*POS*	(2.01)**								
	−0.002								
Δ*NEG*	(2.47)**								

Panel B: long-run coefficient estimates

Constant	*LnEX*	*LnIPI*	*LnCPI*	*LnM*	*POS*	*NEG*
66.48	−0.25	−1.00	−12.34	0.17	−0.03	−0.03
(0.92)	(0.41)	(0.63)	(1.98)**	(0.06)	(1.94)*	(2.79)**

Panel C: Diagnostics

F	t-test	LM	RESET	$\bar{R}^2$	CUSUM (CUSUMQ)	Wald-L	Wald-S
2.98	−0.05	1.08	0.00	0.07	S (S)	0.34	1.93
	(4.48)**						

Notes: a. Numbers inside the parentheses are absolute value of t-ratios. *, ** indicate significance at the 10% and 5% levels respectively.

b. The upper bound critical value of the F-test for cointegration when there are five exogenous variables is 3.35 (3.79) at the 10% (5%) level of significance. These come from Pesaran et al. (2001, Table CI, Case III, p. 300).

c. The critical value for significance of ECM_{t-1} is −4.04 (−4.38) at the 10% (5%) level when k = 6. These come from Pesaran et al. (2001, Table CII, Case III, p. 303).

d. LM is the Lagrange Multiplier statistic to test for autocorrelation. It is distributed as χ^2 with 1 degree of freedom. The critical value is 2.70 (3.84) at the 10% (5%) significance level.

e. RESET is Ramsey's test for misspecification. It is distributed as χ^2 with one degree of freedom. The critical value is 2.70 (3.84) at the 10% (5%) significance level.

f. Both Wald tests are also distributed as χ^2 with one degree of freedom. The critical value is 2.70 (3.84) at the 10% (5%) significance level.

Table 3. Full information estimate of the nonlinear ARDL model for Korea.

Panel A: short-run coefficient estimates									
Lag order	0	1	2	3	4	5	6	7	8
		0.05	−0.10	0.15					
Δ*LnSP*	-	(0.71)	(1.47)	(2.30)**					
	−0.42	−0.20	−0.06	−0.08	0.40				
Δ*LnEX*	(1.94)*	(0.85)	(0.27)	(0.36)	(2.48)**				
	0.42	0.41							
Δ*LnIPI*	(1.95)**	(1.96)**							
	−4.12	0.31	−1.07	−2.85	−0.88	−4.58	0.74	−3.39	
Δ*LnCPI*	(3.24)**	(0.24)	(0.82)	(2.24)**	(0.70)	(3.87)**	(0.62)	(2.98)**	
Δ*LnM*	−0.07								
	(0.38)								
	−0.04								
Δ*POS*	(2.05)**								
	−0.0003								
Δ*NEG*	(0.13)								

Panel B: long-run coefficient estimates						
Constant	*LnEX*	*LnIPI*	*LnCPI*	*LnM*	*POS*	*NEG*
25.32	0.36	−1.27	1.23	−0.61	0.06	−0.002
(0.54)	(0.73)	(1.36)	(0.34)	(0.38)	(2.47)**	(0.13)

Panel C: Diagnostics							
F	t-test	LM	RESET	$\bar{R}^2$	CUSUM (CUSUMQ)	Wald-L	Wald-S
6.84**	−0.13	2.36	0.24	0.31	S (U)	1.92	1.02
	(7.00)**						

Notes: a. Numbers inside the parentheses are absolute value of t-ratios. *, ** indicate significance at the 10% and 5% levels respectively.

b. The upper bound critical value of the F-test for cointegration when there are five exogenous variables is 3.35 (3.79) at the 10% (5%) level of significance. These come from Pesaran et al. (2001, Table CI, Case III, p. 300).

c. The critical value for significance of ECM_{t-1} is −4.04 (−4.38) at the 10% (5%) level when k = 6. These come from Pesaran et al. (2001, Table CII, Case III, p. 303).

d. LM is the Lagrange Multiplier statistic to test for autocorrelation. It is distributed as χ^2 with 1 degree of freedom. The critical value is 2.70 (3.84) at the 10% (5%) significance level.

e. RESET is Ramsey's test for misspecification. It is distributed as χ^2 with one degree of freedom. The critical value is 2.70 (3.84) at the 10% (5%) significance level.

f. Both Wald tests are also distributed as χ^2 with one degree of freedom. The critical value is 2.70 (3.84) at the 10% (5%) significance level.

Table 4. Full information estimate of the nonlinear ARDL model for the U.K.

Panel A: short-run coefficient estimates

Lag order	0	1	2	3	4	5	6	7	8
$\Delta LnSP$									
	−1.19								
$\Delta LnEX$	(2.58)**								
	1.99	1.67							
$\Delta LnIPI$	(2.91)**	(2.57)**							
	0.23								
$\Delta LnCPI$	(0.35)								
ΔLnM	−0.69	−0.67	−1.29	−1.50					
	(1.10)	(1.00)	(1.94)*	(2.32)**					
	−0.04								
ΔPOS	(3.70)**								
	−0.01								
ΔNEG	(4.36)**								

Panel B: long-run coefficient estimates

Constant	*LnEX*	*LnIPI*	*LnCPI*	*LnM*	*POS*	*NEG*
−83.52	−2.55	4.87	1.52	2.60	−0.25	−0.07
(4.10)**	(1.57)	(2.61)**	(0.36)	(3.82)**	(3.17)**	(4.45)**

Panel C: Diagnostics

F	t-test	LM	RESET	$\bar{R}^2$	CUSUM (CUSUMQ)	Wald-L	Wald-S
3.69*	−0.14	0.31	1.73	0.18	S (S)	3.28*	0.13
	(5.05)**						

Notes: a. Numbers inside the parentheses are absolute value of t-ratios. *, ** indicate significance at the 10% and 5% levels respectively.

b. The upper bound critical value of the F-test for cointegration when there are five exogenous variables is 3.35 (3.79) at the 10% (5%) level of significance. These come from Pesaran et al. (2001, Table CI, Case III, p. 300).

c. The critical value for significance of ECM_{t-1} is −4.04 (−4.38) at the 10% (5%) level when k = 6. These come from Pesaran *et al*. (2001, Table CII, Case III, p. 303).

d. LM is the Lagrange Multiplier statistic to test for autocorrelation. It is distributed as χ^2 with 1 degree of freedom. The critical value is 2.70 (3.84) at the 10% (5%) significance level.

e. RESET is Ramsey's test for misspecification. It is distributed as χ^2 with one degree of freedom. The critical value is 2.70 (3.84) at the 10% (5%) significance level.

f. Both Wald tests are also distributed as χ^2 with one degree of freedom. The critical value is 2.70 (3.84) at the 10% (5%) significance level.

Table 5. Full Information Estimate of the Nonlinear ARDL Model for U.S.A.

Panel A: short-run coefficient estimates

Lag order	0	1	2	3	4	5	6	7	8
		0.05	0.03	0.12					
$\Delta LnSP$	-	(1.00)	(0.59)	(2.32)**					
	-0.33								
$\Delta LnEX$	(2.28)**								
	-0.93	0.75	0.61						
$\Delta LnIPI$	(2.49)**	(2.06)**	(1.61)						
	0.25								
$\Delta LnCPI$	(1.80)*								
ΔLnM	-0.79	-0.98							
	(1.14)	(1.40)							
	-0.04	-0.03	0.005	0.03					
ΔPOS	(3.77)**	(2.21)**	(0.39)	(2.45)**					
	-0.01	0.004	0 .03						
ΔNEG	(1.35)	(0.39)	(2.27)**						

Panel B: long-run coefficient estimates

Constant	*LnEX*	*LnIPI*	*LnCPI*	*LnM*	*POS*	*NEG*
-23.17	-0.34	2.00	3.29	0.36	-0.05	-0.01
(1.18)	(0.65)	(2.92)**	(1.86)*	(0.63)**	(2.28)**	(0.94)

Panel C: Diagnostics

F	t-test	LM	RESET	$\bar{R}^2$	CUSUM (CUSUMQ)	Wald-L	Wald-S
2.98	-0.06	0.29	12.03**	0.16	S (S)	0.67	4.83**
	(4.51)**						

Notes: a. Numbers inside the parentheses are absolute value of t-ratios. *, ** indicate significance at the 10% and 5% levels respectively.

b. The upper bound critical value of the F-test for cointegration when there are five exogenous variables is 3.35 (3.79) at the 10% (5%) level of significance. These come from Pesaran et al. (2001, Table CI, Case III, p. 300).

c. The critical value for significance of ECM_{t-1} is −4.04 (−4.38) at the 10% (5%) level when k = 6. These come from Pesaran et al. (2001, Table CII, Case III, p. 303).

d. LM is the Lagrange Multiplier statistic to test for autocorrelation. It is distributed as χ^2 with 1 degree of freedom. The critical value is 2.70 (3.84) at the 10% (5%) significance level.

e. RESET is Ramsey's test for misspecification. It is distributed as χ^2 with one degree of freedom. The critical value is 2.70 (3.84) at the 10% (5%) significance level.

f. Both Wald tests are also distributed as χ^2 with one degree of freedom. The critical value is 2.70 (3.84) at the 10% (5%) significance level.

4. Summary and conclusion

In a recent study by the same authors they asked, "are these adverse effects of different types of uncertainty on stock prices transitory or do they have long run implication?". By using the policy uncertainty measure and a linear ARDL model, they concluded that indeed the effects are short run only.

In this paper, when we separated the increases in uncertainty from the declines and estimated a nonlinear multivariate model for the same five countries, we found that, short-run effects of policy uncertainty lasts into the long run which we attribute to the nonlinear adjustment of policy uncertainty. More precisely, we found that policy uncertainty has short-run asymmetric effects in Canada, Korea, U.K., and the U.S. but not in Japan. Short-run effects translated into significant and meaningful long-run effects in all five countries. However, the results are country-specific. While in the cases of Canada, Japan, and the U.K., we found that increased policy uncertainty hurts stock prices, decreased uncertainty boosts them, though at different rates. In the U.S. however, we found that while increased uncertainty hurts stock returns, decreased uncertainty does not have any long-run effects, a clear sign of long-run asymmetric effects. All in all, it appears that reducing uncertainty could benefit stock returns in the short run as well as in the long run.

Acknowledgements

Valuable comments of two anonymous referees are greatly appreciated. Remaining errors, however, are ours.

Conflict of interest

We, hereby, declare that the submitted paper is not associated with any kind of conflict of interest.

References

Aftab M, Syed KBS, Katper NA (2017) Exchange-rate volatility and Malaysian-Thai bilateral industry trade flows. *J Econ Stud* 44: 99–114.

Al-Shayeb A, Hatemi-J A (2016) Trade openness and economic development in the UAE: an asymmetric approach. *J Econ Stud* 43: 587–597.

Anari A, Kolari J (2001) Stock prices and inflation. *J Financ Res* 24: 587–602.

Apergis N, Miller S (2006) Consumption Asymmetry and the Stock Market: Empirical Evidence. *Econ Lett* 93: 337–342.

Arize AC, Malindretos J, Igwe EU (2017) Do Exchange Rate Changes Improve the Trade Balance: An Asymmetric Nonlinear Cointegration Approach. *Int Rev Econ Financ* 49: 313–326.

Baghestani H, Kherfi S (2015) An error-correction modeling of US consumer spending: are there asymmetries?. *J Econ Stud* 42 : 1078–1094.

Bahmani-Oskooee M (2019) The J-Curve and the Effects of Exchange Rate Changes on the Trade Balance, in Francisco L. Rivera-Batiz, eds., *International Money and Finance*, Volume 3 of Francisco L. Rivera-Batiz, ed., *Encyclopedia of International Economics and Global Trade*, World Scientific Publishing Co., Singapore, chapter 16, In press.

Bahmani-Oskooee M, Saha S (2016) Do Exchange Rate Changes have Symmetric or Asymmetric Effects on Stock Prices. G*lobal Financ J* 31: 57–72.

Bahmani-Oskooee M, Ghodsi H (2017) Policy Uncertainty and House Prices in the United States of America. *J R Estate Portf Manage* 23: 73–85.

Bahmani-Oskooee M, Kanitpong T (2018) Thailand's trade balance with each of her 15 largest partners: an asymmetry analysis. *J Econ Stud* 45: 660–672.

Bahmani-Oskooee M, Ghodsi H (2019) Asymmetric Causality between the U.S. Housing Market and its Stock Market: Evidence from State Level Data. *J Econ Asymmetries,* In press.

Bahmani-Oskooee M, Saha S (2019) On the Effects of Policy Uncertainty on Stock Prices. *J Econ Financ,* In press.

Bahmani-Oskooee M, Maki-Nayeri M (2019) Asymmetric Effects of Policy Uncertainty on Domestic Investment in G7 Countries. *Open Econ Rev*, In press.

Bahmani-Oskooee M, Kutan A, Kones A (2016) Policy Uncertainty and the Demand for Money in the United States. *Appl Econ Q* 62: 37–49.

Bahmani-Oskooee M, Harvey H, Niroomand F (2018a) On the Impact of Policy Uncertainty on Oil Prices: An Asymmetry Analysis. *Int J Financ Stud* 6: 1–11.

Baker SR, Bloom N, Davis SJ (2016) Measuring Economic Policy Uncertainty. *Q J Econ* 131: 1593–1636.

Boonyanam N (2014) Relationship of stock price and monetary variables of Asian small open emerging economy: Evidence from Thailand. *Int J Financ Res* 5: 52–63.

Brogaard J, Detzel A (2015) The Asset-Pricing Implications of Government Economic Policy Uncertainty. *Manage Sci* 61: 3–18.

Durmaz N (2015) Industry Level J-Curve in Turkey. *J Econ Stud* 42: 689–706.

Engle RF, Granger CWJ (1987) Cointegration and Error Correction: Representation, Estimation, and Testing. *Econometrica* 55: 251–276.

Fama EF (1981) Stock returns, real activity, inflation and money. *Am Econ Rev* 71: 545–565.

Gogas P, Pragidis I (2015) Are there asymmetries in fiscal policy shocks?. *J Econ Stud* 42: 303–321.

Granger CWJ, Huang BN, Yang CW (2000) A bivariate causality between stock prices and exchange rates: Evidence from recent Asian flu. *Q Rev Econ Finance* 40: 337–354.

Groenewold N, Paterson JEH (2013) Stock prices and exchange rates in Australia: Are commodity prices the missing link?. *Aust Econ Pap* 52: 150–170.

Gregoriou A (2017) Modelling non-linear behaviour of block price deviations when trades are executed outside the bid-ask quotes. *J Econ Stud* 44: 206–213.

Istiak K, Alam MR (2019) Oil prices, policy uncertainty and asymmetries in inflation expectations. *J Econ Stud* 46: 324–334.

Kang W, Ratti R (2013) Oil Shocks, Policy Uncertainty and Stock Market Return. *Int Financ Mark Inst Money* 26: 305–318.

Ko J-H, Lee C-M (2015) International Economic Policy Uncertainty and Stock Prices: Wavelet Approach. *Econ Lett* 134: 118–122.

Lima L, Foffano C, Vasconcelos J, et al. (2016) The quantitative easing effect on the stock market of the USA, the UK and Japan: An ARDL approach for the crisis period. *J Econ Stud* 43: 1006–1021.

Lin CH (2012) The co-movement between exchange rates and stock prices in the Asian emerging markets. *Int Rev Econ Financ* 22: 161–172.

Liu HH, Tu TT (2011) Mean-reverting and asymmetric volatility switching properties of stock price index, exchange rate and foreign capital in Taiwan. *Asian Econ J* 25: 375–395.

McFarlane A, Das A, Chowdhury M (2014) Non-linear dynamics of employment, output and real wages in Canada: Recent time series evidence. *J Econ Stud* 41: 54–568.

Moore T, Wang P (2014) Dynamic linkage between real exchange rates and stock prices: Evidence from developed and emerging Asian markets. *Int Rev Econ Financ* 29: 1–11.

Nieh CC, Lee CF (2001) Dynamic relationship between stock prices and exchange rates for G-7 countries. *Q Rev Econ Financ* 41: 477–490.

Nusair Salah A (2017) The J-curve Phenomenon in European Transition Economies: A Nonliear ARDL Approach. *Int Rev Appl Econ* 31:1–27.

Olaniyi C (2019) Asymmetric information phenomenon in the link between CEO pay and firm performance: An innovative approach. *J Econ Stud* 46: 306–323.

Pan MS, Fok RCW, Liu YA (2007) Dynamic linkages between exchange rates and stock prices: Evidence from East Asian markets. *Int Rev Econ Financ* 16: 503–520.

Pastor L, Veronesi P (2013) Political Uncertainty and Risk Premia. *J Financ Econ* 110: 520–545.

Pesaran MH, Shin Y, Smith RJ (2001) Bounds Testing Approaches to the Analysis of Level Relationships. *J Appl Econ* 16: 289–326.

Phylaktis K, Ravazzolo F (2005) Stock prices and exchange rate dynamics. *J Int Money Financ* 24: 1031–1053.

Richards ND, Simpson J, Evans J (2009) The interaction between exchange rates and stock prices: An Australian context. *Int J Econ Financ* 1: 3–23.

Shin Y, Yu B, Greenwood-Nimmo M (2014) Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework. In *Festschrift in Honor of Peter Schmidt*, Springer, New York, NY, 281–314.

Tsagkanos A, Siriopoulos C (2013) A long-run relationship between stock price index and exchange rate: A structural nonparametric cointegrating regression approach. *J Int Financ Mark Inst Money* 25: 106–118.

Tsai IC (2012) The relationship between stock price index and exchange rate in Asian markets: A quantile regression approach. *J Int Financ Mark Inst Money* 22: 609–621.

Wang Y, Chen CR, Huang YS (2014) Economic Policy Uncertainty and Corporate Investment: Evidence from China. *Pac-Basin Financ J* 26: 227–243.

Wimanda RE (2014) Threshold effects of exchange rate depreciation and money growth on inflation: Evidence from Indonesia. *J Econ Stud* 42: 196–215.

Yau HY, Nieh CC (2006) Interrelationships among stock prices of Taiwan and Japan and NTD/Yen exchange rate. *J Asian Econ* 17: 535–552.