



SENIOR RESEARCH

Topic: Measuring Economic Impact of Political Protest by Using The
Global Database of Events Languages and Tone (GDELT)

Name: Sirirut Sonjai

ID: 564 59192 29

Advisor: Pongsak Luangaram, Ph.D.

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Chairman

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Measuring Economic Impact of Political Protest by Using The Global Database of Events Languages and Tone (GDELТ)¹

Sirirut Sonjai

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Abstract

This paper address the key question whether political protests significantly affect the economy and how long that the effects will spread in the case of Thailand. By scoping into one dimension of political events that categorized by CAMEO ontology in the Global Database of Events Languages and Tone (GDELТ) dataset, the impact from political protest will be examined by vector autoregression analysis. The results suggest that political protests significantly affect real economy mainly through import and investment channel respectively. In particular, one standard deviation shock from political protests could make GDP drop as much as 1.41% one year after the events. In addition, confidence of foreign investment drops substantially in no time but the effects dissipate faster compared to real economy.

¹ This research is a research project submitted to the undergraduate degree, Faculty of Economics, Chulalongkorn University.
Email: Sirirutsonjai@gmail.com

This is my first time using SQL programming to construct the political intensity. All errors are mine.

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1. Introduction

“We are dealing with a world where change is ever greater, where the future is less predictable”².

The world under VUCA, which represents volatility, uncertainty, complexity and ambiguity, is the hardest time for making any policy decisions. One of the problems arising is that for many decades we believed that the world is predictable. However, existing political repercussion and economic outcome are reversal from initial assumptions and beliefs. It is essential to understand underlying relationship between socio-political factors and economic performance. Hence, several studies try to measure the relationship between political instability and economic activities. However, the measurements of political stability not thoroughly reflect the momentum from society. With the advancement in machine learning, it is possible to capture the social events from the whole population of online newspaper articles, which means every country at every point in time by using the Global Database of Events Languages and Tone (GDELT) dataset.

This paper aims to measure one dimension of political instability, which is ‘the intensity of protests’ in Thailand from the Global Database of Events Languages and Tone (GDELT), and estimate the impact on the real economy and foreign investment in the capital market. The remaining sections are structured as follows. Section 2 provides a review of existing literatures. Section 3 and 4 discusses the measurement of protest intensity and the results obtained from the Global Database of Events Languages and Tone (GDELT). Section 5 presents the empirical results of protests on the economy and capital market. Section 6 concludes.

² Leadership challenges in the V.U.C.A world, Pablo Tova

2. Literature Review

Economics and politics are intricately intertwined and often influence each other. The economic outcomes are one of the key factors that shape the political arena and economic decisions are seen through the lens of political beliefs. According to Acemoglu and Robinson (2013) both theoretical and empirical economic analyses have to acknowledge the conditions when politics and economics run into a conflict. It does not suffice to merely focus on costs and benefits, but one must also take the political consequences into account.

Economic growth and political stability are interconnected. The uncertainties that arise from unstable political circumstances could have detrimental effects on investment and economic development. On the contrary, a weak economic performance may lead to a political repercussion (Alesina et al., 1996). Several studies try to estimate the economic impact of political instability. Aisen and Veiga (2013) found that higher degrees of political instability would lower the rate of productivity growth, and the annual real GDP per capita growth rate will decrease by 2.39 percent after an additional change in cabinet. In addition, socio-political uncertainty influenced from income inequality will reduce investment by lowering productivity of labor and capital (Alesina and Perotti, 1996). Moreover, Ales and Chua (1997) show that political instability in neighboring countries can have significant negative effects on the economy. Their regional instability index indicates that an additional number of revolutions and coups per decade reduce income per capita by 17.6 percent because it will reduce trade flow and increase military outlays.

Even though there is much empirical evidence to suggest that political instability has negative effects on economic performance, Rose (1991) uses the theoretical framework to point out that political uncertainty can in fact benefit society. He argues that when policy makers have uncertain objectives from political instability could provide an incentive to set lower wage rate. Londregan and Poole (1990) suggest that political instability does not reduce growth. The propensity for a coup or past record of coups do not affect growth rate. In addition, economic growth is not significantly different when compared democracy to authoritarian regime (Alesina et al., 1996).

According to Jong-A-Pin (2009), political instability cannot be measured directly. Most studies have to use proxies such as the number of revolutions, coups d'état and assassinations for cross-country analysis. These indicators only capture some aspects of political instability and they are far from perfect. Using Exploratory Factor Analysis (EFA), he found that political instability measures could be classified

into four categories³ *i)* mass civil protest *ii)* politically motivated aggression *iii)* instability within the political regime *iv)* instability of the political regime. Matta et al., (2017) distilled this classification to investigate the effects of political regime crises and mass civil protest. They found that political crises followed by mass civil protest significantly affects output, and it does not recover within subsequent five years.

Recent works have been applying big data and text mining to capture the political uncertainty by measuring partisan conflict. Azzimonti (2015) constructed a high-frequency partisan conflict index⁴ from 1891 to 2013 by using newspaper articles, which reported about disagreements on policies in the United States. She found that partisan conflict significantly decreased unemployment, investment and output. Gentzkow et al. (2016) studied the partisanship by using structural estimation and machine learning to investigate US Congress language from 1873 to 2009. The partisanship of language substantially increased overtime, and it could lead to cross-party polarization both in Congress and the public.

Across the spectrum of existing literatures in this area, the empirical studies of political uncertainty are rarely found in the case of Thailand, even though the country has been ranking among the highest number of constitutional changes and military coup d'etats in the world since 1932. Hence, this paper aims to measure political instability in Thailand. In particular, the protest intensity from The Global Database of Events Languages and Tone (GDELT) that uses the most sophisticated deep learning algorithms to date. The paper will utilize the database of electronic articles at every point in time since 1979. Protest intensity index will be constructed and used to estimate the impact on economy and capital market.

³ See table 1 in appendix

⁴ Partisan conflict index: <https://www.philadelphiafed.org/research-and-data/real-time-center/partisan-conflict-index>

3. Data

“GDELT uses some of the world's most sophisticated natural language and data mining algorithms, including the world's most powerful deep learning algorithms, to extract more than 300 categories of events, millions of themes and thousands of emotions and the networks that tie them together.”

(Leetaru and Schrod, 2013)

The Global Database of Events Languages and Tone (GDELT)⁵ is constructed from printed, broadcast, and electronic news from every country since 1979 and updated every 15 minutes. With approximately 250 million observations, it is the first global event database that can trace back multi-decade, using machine translation to monitor streaming news in 65 languages. GDELT records more than 300 categories of georeferenced events and associated 58 attributes⁶ such as average tone or involved figures.

The Textual Analysis By Augmented Replacement Instructions (TABARI) system is used to extract important keywords from archived articles, quantitatively codify the attributes and categorize into event codes based on pattern recognition. The system will capture three distinct types of information, which are actors, verbs and phrases. Actors represent the interacting figures or organizations reported in the articles, and phrases provide contexts that determine syntactic information on the geolocation within sentences. Most importantly, the system will assign “event code” to the verbs that signify performed action between actors. Event code is classified by the Conflict and Mediation Event Observations (CAMEO) ontology and stored in CAMEO coding format (Gerber et al., 2002). CAMEO is developed to code events related to mediation of violent conflict and international interaction. The assigned code numbers are ranging from the level of cooperation to the severity of conflict along with specific behaviors subcategory for more precise and inclusive.

However, Hammond and Weidmann (2014) pointed out that datasets generated from automated coding techniques could be different from human-coded ones. The data from machine detected may fail to extract events or instead capture ones that excluded from human coding because of ambiguity and non-standard language patterns. Moreover, without understanding context and background information,

⁵ Full database can be downloaded from <http://www.gdelproject.org>

⁶ Codebook can be obtained from http://data.gdelproject.org/documentation/GDELT-Data_Format_Codebook.pdf

automatic algorithms are much less selective as they entirely rely on sources from single article. Discrepancies can also happen even though events are included in machine and human coded datasets owing to coding approach. Automatic geo-referencing process is far from perfect and contains errors from the difficulties to distinguish locational information of articles and the event's position. The findings suggest that GDELT has mediocre correlation with the GED (Sundberg and Melander, 2013) and ACLED (Raleigh et al., 2010) which are human coded data on political events.

GDELT advantages are manifold but we have to use it with caution. It is the first time that comprehensively monitors the behavior and driving force of global scale events from micro-level foundation which human coding cannot achieve. With close to real time and quantitatively rich database, several studies leverage these benefits to understand comparative social behavior and political events. Yonamine (2013) studied dynamics of large-scale political violence in Afghanistan to predict future violence intensity and understand the variation in Tel Aviv 100 index return. Franklin (2014) assessed factors of regime change from impact of protest waves by understanding context of democratic revolutions.

The attributes that are specific to this paper are '*EventRootCode = 14*' representing 'protest' and '*ActionGeo_CountryCode= TH*' representing the country 'Thailand'. By assigned the CAMEO code, these can capture an action among the figures mentioned in the article that happened in the origin of events. The algorithm will extract the event that related to a protest or demonstration, for example⁷ the statements:

“ Palestinian riots against Israeli military policies are still continuing with no end in sight.”

In this case, *EventCode* is *1452* representing 'Engage in violent protest to demand policy change' which is sub-event under category '*EventRootCode 14*'. The following are the whole domain of protest and associated CAMEO code used in this study.

⁷ List of all event codes and example: <http://data.gdelproject.org/documentation/CAMEO.Manual.1.1b3.pdf>

- 14 Protest
- 140 Engage in political dissent, not specified below
- 141 Demonstrate or rally
- 1411 Demonstrate for leadership change
- 1412 Demonstrate for policy change
- 1413 Demonstrate for rights
- 1414 Demonstrate for change in institutions, regime
- 142 Conduct hunger strike, not specified below
- 1421 Conduct hunger strike for leadership change
- 1422 Conduct hunger strike for policy change
- 1423 Conduct hunger strike for rights
- 1424 Conduct hunger strike for change in institutions, regime
- 143 Conduct strike or boycott, not specified below
- 1431 Conduct strike or boycott for leadership change
- 1432 Conduct strike or boycott for policy change
- 1433 Conduct strike or boycott for rights
- 1434 Conduct strike or boycott for change in institutions, regime
- 144 Obstruct passage, block
- 1441 Obstruct passage to demand leadership change
- 1442 Obstruct passage to demand policy change
- 1443 Obstruct passage to demand rights
- 1444 Obstruct passage to demand change in institutions, regime
- 145 Protest violently, riot
- 1451 Engage in violent protest for leadership change
- 1452 Engage in violent protest for policy change
- 1453 Engage in violent protest for rights
- 1454 Engage in violent protest for change in institutions, regime

Hence, This paper will utilize the richness of GDELT protest measurement to construct the protest intensity in Thailand from January 1979 to April 2017 in the next section.

4. Protest Intensity

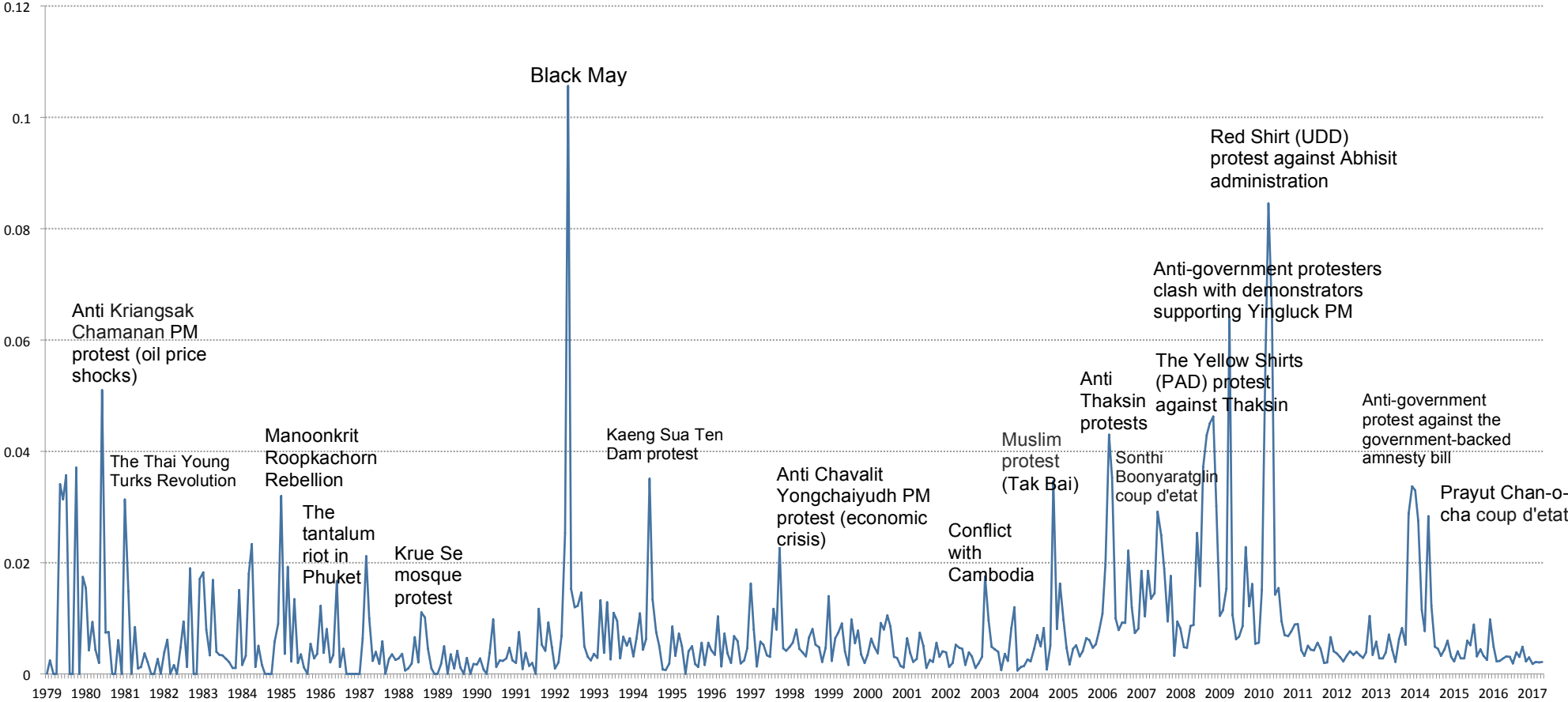
What is political protest and how can we measure it? This section will discuss the concept of political protest and instruments to measure it. Following the discussion, protest intensity index in Thailand obtained from GDELT dataset will be illustrated.

First of all, political protest is considered as ‘unconventional political participation’ that happen without intermediary actors. It is direct action from wide array of societal agents to alter or influence the current state of affairs (Della Porta and Diani 2006). Protests have to be organized by civil society, not the governmental actors aiming for support. It requires some level of conflict, but not necessarily to achieve the objective (Tilly and Tarrow 2006).

Marsh (1974) first attempted to capture the ‘protest potential’, which is an extent of individual to participate protest actions, by measuring an incentive to choose between participate in strikes or refuse to pay taxes. Barnes and Kaase (1979) extended the previous study to include other forms of political participation such as boycotts and demonstration using Marsh’s framework. However, this scale is far from the real potential of protest and cannot compared among countries. After this, Protest Event Analysis (PEA) has gradually developed by scholars and played an important role to study social movement overtime. According to Hutter (2014), PEA is quantitative content analysis that turns words into numbers and can measure protests and social movements across geolocation. He comprehensively analyzed the evolution of hand-coded methodology to measure protests from newspaper articles. Most conventional coding procedures were suffered from sources selection bias and did not obtain enough representative samples of all events. The lack of high quality and frequency of protest data still persisted due to the availability of sources and speed of hand coding. Given the expanding sources of electronic news that can identify protest event, Hanna (2017) is the first one among social movement scholars that currently trying to use machine learning and natural language processing to extract the information of protests. The MPEDS (Machine-Learning Protest Event Data System) project is still developing and plans to extend its coverage to global new sources available for public in the near future.

After understanding the concept of political protest and existing measurements, the protest intensity of Thailand since 1979 is constructed from GDELT database and normalized by the total number of protest news in that period. This illustrated in Figure 1 below. The political protest index can capture important political events that followed by mass civil protest. The highest point of the index is in Black May when more than 50,000 people protested against Gen Suchinda Kraprayoon’s “undemocratic” rise to the premiership. International conflict also plays an important role in Thai media as we can see from the incidents in 2003 that Thailand has conflict with Cambodia.

Figure 1: Protest Intensity in Thailand since 1979



5. Empirical Results

This section will investigate the impact of protests on the economy. I use vector autoregression model (VAR) because VARs can express the dynamic relationship of variables in the model and indicate the magnitude of the political protest. It will allow us to test the hypothesis whether the shocks from a political protest will lead to weaker macroeconomic performance conditional on lags of variables in the model. The impact on the economy will be illustrated in impulse-response function as it can trace out the dynamic paths of variables in the system after the shocks from protest innovation.

5.1 Real Economy

Beginning the analysis by constructing VAR, I use quarterly data from 1993Q1 to 2016Q4. Although protest intensity index have been generated since 1979, the model starts from 1993 due to limitations in macroeconomic data. In order to recover the orthogonal shocks, I use the Cholesky decomposition as the following: the protest index, the log of SET index, interest rate, and GDP gap⁸. The baseline VAR specification includes two lags of all variables. Figure 2 illustrates impulse-response function of GDP when there is a political protest innovation one standard deviation, and also shows the persistence of protest shocks, with standard error of the forecasts relatively small compared to the magnitude.

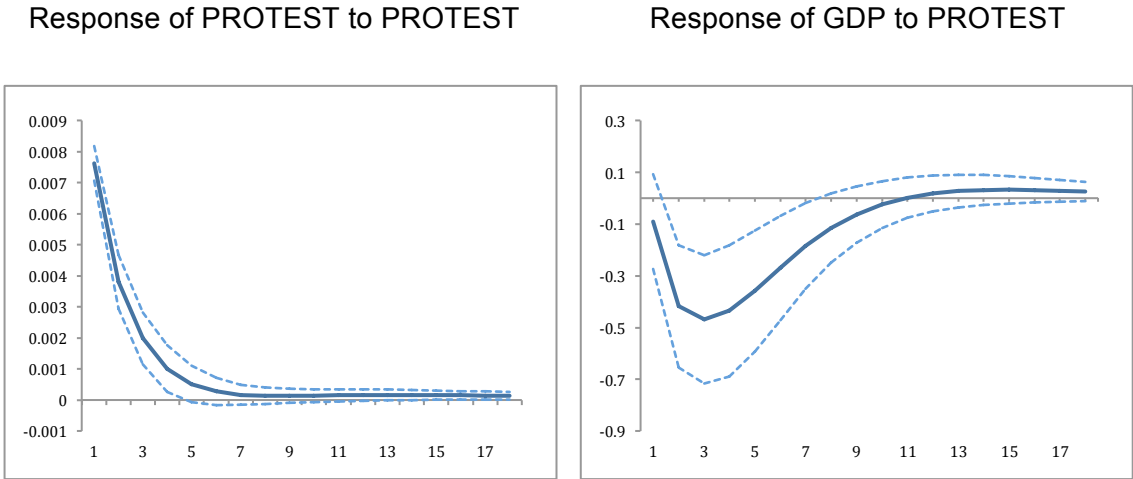


Figure 2: Impulse-response function of one S.D. protest innovation. Solid line: mean estimate; dashed lines: two-standard-error bands.

⁸ Potential GDP and GDP gap is obtained by applying Hodrick-Prescott (HP) filter to the quarterly GDP (seasonally adjusted). The restriction parameter λ is set at 1,600.

The response is statistically significant, the immediate impact of an increase in the protest index one S.D. is a decline in GDP 0.09% from the potential level. The largest effect occurs in the third quarter after the shocks, when the estimate drops to 0.46%. The economy fully recovered back to the potential level after 11 quarters. Considering cumulative effect, GDP will drop from its potential level to 1.41% 1 year after the shocks.

The basic VAR is now extended to investigate which components of real GDP are most affected by protest. This is achieved by using the same Cholesky decomposition and changing GDP gap from the potential level to private consumption, investment, imports, and exports gap⁹ from the potential level. Figure 3 illustrates the response of each component of GDP to the shocks. The graphs are presented on the same scale with one S.D. protest innovation for all cases.

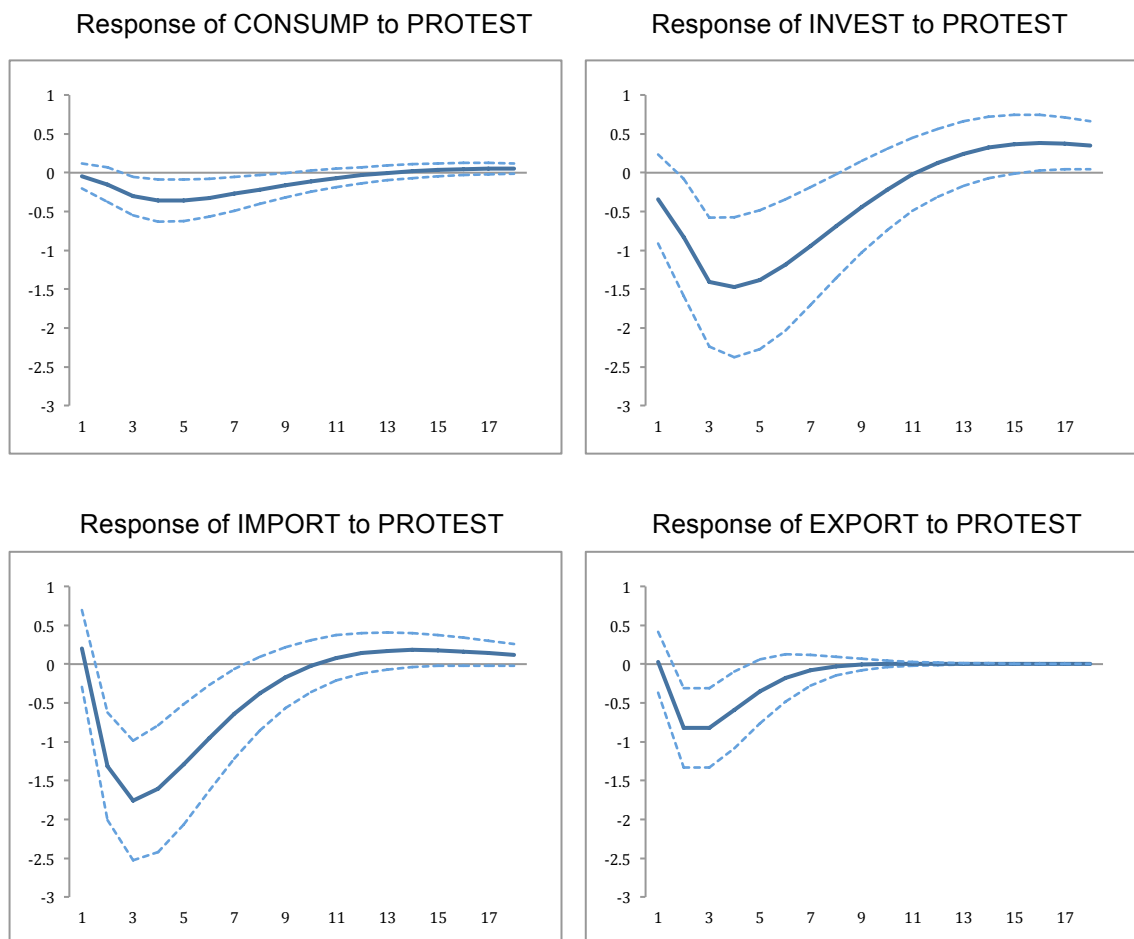


Figure 3: Impulse-response function of one S.D. protest innovation. Solid line: mean estimate; dashed outer lines: two-standard-error bands. Estimated using quarterly Cholesky VAR model with the protest index, the log of SET index, interest rate, and each component gap respectively.

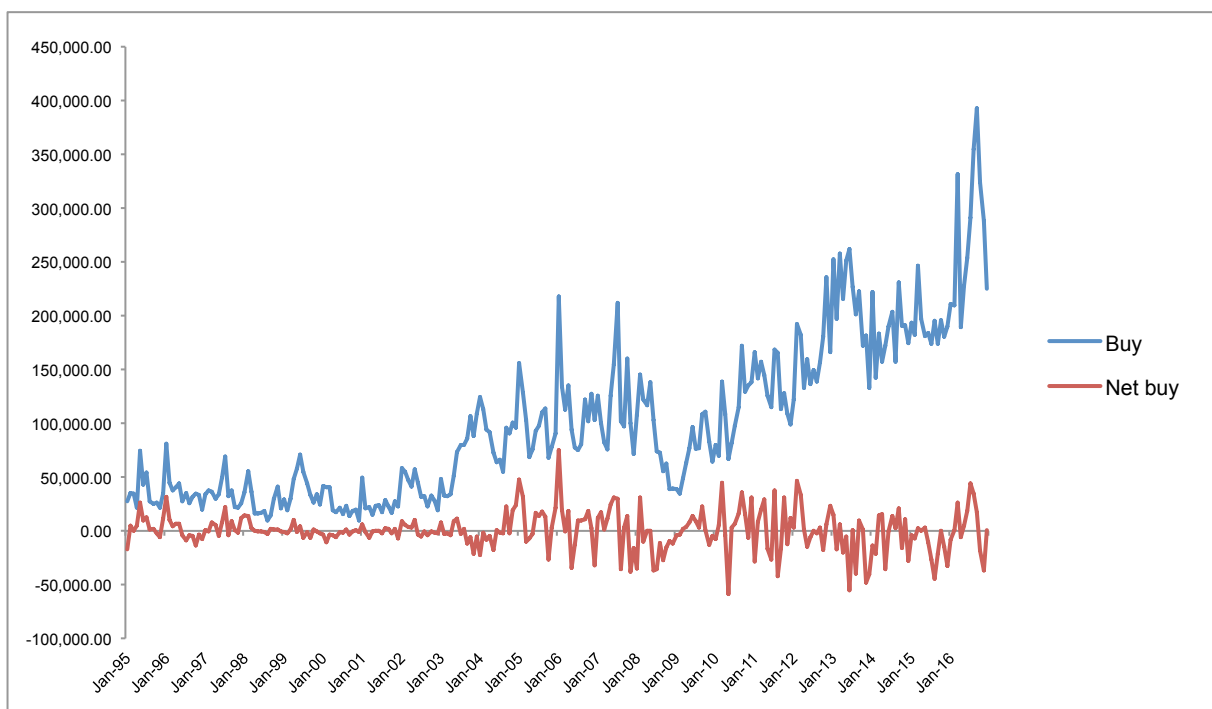
⁹ Using the same calculation as GDP gap

The results show that shocks from the protest largely impact on imports and investments. An innovation in the protest index lowers imports steeply, and it bottoms out after three quarters at approximately 1.76% below baseline. Imports eventually returned the potential level after ten quarters while investments are adjusted relatively slowly but take one more quarter to fully recover. In contrast, consumptions are only slightly decreased to 0.36% in four quarters after one S.D. protest innovation, but take more time to dissipate the effect in 12 quarter. Exports adjusted quickly compared to other components. It bottomed out from 0.82% after three quarters similar to imports but the effects dissipate more quickly in 7 quarters.

5.2 Capital Market

According to the Asian Development Bank Institute (ADBI), foreign capital flow had a stable trend with a low level of magnitude until 2004. After the Thai Baht's depreciation, the amount of inflow and outflow eventually declined to reach the lowest particularly in 2000 and net flows become negative a year later. In order to regain investors' confidence and to stabilize the exchange rate, the government tightened the monetary policy after "the Asian Financial Crisis" in 1997. However, it had adverse effects on the economy and discouraged foreign capital flow in Thailand. The magnitudes of inflow substantially expanded since 2005 and sharply declined in 2008 after the economic crisis. After the net flow rose back in 2009, the trend consistently increased and remained highly volatile depending on the level of confidence.

Figure 4: Foreign capital flow in Thailand



Source: The Stock Exchange of Thailand

At the outset, VAR is extended from the previous model to test the impact of political protest on foreign capital flow. I construct vector autoregression (VAR) model and fit a VAR to quarterly, seasonally adjusted data from 1995Q1 to 2016Q4 due to capital market data availability. Orthogonal shocks are recovered by using Cholesky decomposition as ordering: the protest index, the difference of foreign buy¹⁰, the log difference of SET index, interest rate and GDP gap. The estimation is done by using two lags of all variables. Figure 5 depicts the response of capital market variables to innovation one standard deviation in political protest index.

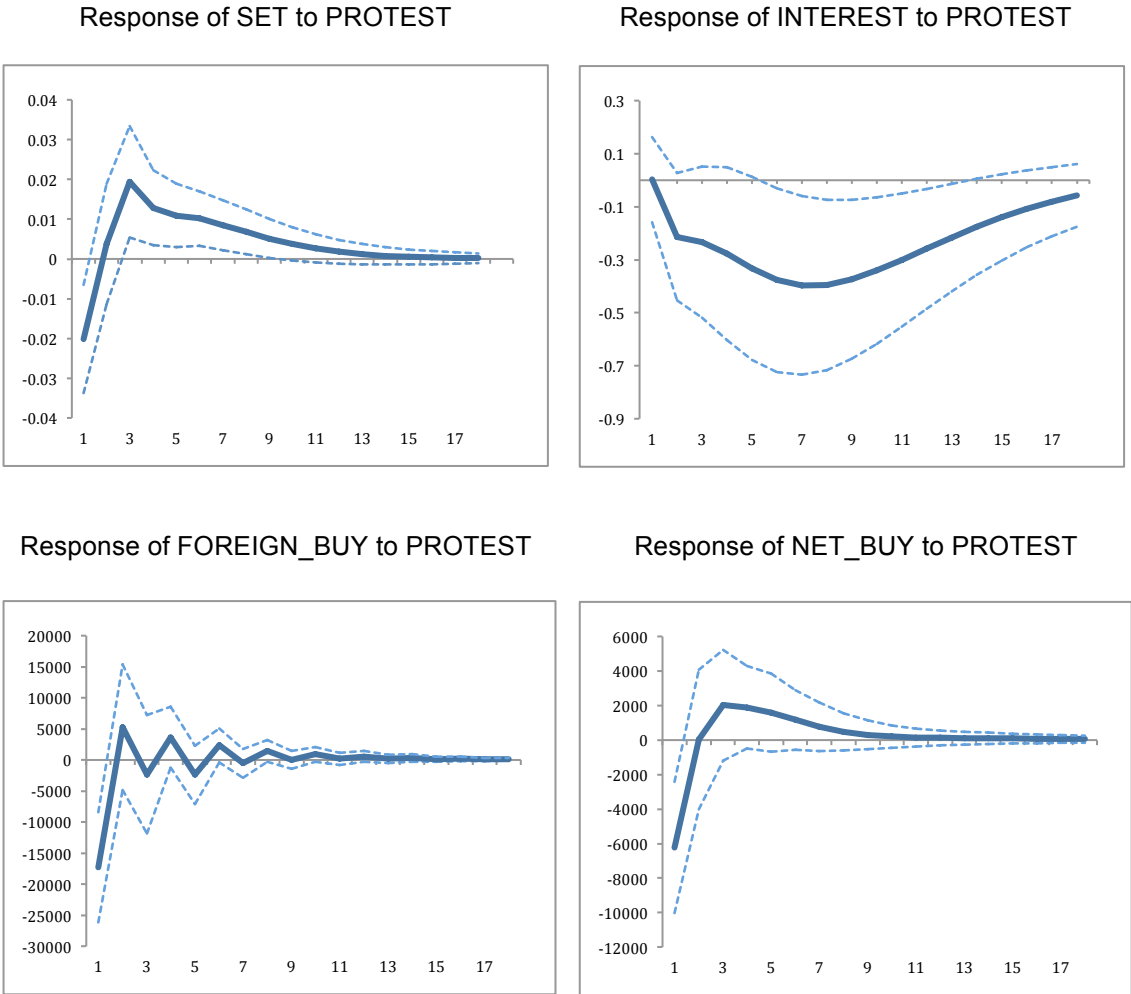


Figure 5: Impulse-response function of one S.D. protest innovation. Solid line: mean estimate; dashed outer lines: two-standard-error bands. Estimated using quarterly Cholesky VAR model with the protest index, the difference of foreign buy (in the case of net buy use: foreign net buy), the log of SET index, interest rate, and GDP gap respectively.

¹⁰ Construct another VAR estimation for the case of foreign net buy by using the same Cholesky decomposition but change from the difference of foreign buy to foreign net buy (foreign buy - foreign sell)

The results indicate that a typical innovation in protest index significantly lowers foreign capital inflows very sharply. The immediate impact of an increase in protest intensity one standard deviation is 0.37% fall in SET index. The effects on capital market are dissipated quickly in relation to real economy, and recovered two quarters after the protest shocks. Political protest immediately bring about 6.23 billion Baht of foreign capital outflows and cumulatively loss 2.27 billion Baht one year after the shocks because the confidence regain within six months back to positive net flows in the capital market.

6. Conclusion

Political uncertainty has increased overtime. Several literatures studied the causal relationship between political instability and economic impact and it is believed that political factors can have an adverse effect to the economy. Further understanding of the relationship between different political dimensions and economy is still needed. This paper try to explore the GDELT database that generated by most sophisticated algorithms and extracted the political events from online newspaper every country at every point in time since 1979. Because of high frequency and richness of the dataset, this paper try to estimate the impact of political events, in particular, the political protest in Thailand, on the economy and capital market by using vector autoregression model. The results indicate that political protest significantly affects macroeconomic performance and capital flows. One standard deviation shock from political protests make GDP drop 1.41% one year after the events. The protest impacts largely spread through imports and investments channel dropping from their potential level. Confidence of foreign investors is examined by using the flows of capital and stock market index. An immediate effect is larger than real economy but overtime the effect dissipate more quickly. Due to the time limitation, the study can expand to measure the impact on bonds market so that it can understand more broadly of the impact on financial sector. Moreover, other dimensions of political events recorded in GDELT need to be explored to understand the underlying socio-political causes in economic performance.

Appendix

Table1: political instability from Jong-A-Pin classification.

Indicator	definition	Source
Assassinations	Any politically motivated murder or attempted murder of a high government official or politician	Banks (2005)
Cabinet changes	The number of times in a year that a new premier is named and/or 50% of the cabinet posts are occupied by new ministers.	Banks (2005)
Civil war	dummy variable, 1 if at least 1000 battle related deaths per year in a conflict between the government of a state and internal opposition groups without foreign intervention and 0 otherwise.	Gleditsch et al. (2002)
Coups d'etat	The number of extraconstitutional or forced changes in the top government elite and/or its effective control of the nation's power structure in a given year.	Banks (2005)
Major government crises	Any rapidly developing situation that threatens to bring the downfall of the present regime, excluding situations of revolt aimed at such overthrow	Banks (2005)
Demonstrations	Any peaceful public gathering of at least 100 people for the primary purpose of displaying or voicing their opposition to government policies or authority, excluding demonstrations of a distinctly anti- foreign nature	Banks (2005)
Ethnic tensions	An assessment of the degree of tensions within a country which is attributable to racial, nationality or language divisions	ICRG
Executive changes	The number of times in a year that effective control of the executive Dower changes hands.	Banks (2005)
Fractionalization	The probability that two deputies picked at random from the legislature will be of different parties.	Beck et al. (2001)
Government Stability	An assessment of the governments ability to carry out its declared programs and its ability to stay in office	ICRG
Guerilla warfare	Any armed activity, sabotage, or bombings carried on by independent bands of citizens or irregular forces and aimed at the overthrow of the present regime.	Banks (2005)
Internal conflicts	an assessment of political violence in the country and its actual or potential impact on governance	ICRG

Major constitutional changes Medium civil conflicts	The number of basic alterations in a state's constitutional structure, the extreme case being the adoption of a new constitution that significantly alters the prerogatives of the various branches of government. Dummy variable, 1 if there are more than 25 battle related deaths per year and a total conflict history of more than 1000 battle related deaths, but fewer than 1000 per year (between the government of a state and internal opposition groups without foreign intervention) and 0 otherwise	Banks (2005) Gleditsch et al. (2002)
Minor civil conflicts	Dummy variable, 1 if there are at least 25 battle related deaths per year for every year in the period in a conflict between the government of a state and internal opposition groups, without foreign intervention and 0 otherwise	Gleditsch et al. (2002)
Number of elections Polarization	The number of elections held for the lower house of a national legislature in a given year. Maximum polarization between the executive party and the four principle parties of the legislature.	Banks (2005) Beck et al. (2001)
Years of ruling party in office Purges	Number of years that the party of the chief executive has been in office Number of systematic repressions (or eliminations) by jailing or execution of political opposition within the rank of the regime or the opposition	Beck et al. (2001) Banks (2005)
Regime changes (I)	Dummy variable, 1 if the variable "durable" is 0 in the polity IV dataset, which means that a new regime has started or that the state is in anarchy, 0 otherwise	Polity IV
Regime changes (II) Religious tensions Revolutions	Dummy variable, 1 if according to the Banks data archive the type of regime has changed An assessment of the degree of tensions within a country which is attributable to religious divisions Any illegal or forced change in the top governmental elite, any attempt at such a change, or any successful or unsuccessful armed rebellion whose aim is independence from the central government.	Banks (2005) ICRG Banks (2005)
riots	Any violent demonstration or clash of more than 100 citizens involving the use of physical force	Banks (2005)
Number of veto players who drop from office Strikes	The percent of veto players that drop from the government given the senate does not change Any strike of 1,000 or more industrial or service workers that involves more than one employer and that is aimed at national government policies or authority.	Beck et al. (2001) Banks (2005)

Sources: Jong-A-Pin (2009)

References

- Abadie, A., & Gardeazabal, J. (2003). The economic costs of conflict: A case study of the Basque Country. *The American Economic Review*, 93(1), 113-132.
- Acemoglu, D., & Robinson, J. A. (2013). Economics versus politics: Pitfalls of policy advice. *The Journal of Economic Perspectives*, 27(2), 173-192.
- Ades, A., & Chua, H. B. (1997). Thy neighbor's curse: regional instability and economic growth. *Journal of Economic Growth*, 2(3), 279-304.
- Aisen, A., & Veiga, F. J. (2013). How does political instability affect economic growth?. *European Journal of Political Economy*, 29, 151-167.
- Alesina, A., & Perotti, R. (1996). Income distribution, political instability, and investment. *European economic review*, 40(6), 1203-1228.
- Alesina, A., & Rodrik, D. (1991). *Distributive politics and economic growth* (No. w3668). National bureau of economic research.
- Alesina, A., Özler, S., Roubini, N., & Swagel, P. (1996). Political instability and economic growth. *Journal of Economic growth*, 1(2), 189-211.
- Ali, A. M. (2001). Political instability, policy uncertainty, and economic growth: An empirical investigation. *Atlantic Economic Journal*, 29(1), 87-106.
- Azzimonti, M. (2015). *Partisan Conflict and Private Investment* (No. 21273). National Bureau of Economic Research.
- Azzimonti, M., & Talbert, M. (2014). Polarized business cycles. *Journal of Monetary Economics*, 67, 47-61.
- Baker, S. R., Bloom, N., & Davis, S. J. (2015). *Measuring economic policy uncertainty* (No. w21633). National Bureau of Economic Research.
- Barnes, S. H., & Kaase, M. (1979). Political action. *Beverly Hills: Sage*, 381-447.
- Benhabib, J., & Rustichini, A. (1996). Social conflict and growth. *Journal of Economic growth*, 1(1), 125-142.
- Benson, M., & Rochon, T. R. (2004). Interpersonal trust and the magnitude of protest: A micro and macro level approach. *Comparative Political Studies*, 37(4), 435-457.
- Brunetti, A. (1997). Political Variables in Cross-country Growth Analysis. *Journal of Economic Surveys*, 11(2), 163-190.
- Carmignani, F. (2003). Political instability, uncertainty and economics. *Journal of Economic Surveys*, 17(1), 1-54.
- Dalton, R. J. (2005). The social transformation of trust in government. *International Review of Sociology*, 15(1), 133-154.
- Della Porta, D., & Diani, M. (2009). *Social movements: An introduction*. John Wiley & Sons.
- Disyatat, P., & Vongsinsirikul, P. (2003). Monetary policy and the transmission mechanism in Thailand. *Journal of Asian Economics*, 14(3), 389-418.
- Fosu, A. K. (2001). Political instability and economic growth in developing economies: some specification empirics. *Economics Letters*, 70(2), 289-294.

- Franklin, J. (2014). Democratic revolutions and those that might have been: Comparing the outcomes of protest waves under authoritarian rule.
- Gentzkow, M., Shapiro, J. M., & Taddy, M. (2016). *Measuring polarization in high-dimensional data: Method and application to congressional speech* (No. w22423). National Bureau of Economic Research.
- Hammond, J., & Weidmann, N. B. (2014). Using machine-coded event data for the micro-level study of political violence. *Research & Politics*, 1(2), 2053168014539924.
- Hutter, S. (2014). Protest event analysis and its offspring.
- Hanna, A. (2017). MPEDS: Automating the Generation of Protest Event Data.
- Jiang, L., & Mai, F. (2014, April). Discovering bilateral and multilateral causal events in GDELT. In *international conference on social computing, behavioral-cultural modeling, and prediction, Washington, DC*.
- Jong-A-Pin, R. (2009). On the measurement of political instability and its impact on economic growth. *European Journal of Political Economy*, 25(1), 15-29.
- Kawai, M., & Lamberte, M. B. (Eds.). (2010). *Managing capital flows: the search for a framework*. Edward Elgar Publishing.
- Leetaru, K., & Schrodtt, P. A. (2013, April). Gdelt: Global data on events, location, and tone, 1979–2012. In *ISA Annual Convention* (Vol. 2, No. 4).
- Londregan, J. B., & Poole, K. T. (1990). Poverty, the coup trap, and the seizure of executive power. *World politics*, 42(02), 151-183.
- Luangaram, P., Sethapramote, Y. (2017). The Price of Political Uncertainty in Thailand.
- Madestam, A., Shoag, D., Veuger, S., & Yanagizawa-Drott, D. (2013). Do political protests matter? evidence from the tea party movement. *The Quarterly Journal of Economics*, qjt021.
- Marsh, A. (1974). Explorations in unorthodox political behaviour: a scale to measure “protest potential”. *European Journal of Political Research*, 2(2), 107-129.
- Matta, S., Appleton, S., & Bleaney, M. (2017). *The Economic Impact of Political Instability and Mass Civil Protest* (No. 2017-03).
- Quaranta, M. (2015). *Political Protest in Western Europe: Exploring the Role of Context in Political Action*. Springer.
- Rose, J. (1991). Political uncertainty and macroeconomic performance. *Economics Letters*, 37(4), 377-381.
- Schintler, L. A., & Kulkarni, R. (2014). Big data for policy analysis: the good, the bad, and the ugly. *Review of Policy Research*, 31(4), 343-348.
- Schrodtt, P. (2012). Conflict and Mediation Event Observations event and actor codebook V. 1.1 b3.
- Stock, J. H., & Watson, M. W. (2001). Vector autoregressions. *The Journal of Economic Perspectives*, 15(4), 101-115.
- Yonamine, J. E. (2013). *A nuanced study of political conflict using the Global Datasets of Events Location and Tone (GDELT) dataset* (Doctoral dissertation, The Pennsylvania State University).