Policy Agendas and Financial Markets: An Aggregate Level Analysis of Stock Market Reactions to Issue Attention Dynamics

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Stock markets translate information about firm's current and future performances into firm valuations. Firms' performances are affected by numerous factors, among which public policy decisions play a prominent role. Policy changes create winners and losers, and the market participants try to deduce whether the whole market, some industry or a specific firm is on the winner or the loser side. In this dissertation, I study stock market reactions to the changes in the dynamics of policy agendas. I focus on the attention allocation stage of the policy process and I argue policy actors' attention allocation across issue topics will affect investors' expectations; thus, I expect issue attention allocation dynamics will affect pricing action.

I study a few specific questions related to the asset pricing implications of issue attention dynamics. First, I analyze how attention diversity in legislative processes affect stock return volatility. Second, I analyze how the extent of short-term changes in issue attention allocation affect the mean and volatility of aggregate stock returns. Third, I analyze how salience of policy reform issues, such as tax reform and healthcare reform, affect the mean and volatility of aggregate stock returns. Last, I analyze how the level of noisy politics, i.e. the overall salience of high salience political issues – affect aggregate volatility and trading activity. The findings from those analyses largely support my argument that issue attention allocation dynamics will have asset pricing implications.

This study also introduces new ways to measure attention changes and issue salience. I use multidimensional similarity metrics to measure macro level short-term changes in attention allocation. I also develop an index of noisy politics, which aims to capture the overall attention to high salience political issues. I use these novel measurements to study how stock markets react to issue attention and salience dynamics.

Dedication

For my parents Rukiye and Özkan

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Chapter 1: Introduction

1.1 The Policy Process and the Financial Markets

Stock markets run on information generated by processes that might affect the current and future performances of firms. One of these processes is the policy process which translates inputs from many different policy actors such as the electorate, interest groups, and politicians into policy decisions. Predicting the outputs of the policy process is an important task for market participants. Any process or event that generate information about the content and timing of future policy outputs, such as election polls, election results, or policymakers' speeches, might affect stock pricing dynamics. In this dissertation, I study the asset pricing implications of a political process that might generate price-relevant information to the markets. Attention allocation decisions by policymakers and other policy actors provide price-relevant information because changes in policy agendas might affect expectations about the timing of policy change, the direction of policy change, and the extent of policy change. I argue that stock markets will react to changes in the structure of policy actors' attention allocation.

In modern advanced economies, stock markets play an essential role in the allocation of resources. In some economies, a large share of the population has investment in the stock market, and many firms use stock markets to finance their investments and operations (Demirguc-Kunt and Levine, 1999). Therefore, in those countries, the financial health of households and firms might be sensitive to the performance of stock markets. If a considerable share of the population and firms has exposure to the stock markets, then it might be difficult for the society and the politicians to ignore the behavior of the stock markets. Especially in countries with a market-based financial system, the stock market might also be used as a reference to gauge the health of the national economy.

The stock market can be described as an information processing machine that translates information from the environment – i.e. the economic, political and other realms outside the markets – into stock prices. The developments in the political environment can be an important source of price-relevant information. Governmental actors' policy decisions have the power to affect future cash flows; thus, investors tend to pay close attention to what happens in the political environment. The political economy of asset pricing literature provides many examples where developments in the political environment had asset pricing implications (Leblang and Mukherjee, 2004; Jensen and Schmith, 2005; Jensen, 2007; Snowberg, Wolfers, and Zitzewitz; Bernhard and Leblang, 2006; Füss and Bechtel, 2008; Bechtel, 2009; Sattler, 2013). A common topic in that literature is the effect of a change in the partisan orientation of government on the return and volatility of stocks or on other financial market outcomes, such as interest rates and exchange rate volatility (Leblang and Mukherjee, 2005; Jensen and Schmith, 2005; Sattler, 2013). Another large strand of literature focuses on the institutional sources of variation in stock market related outcomes (Bernhard and Leblang, 2002; Bittlingmayer, 1998; Hays et al., 2003). Due to the slow changing nature of institutions, this literature has a more long-term focus. While these research efforts have shown important links between politics and markets, the political economy of asset pricing literature has not gone much beyond the partisan and institutional explanations. My dissertation contributes to this literature by shifting the focus to dynamics of the policy process which can be independent from partisan and institutional dynamics of politics.

Policy-relevant information flow into the policy process is much larger than the information processing capacity of a policy system; thus, policymakers must choose a subset of the policy issues to include in their policy agendas. This is the issue attention allocation stage of the policy process, and the policy issues that are selected in this stage go into the agendas of policy actors. A stylized fact in the policy agendas literature is the stick-slip pattern in issue attention allocation stage, which is argued to be driven largely by cognitive constraints and to some extent by the institutional constraints (Jones and Baumgartner, 2005). There is a large literature investigating the implications of attention allocation related factors for the policy outputs. In this dissertation, I focus on issue attention allocation related factors that provide information about the stick-slip conditions in a policy system, and I analyze the asset pricing implications of attention allocation related factors. The structure of attention distribution across policy issue topics is the central focus of the analyses in the three empirical chapters of this dissertation. I specifically focus on the diversity of attention across issue topics, the extent of short-term changes in attention allocation, the salience of policy reforms issues, and the overall salience of high salience issues.

1.2 Literature Review

The political economy of asset pricing literature is relatively new, but the growth of the literature has been stagnant for a long time. The explanatory toolkit of the literature largely consists of partisanship and institutions related variables (Bernhard and Leblang, 2002; Bittlingmayer, 1998; Hays et al., 2003; Leblang and Mukherjee, 2004; Jensen and Schmith, 2005; Jensen, 2007; Snowberg, Wolfers, and Zitzewitz; Füss and Bechtel, 2008; Bechtel, 2009; Sattler, 2013). These efforts revealed very interesting and substantively important relationships between politics and the markets, but the scope of politics in these studies is too limited. In addition to partisan and institutional explanations, there is a group of studies investigating the effects of political processes and political events, such as elections, coalition negotiations, and policy change announcements (Bernhard and Leblang, 2006). However, based on the arguments and findings in this branch of the literature, one might think policy change expectations only change during election campaign periods or during other political processes that precedes big changes in the composition of governments. Politics happen beyond these periods, and policy change expectations continue to evolve.

While the political science efforts to understand the politics and markets nexus has slowed down over time, recent developments related to the measurement of policy uncertainty (Baker, Bloom & Davis, 2015; Hassan et al., 2016) have substantially increased the interest of researchers from finance and economics to the nexus between politics and economic outcomes (Pastor & Veronesi, 2012; Pastor & Veronesi, 2013; Gulen & Ion 2015; Brogaard & Detzel, 2015; Kelly, Pastor & Veronesi, 2016; Hassan et al., 2016;). Most studies in this rapidly growing literature focus on the consequences of economic policy uncertainty on various economic outcomes, but they pay no attention to the specific political factors that might affect these outcomes through the channel of economic policy uncertainty or through other policy uncertainty channels. The political economy literature offers important insights as to the potential sources of policy uncertainty. However, this political economy literature is older than the economic policy uncertainty literature in finance, and these two literatures are largely disconnected from each other.

Incorporating uncertainty to the models of investment decisions and asset pricing has been one of the most important innovations of the recent scholarship in finance and economics (Rodrik, 1991; Dixit & Pindyck, 1994). According to Dixit and Pindyck (1994) most investment decisions share three important characteristics: partial or complete irreversibility, uncertainty over future returns, and an option to invest now or later. As the degree of irreversibility of an investment increases, a larger share of the upfront investment costs will be sunk costs. An investor has two options at a certain time point: to invest now or delay the investment to a later period. By choosing to invest now, the investor foregoes the option of delaying the investment. An investor's decision to invest now or later will depend on the expected utility from investing now and the expected utility of delaying investment to the next period. Increasing uncertainty about the future profits and costs will make investors to demand a higher risk premium to compensate the extra risk they are going to take by deciding to invest now. Waiting until the next period will increase information about future profits and costs, and uncertainty will decline. This will cause a lower risk premium demanded by an investor. If the degree of irreversibility is low for an investment, then at least some portion of the initial cost could be recovered, and this would decrease the opportunity cost due to not choosing the delay option.

This model of investment significantly differs from the earlier models of investment particularly in terms of the role of uncertainty in determining the timing and amount of investment. According to the orthodox model of investment, an investment decision will be done if the present value of expected future revenues exceed the present value of expected future costs. In this model there is no uncertainty assigned to the future costs and profits. This applies to some of the asset pricing models, as well. Discounted cash flows valuation model has been one of the most commonly used asset pricing method, and the model underlying this method has a very similar logic to the orthodox capital investment theory. According to this valuation method, a company's current market value should be the present value of future cash flows. The earlier versions of this model do not assign uncertainty to future cash flows, and usually cannot account for the volatility patterns and risk premium in returns (French & Gabrielli, 2005).

Incorporation of uncertainty into traditional models improves predictability of volatility patterns and risk premiums in asset returns. Pastor & Veronesi (2012) develop an asset pricing under uncertainty model, but they constrain the source of uncertainty to politics. They define two political sources of uncertainty: policy change uncertainty and policy impact uncertainty. The latter one is activated when probability of policy change is positive. This work is part of a rapidly growing literature in finance about the impact of policy uncertainty on asset prices. While this literature focuses on developing good measurements of policy uncertainty and illuminating mechanisms of the causal process between policy uncertainty and asset prices, most works do not explicitly specify the political factors that create policy uncertainty patterns.

The political economy studies that try to explain the public policy output with political factors such as partisanship (Hibbs, 1975; Alesina, 1987; Hibbs, 1994), institutional structures (Przeworski, 1991; Tsebelis, 2003; Persson & Tabellini, 2004; Henisz, 2004) and political processes (Bernhard & Leblang, 2006) could help finding root causes of policy uncertainty and could help developing a more sophisticated explanation of market outcomes. However, political economy research on policy outcomes has slowed down and has been largely disconnected from the finance research on the asset pricing implications of public policies. Agenda setting literature has revealed that the dynamics of the agenda setting process create constraints to policy decisions which are different and independent from institutional or partisan constraints (Baumgartner & Jones, 2015). Political economy literature on policy outcomes has failed to appreciate the role of agenda dynamics on policy outcomes. This study is an attempt to fill this gap in the political economy literature, but also it is an attempt to build a bridge between largely disconnected political economy and finance research on policy uncertainty.

1.3 The Argument

Policy change expectations affect how stock markets behave. Discounted cash flow valuation model takes into account the expected future cash flow, which is likely to be affected by policy decisions today. Sometimes the effect of a policy decision on future cash flow is straightforward and less uncertain. For example, a tax cut will have a direct effect on the future earnings of firms by increasing or decreasing the size of the slice the government gets from the earnings of firm and consumers. However, for most policy decisions, the future cash flow effects are more complicated and more uncertain. For example, policy decisions about carbon emissions are likely to affect future cash flows of many firms, but the impact is likely to differ significantly across industries and sectors, which causes greater uncertainty on the aggregate market effects, and the impact will probably be induced by a more complicated network of mechanisms. Therefore, changes in the dynamics of the policy process that potentially affect the timing, the direction, and the extent of policy changes generally induce future cash flow uncertainty, which might translate into greater volatility in stock prices. In this dissertation, I argue that issue attention allocation dynamics will affect expectations about future policy changes and consequently expectations about future cash flows; thus, the stock market will react to changes in the issue attention allocation dynamics.

A structural property of issue attention allocation processes is the diversity of attention across different policy issue categories. Attention is scarce, and there are many issue that compete for the attention of policy actors. Big policy changes require big attention to the issue topic(s) underlying the reform process. Due to scarcity of attention, increases in attention to some issue topics during periods in which the policy system in a policy reform state generally leads to higher concentration (lower diversity) of attention. I argue that increasing concentration of attention in legislative processes will lead to greater market return volatility. The market will interpret increasing concentration (decreasing diversity) as a signal emitted by a policy reform state (policy stasis state), and due to higher (lower) impact uncertainty of bigger (incremental) policy changes, the uncertainty about future cash flow will increase (decrease). I argue this effect will be observed in the volatility of stock market returns, which is a function of fundamental uncertainty of a return process and cash flow uncertainty.

Another structural property of issue attention allocation processes is the instability of issue attention over time. Issue attention allocation changes are generally incremental, but sometimes punctuated changes happen. Attention instability is a property that can be measured at higher frequency and allows us to analyze short-term reactions of stock markets to short-term changes in issue attention allocation. I argue that when attention allocation is more instable in the short-term – i.e. more punctuated daily changes – the market participants' expectations of a larger policy change will increase, and this will lead to greater aggregate return volatility. Due to the negative relationship between short-term volatility and short-term returns, I also argue increasing attention instability will lead to lower aggregate return.

The most common way to study issue attention allocation and its consequences is to focus on a specific issue topic or a small number of issue topics that might be related to each other. Issue-specific attention allocation dynamics might be important for stock markets. The markets care more about some issue topics than others. For example, tax policy related issues generally get more attention from the market participants than other issues. The changes in the salience of a specific issue topic can sometimes be useful to explain volatility and return dynamics. During times when the policy system is in a reform state and the tax policy is the subject of the reform, fluctuations in the salience of tax reform topic will affect how the mean and volatility of the return process. The direction of these effects will depend on the aim of the reform. If the reform will introduce lower (higher) tax rates, then I argue increasing salience of tax reform topic will decrease (increase) volatility and increase (decrease) returns. These effects might be conditioned by salience of competing policy reform issues. Since big policy changes require concentrated attention on the issue topic which is the subject of reform, if the salience of issue topic(s) that compete for attention is also high, then the magnitude of the effects I mentioned above will be smaller.

In this dissertation, I also study how the stock market reacts to fluctuations in the overall salience of high-salience issue topics, which can be conceptualized as noisy politics (Culpepper, 2011). I argue that increasing attention to information flow about noisy politics issues will increase volatility and trading activity in the stock market. During times when noisy politics salience is high, there will be greater political information flowing into the markets, and this will generate greater political uncertainty and greater buying and selling activity, which will respectively manifest in stock markets as higher return volatility and higher trading volume.

1.4 Data

In this dissertation, I only focus on aggregate market reactions to agenda setting dynamics. My theory is not issue-specific and the large policy changes might affect many firms in a similar way; thus, I expect the implications of policy agenda changes to be observable at the market level. In all empirical analyses I present in this dissertation, I use variables related to the Standard and Poors 500 Index (S&P 500), which is widely used to gauge the aggregate stock market performance. In all chapters, I use the S&P 500 price data to analyze the return and volatility effects of issue attention allocation dynamics. In the second and fourth chapters, I also use the VIX index, which aims to capture the one-month ahead expected volatility of the S&P 500 Index. In third chapter, I also use trading volume of the S&P 500 Index, which I use to analyze the relationship between volume of political information flow and stock trading activity.

For issue attention related variables, I use data from the Comparative Agendas Project (CAP) and Google Trends. The CAP is a rich source of data related to issue attention dynamics at different levels of government, society, and the media (Bevan, 2019). From the CAP database, I use legislative issue attention data, and media issue attention data. In the fourth chapter, I use Google Trends data to measure the salience of specific policy reform issues, and the level of noisy politics.

1.5 Outline of the Dissertation

In the second chapter, I focus on attention allocation dynamics in legislative processes across five advanced democracies. I specifically focus on the question how the diversity of attention in legislative processes affect realized monthly volatility. I develop a model that characterizes how issue attention diversity dynamics translate into return volatility. In that model, I define two states of a policy system. The first state is the policy stasis state, which features relatively high attention diversity in the policymakers' attention allocation vector. The second state, which is the less likely state, is the policy reform state in which the policymakers' attention allocation vector feature low diversity (high concentration) across policy issue categories. The impact of issue attention diversity on volatility is transmitted through the mechanism of dividend uncertainty. In the policy reform state, there is greater uncertainty about the potential impacts of the expected policy change, which translates into greater uncertainty about firm performance and dividend uncertainty. Based on this model, I argue that greater issue attention diversity (concentration) will decrease lower (higher) realized monthly volatility. To test this argument, I use legislative issue attention data and monthly closing price data. The results suggest a delayed response of volatility to fluctuations in legislative attention diversity.

In the third chapter, I analyze how short-term issue attention changes affect aggregate stock market dynamics. The punctuated equilibrium studies in the policy agendas literature show that the distribution of the size of policy changes and the distribution of the size of attention changes both exhibit heavy-tailedness and high-peakedness, which are features of a system with long periods of stability and occasional bursts of large changes. Based on this relationship, I expect that the market actors will interpret large short-term changes in issue attention allocation as signals of approaching large policy changes, and this will cause greater uncertainty about the impact of future policy changes. Large attention changes sometimes might be a manifestation of the arrival of new issues to the policy agendas. In this scenario, I expect a similar effect due to greater uncertainty associated with new issues. I use daily prices of S&P 500 and data on the topic category of the New York Times front page articles to analyze the return and volatility implications of short-term issue attention changes. I found increasing instability of attention leads to greater return volatility and lower daily returns.

In the fourth chapter, I narrow my focus to a shorter time frame. I study how issue salience dynamics in the United States of America affected aggregate stock market outcomes during the post-2016 presidential election and the first year of Donald Trump's presidency. Tax reform and healthcare reform were among the largest items in Donald Trump's policy agenda during the election campaign period, and they continued to be among the most salient issues in all venues of the policy system during the first year of Donald Trump's presidency. If attention allocation affects the timing of policy change, then the fluctuations in attention to reform issues might have asset pricing implications. I argue that increasing salience of tax reform issue will positively affect the mean of returns and will negatively affect the variance of returns. I expect the opposite for the affect of the salience of health reform issue because of the greater impact uncertainty and lower desirability by the market. I find support to my expectations about market reactions to tax reform salience, but the support to my expectations about market reactions to healthcare reform salience is weaker. In that chapter, I also study the implications of noisy politics for the aggregate stock market behavior. I define noisy politics as the overall salience of the attention grabbing – i.e. high salience – political issues. I argue higher level of noisy politics will positively affect trading activity and return volatility. I develop a measure of noisy politics using Google Trends, and using that index I find strong evidence for the trading volume effect, but I find weak evidence for the volatility effect.

Chapter 2: Issue Attention Dynamics in Legislative Processes and Stock Return Volatility

2.1 Introduction

How do policy issue attention dynamics affect asset pricing dynamics? Numerous studies on the link between politics and asset pricing indicate stock markets respond to political news, but their understanding of politics is limited. Some set of studies present the impact of a specific event, such as an election, on stock price dynamics as evidence for the link between politics and stock markets. Another set of studies investigate the impact of political institutions and partisanship on stock market dynamics. While these efforts have produced valuable knowledge about the link between politics and stock markets, we do not have sufficient knowledge about the political determinants of short term variation in stock market dynamics. The first group of works are useful to explain sudden jumps in return and volatility of stock returns after significant events, and the second group of works can be useful to explain long term variation in those outcomes. In this chapter, I focus on policy issue attention dynamics, and particularly on the diversity of attention across issues at a certain time point in a policy system. I argue that greater concentration of attention allocation across policy issues will cause the volatility of stock returns to increase. Evidence from the issue attention literature indicate big policy changes are preceded by concentration of issue attention in the policy system. Policymakers' attention allocation across policy issues might contain important information about their policy priorities and the magnitude of potential policy change. Given that, the fluctuations in the diversity of issue attention allocation might be translated into fluctuations in asset pricing dynamics.

In this study I narrow my focus to the second moment of asset returns. I develop a model that characterizes the relationship between policy issue attention dynamics and stock return volatility. In the following section, I review the political economy of asset pricing literature. In the next section, I describe the basic architecture of the model, elaborate on the meaning and scope of the important concepts of the model, and formalize the process that translates issue attention allocation information into stock return volatility. In the final section, I test the main theoretical implication of the model empirically and discuss the results.

2.2 A Model of Asset Pricing Implications of Policy Issue Attention Dynamics

A common stock is a claim to uncertain stream of cash flows – i.e. dividends and capital gains. Asset pricing models try to explain the market price of a common stock at a certain time point (Cochrane, 2001). There are a considerable number of different modelling strategies used by scholars of asset pricing, however most of them rely on the discounted cash flows framework to explain the prices at a certain time. While older models assume a deterministic dividend process, more recent models assume that dividends are outputs of a stochastic process. Because of the uncertainty surrounding the stream of cash flows, the prices are determined by expectations about future payments. Since the underlying parameters of the stochastic dividend process – i.e. drift and volatility – are not directly observable, investors form beliefs about these parameters. An essential feature of learning models of asset pricing is the signal processing technology that is used to explain how beliefs are formed about an underlying parameter of the dividend process from the signals that are transmitted via news (Pastor and Veronesi, 2009). In a generic learning model of asset pricing positive news about a firm's performance move investors' beliefs about the mean profitability upwards, and negative news move their beliefs downwards. Another important input of belief updating functions is the precision of signals. Precise signals – i.e.

signals with low variance— lead to larger updating in prior beliefs, whereas vague signals – i.e. signals with high variance – lead to smaller updating in prior beliefs.

In a political economy model of asset pricing that utilizes the signal processing technology the news are related to the political conditions such as the likelihood and direction of policy change, magnitude of potential policy change, and also the impact of policies on economic outcomes. For example, in Pastor and Veronesi (2013) the agents – i.e. stock market investors – learn about the cost policymakers incur when they select a certain policy. They update their beliefs in a Bayesian fashion by using the information from the flow of political news. The agents' beliefs about the policymakers' cost shape their expectations about the policy change which in turn shape their valuation of stocks. When they observe signals that imply the cost of policy change is low, their belief about policy change increases, and the uncertainty surrounding the direction and impact of new policies translates into larger risk premium and higher volatility. The uncertainty about the costs policymakers incur is the source of political uncertainty in their political economy model of asset pricing. In the model I develop in this section, the source of political uncertainty is the structure of policymakers' issue attention allocation. Overwhelming evidence indicate that greater attention to a policy issue in various stages of policy making process usually translates into greater policy change on that issue (Peters & Hogwood, 1985; Klingemann, Hofferbert, and Bulge, 1994; Jones & Baumgartner, 2005; Walgrave & Nuytemans, 2009; Bevan, John & Jennings, 2011; Breunig, 2011; Brouard, 2013). One remarkable example by Klingemann, Hofferbert and Bulge (1994) which covers 40 years and ten countries shows that governments are more likely to increase public spending on issues to which they allocated attention in their manifestos, and also the magnitude of increase is proportional to the extent of attention.

Therefore, issue attention allocation of policymakers might carry important information about their policy priorities and their future policy decisions.

Policymakers have finite attention space which can be represented with a multidimensional vector whose elements are attention weights assigned to each policy issue that exists in the policy issue space. The below vector is a generalized example of an attention allocation vector.

$$A_t = \begin{bmatrix} a_{1t} \\ . \\ : \\ a_{jt} \end{bmatrix}$$

In this vector each row represents the share of total available attention a policymaking actor dedicates to policy issue category *i* at time *t*, or the average attention the members of a group of policymaking actors dedicate to the policy issue category *i* at time *t.* The sum of the weights are constant over time and normalized to one. Investors use various information that could be derived from this vector to form beliefs about the state of a policy system.

The outputs and the characteristics of the policy process in some policy subsystems, such as policy subsystems whose outputs are related to macroeconomic policy, potentially affect all firms in an economy. The risk that emanates from such policy processes are characterized as aggregate risk or market risk since all firms are exposed to it. However, the outputs of some policy subsystems, such as the renewable energy policy subsystem, only affect a subset of firms – i.e. a group of firms that consist an industry – in the economy and therefore the risk that emanates from such policy processes are characterized as industry risk. Firms are concerned about outputs of policy subsytems – i.e. policy decisions – that pose aggregate and industry level risk. The overall policy risk a firm is exposed to equals to the combination of aggregate and industry risk. This distinction between aggregate and industry risk is important because while industry risk could be eliminated to some extent via portfolio diversification, aggregate risk cannot be eliminated. In stochastic dividend process models these two risk components are treated separately and their effect on asset prices can be different. In this study I will analyze the aggregate level policy risk factors, and will focus on the information about the policy system in general.

In this model of the policy process, a policy system has two states. The first state is the policy stasis state *(L)* in which policymakers change the status quo slightly or keep the status quo. The second state is the reform state *(H)* in which policymakers change the status quo policy largely. A policy system is mostly in a policy stasis state, and occasionally in policy reform state. Many studies from the policy issue attention literature indicate that this representation of the states of the policy system is supported by empirical evidence from developed democracies (Jones & Baumgartner, 2005; Breunig and Koski, 2006; John & Margetts, 2003). The pattern described in these studies point to a leptokurtic distribution of policy change – typically measured as budgetary change – in which kurtosis and skewness are greater than a normal distribution. The leptokurtic distribution is usually interpreted as the evidence for punctuated equilibrium in public policy processes which refers to "long periods of policy stasis interrupted episodically with bursts of rapid policy change" (Jones & Baumgartner, 2004). An explanation of the leptokurtic distribution of policy change can be developed using the advocacy coalition framework. According to this approach the transition from the policy stasis state to the reform state occurs when the balance of competing forces – i.e. the balance of power between advocacy coalitions –

changes in favor of those supporting change (Wilkerson et al., 2002). According to another explanation the leptokurtic distribution of policy change can be a result of the pattern that is called the stick slip process in attention allocation. Due to human cognition and institutional friction, policymakers' attention sticks to a certain subset of policy issues for quite a while and then abruptly slips to another subset of policy issues (Brouard, 2013). Jones & Baumgartner's (2005) model of how policy systems respond to information from their environment provides a parsimonious and useful characterization of this pattern in formal terms. They argue policymakers' response to information can be written as

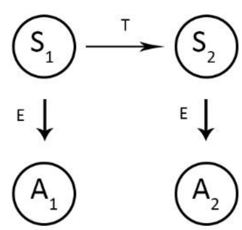
$$R = \beta S - C$$

where R is policy response, S is information (signal), β is benefits from information flow and C is decision-making costs. This model is built upon the assumption that human beings are boundedly rational which suggest they do not have full information and also they disproportionately process the raw information they obtain. They also offer a non-linear alternative model in which the information and cost components interact. However, the basic idea behind both models is the role of cognitive and institutional frictions – represented by C – in causing delayed policy response to new information and creating a punctuated policy equilibrium pattern. According to this model, a policy system does not respond to information flows from its environment unless information gain βS is larger than C.

Policy response R can be defined in different ways depending on the stage of policy process being studied. A study of agenda setting can define policy response as attention allocation across policy issues by policymakers or by public, whereas a study of public budgeting can define it as a government's budget allocation decision across policy issues or policy domains. In this study, policy response mainly refers to attention allocation by policymakers which is represented by the attention allocation vector $A_{t.}$ The information component of the response function within an agenda setting context consists of multiple dimensions such as information about public and media attention, preferences of actors in a policy subsystem etc. Policymakers' response to information flows from their environments contain signals about their policy priorities and magnitude of potential policy change. When a policy system is in policy stasis state policymakers' willingness and capacity to do a policy reform is small, and when it is in a policy reform state their willingness and capacity to do policy reform is high. The state of a policy system is not known by market agents, but they form beliefs about it by using signals from policymakers' issue attention allocation. As their beliefs that a policy system is in the reform state increase, their expectation that the future policy will deviate largely from the status quo policy is going to increase. In the asset pricing model proposed in this study, the investors learn about the state of a policy subsystem and this belief conditions their expectations of the firms' profitability. The potential impacts of future policies have different probability distributions in different states of the policy system. This difference is the central dynamic of the process characterized in this model. In formal terms the agents learn about $P(S_t = H| A_{t-1,} A_{t,} S_{t-1})$, the probability that the policymaking system is in reform state H at time *t* given the previous state, attention allocation at time *t* and *t-1*.

This learning process can be modelled by using a Hidden Markov Model (HMM) framework. The process that generates the attention allocation vector can be considered a Markov process in which the state of a system at time *t* only depends on the state of the system at time *t-1*. In a HMM model, a transition probability matrix contains the probabilities of all possible transitions between states of the system at any time point. Another important component of a HMM is an emission probability matrix which contains the probability of all possible outputs under a certain state. The output of a system at time *t* is a function of the state of the system at time *t*. The distribution of system outputs is different under different states of the system, therefore the probability of a certain output is different under different states of the system. Unlike a regular Markov Chain, in a HMM, at least one of these components is not observable – i.e. hidden. In the example studied in this work, the state of a policy system -- i.e. policy stasis or policy reform— is not directly observable. Agents learn about the state of the system at time *t* from the sequence of outputs from the first period until time *t.* A graphical representation of the HMM framework applied to the process of policymakers' issue attention allocation in a policy subsystem is given below.

Figure 2.1 An HMM model of policy system states and attention allocation output



This a two period HMM, and in this diagram $S_t \in \{H, L\}$ refers to the state of the policy system at time *t,* and A_t is the output of the system which is defined as the attention allocation vector above. To simplify the model I define two discrete categories of $A_{t.}$ In this setup, the attention allocation vector can either be A_H or $A_{L,}$, which respectively correspond to attention allocation vectors with high diversity and low diversity. While in reality the diversity of the attention allocation vector is continuous, this simplification is not an unrealistic representation of the reality, and it significantly simplifies the inference of the probability of different attention diversity scenarios within the HMM framework. The state of a policy system S_t is a binary variable. It equals to *H* when a policy system is in reform state and it equals to *L* when the system is in policy stasis state. The letters *E* and *T* respectively represent the emission probabilities matrix and the transition probabilities matrix. These two matrices are constant over time for a certain policy system, but they could vary across different policy systems. The emission probabilities matrix for the HMM presented here is given below. The columns represent the state of the system, and the rows represent the possible outcomes of the system.

Table 2.1 Emission Probabilities

	H	**L**
A_H	p	q
A_L	1-p	1-q

Given that attention allocation tends to be more concentrated in reform states and more diverse in policy stasis states, *p* must be greater than *1-p*, and *q* must be smaller than *1-q*. This suggests $p > 0.5$ and $q < 0.5$. To be able to characterize the representative agent's belief about the state of the policy system at time *t* we also need to know transition probabilities and prior probabilities of the two possible attention allocation vectors. The below table presents transition probabilities.

Table 2.2 Transition Probabilities

	S_t= H	**S_t= L**
S_{t-1}= H	a	1-a
S_{t-1}= L	b	1-b

The empirical distribution of the magnitude of budgetary changes from developed democracies suggests a policy system is mostly in policy stasis state and occasionally in policy reform state (Baumgartner & Jones, 2015). Given that we can assume $a < 1\text{-}a$, and $b < 1\text{-}b$. The prior probabilities of A_L and A_H are respectively *c* and *d,* and we can assume $c > d$.

To analyze how increasing concentration of issue attention allocation affects the beliefs about a reform state, we can compare two sequences of attention allocation vectors. In the first example the representative agent observes A_L and A_L , and in the second example she observes A_L and A_H . In the first scenario the agent believes the state sequence of (*L*,*L*) has probability

$$P(S_t = L | A_{t-1} = A_L , A_t = A_L , S_{t-1} = L) = c *(1-q)^2 *(1-b)$$

and the state sequence of (*L*,*H*) has probability

$$P(S_t = H | A_{t-1} = A_L , A_t = A_L , S_{t-1} = L) = c* (1-q)*(1-p)*b$$

We know that *b* is smaller than *1-b*, because the policy system is mostly in policy stasis state, and this difference is likely to be large. We also know *1-q* is greater than 0.5 and *1-p* is smaller than 0.5, therefore $(1-q)^2$ is greater than *(1-q)*(1-p)*. Given that, the representative agent will infer that *(L,L)* is more likely to be the state sequence that generated the output sequence (A_L, A_L).

What happens if the agent observes an output sequence (A_L, A_H). The agent believes the state sequence of *(L,L)* has probability

$$P(S_t = L | A_{t-1} = A_L , A_t = A_H, S_{t-1} = L) = c *q*(1-q)*(1-b)$$

and the state sequence of *(L,H)* has probability

$$P(S_t = H | A_{t-1} = A_L , A_t = A_H , S_{t-1} = L) = c* (1-q)*p*b$$

The second probability will be larger than the first probability if the difference between p and q is sufficiently large to at least offset the negative contribution of the difference between b and 1-b. If the increase in the concentration of attention from A_L to A_H is large, we can assume that p will be large, and the agent will infer that *(L,H)* is more likely to be the state sequence that generated the output sequence (A_L, A_H).

In the policy stasis state L the probability distribution of the magnitude of policy change has a small variance and its mean is very close to zero. In the reform state H, the mean of this probability distribution is significantly larger than zero, but the variance is similar to the distribution of the policy stasis state. The similarity of variance can be justified given the fact that agents learn about the direction and magnitude of policy change about a reform from political news. While in reality there is uncertainty about the position of future policies, for simplifying the model and isolating different sources of uncertainty, I assume there is no uncertainty about the position of policies that could be adopted in both states. In the policy stasis state, the position of the policy equilibrium will be at Q_L, and in the reform state it will be at Q_H. However, there is uncertainty about the impact of these future policies on the profitability of firms and the dividends they pay to the investor. This is the source of policy uncertainty in this model. The impact of Q_L on the dividend process is $\propto_L$ and it follows a normal distribution with prior mean of g_L and variance of σ_L. The impact impact of Q_L on the dividend process follows a normal distribution with prior mean of g_H and variance of σ_H. For simplicity, I assume the mean of the two distributions are equal, meaning $g_L = g_H$, but the variances are different and $\sigma_H > \sigma_L$.

To link this information processing process to stock market dynamics and analyze the implications of it on outcomes such as stock volatility we first need to determine what kind of valuation method investors use. In asset pricing research there are three alternative valuation methods (Damodaran, 2005). The first one is called the intrinsic valuation. In this valuation method the value of an asset is estimated on the basis of its financial performance and the value it generates – i.e. the fundamentals. Intrinsic valuation method is useful for cash flow generating assets like bonds and stocks, but not so useful for assets like gold which do not generate regular cash flow like dividend or coupon payment. The second method is relative valuation in which the price of an asset is estimated based on the value of an analogous asset. The value of a stock according to this method is estimated by using standardized measures of fundamentals such as price to earnings ratio. If an asset has smaller (larger) price to earnings ratio compared to another asset with very similar fundamentals, then it is considered an undervalued (overvalued) asset. The last method is called the contingent claims valuation method and it is useful for assets that exhibit similar characteristics to an option contract. In the model presented here, it is assumed that agents use the intrinsic value method to estimate the value of a stock or an index of stocks, and they incorporate the information about the state of policy system that they derive from the signals, that the attention allocation vector contains, to develop their expectations about the future performance of firms. Since I focus on stocks, which are cash flow generating assets, the intrinsic value approach will be more useful. Another reason for preferring intrinsic value method is the use of this modelling strategy in most political economy models of asset pricing.

Market valuation of a firm's stock is determined by many factors. Public policy is one of the many sets of factors that affect valuation (Bittlingmayer, 1998). Since basic asset pricing models try to maximize generality and parsimoniousness, they do not explicitly model the pricing impact of specific factors such as public policy decisions or firms' managerial decisions. One of these basic models is the dividend discount model (DDM), which is an example of an intrinsic valuation method. The departure point of this model is the assumption that an asset is a right on or claim to future cash flows. A common stock offers two types of future cash flows. The first one is capital gain which is simply the difference between the current price of a common stock and its price at a future time point. This source of cash flow is not taken into account in simpler versions of DDM. The second source of cash flow for the investors of a common stock is dividend payments by firms. Firms are not obligated to pay dividends, but most large firms – approximately 80 percent of the firms in the S&P 500 index[1] – pay dividends to their investors. In various versions of DDM, firms that do not pay dividends are assumed to wait until the last day of the life of an asset to pay all dividends accumulated over time, so DDM models become applicable to all types of firms.

In most versions of the DDM model the intrinsic value of a stock at time *t* equals to the net present value of future dividend payments at time *t.* The equation below characterizes the price of a cash flow generating asset according to a DDM model.

$$P_t = \sum_{t}^{\infty} D_t \frac{(1+g)^t}{(1+r)^t}$$

In the above equation P_t represents the price of the asset at time *t*, D_t represents the dividend payment at time *t*, *g* represents the constant growth rate of dividends, and *r* represents the constant required rate of return a representative investor expects from the asset. The required rate of return is the discount factor in this generic DDM model. While in more simplistic versions dividends are assumed to be constant or having a constant growth rate over time, in more complex and realistic versions the dividend component is modeled as a stochastic process. The

[1] Visit the following link for data on dividend payments by American firms: https://bit.ly/2SHntJN

equation below is an example that characterizes the dividend process as a geometric Brownian motion process.

$$\frac{dD_t}{D_t} = \propto d_{t\,+}\, \sigma dW_t$$

In this equation $\propto$ represents the drift rate or the systematic growth rate of the dividend process. In political economy models of asset pricing this parameter equals to the average impact of an exogenous political factor on dividends. For example in Pastor and Veronesi (2013) this parameter is determined by the average impact of a policy decision. In another example, which deals with a non-political exogenous factor, Pan et al. (2015) defines $\propto$ as the average impact of CEO capability on a firm's dividends. In the model proposed here, $\propto$ represents the expected impact of the policy on the dividend process. In the above model W_t is a Wiener process – i.e. Brownian motion – and σ is the fundamental uncertainty parameter which is also called fundamental volatility of dividends. A Wiener process is a stochastic process whose time increments W_{t+dt} - W_t has a standard normal distribution and in which W_{t+dt} only depends on W_t. This component introduces randomness to the dividend process and the σ parameter determines the extent of randomness. The fundamental volatility is the level of volatility that still exists even when there is no uncertainty about $\propto$. In a DDM model, return volatility of a stock is a combination of fundamental dividend volatility and the uncertainty about $\propto$. The below equation is a formulation of return volatility based on the fundamental volatility and the uncertainty surrounding the drift parameter. [2]

[2] A proof of this can be found in Pan (et al. 2015).

$$\sigma_R = \sigma\,(1 + \frac{\delta \log\left(\frac{P}{D}\right)}{\delta g} * \frac{\sigma_\propto}{\sigma})$$

where σ is the fundamental uncertainty of the dividend process, σ_α is the variance of the agent's belief about the average impact of the future policy on the dividend process, and $\frac{\delta \log\left(\frac{P}{D}\right)}{\delta g}$ is the marginal return to expected policy impact. The contribution of the uncertainty of the impact distribution to the return volatility is accounted for by the $\sigma_\propto$ component. Other components of this equation do not depend on the policy system state. The value of $\sigma_\propto$ is determined by the variance of the agent's belief about the impact of future policy. When the agent infers the state sequence is (L,L), $\sigma_\propto$ equals to σ_L, and when she infers the state sequence is (L,H), $\sigma_\propto$ equals to σ_H. Since $\sigma_H > \sigma_L$, the contribution of impact uncertainty on the return volatility will be greater when the agent infers the policy system is in reform state. Since the agent's belief is conditional on the issue attention diversity, based on this model we can formulate the following hypothesis.

H1: Increasing policy issue attention concentration leads to increasing stock return volatility.

In the next section, I describe the data and empirical strategy I will use to test this empirical implication.

2.3 Data and Empirical Strategy

To test the hypothesis from the previous section I will use policy issue attention data from the Comparative Policy Agendas (CPA) database, and stock market data from the Yahoo Finance database. The resulting dataset includes data from 5 developed democracies – Belgium, Denmark, Spain, the UK and the USA. In this study I present results from single country time series analyses of asset pricing implications of policy issue attention dynamics as well as results from time series cross sectional analysis.

The CPA Project provides very comprehensive collection of data about different stages of the policy making process. All countries in the database have democratic political systems and most of them are Western countries. In this analysis, I am focusing on the attention allocation stage of the policy process and the CPA Project provides relevant data for the abovementioned five countries. In both presidential and parliamentary democracies the entity that is primarily responsible for policy making is the legislative branch. While there is variation across different democratic institutional arrangements in terms of the degree of the legislative branch's discretion in policy making activity relative to other governmental entities i.e. – the executive branch or the bureaucracy—, in all democracies the legislative branch is the main entity that is entitled to discuss and decide policy change. Thus, I operationalize the attention allocation of policymakers as the attention allocation in the legislative branch. The CPA database does not include readily available data on the issue attention related variables I will use in my analyses such as issue attention diversity and attention space size. Each row in policy agendas data includes raw information about the date and content of a policy making related activity by a governmental entity or by the media. My theory is about the impact of the policy issue attention dynamics at the agenda setting stage of the policy process on market outcomes, therefore I only use data about policy making activities that happen before a policy change decision is made and I narrow my focus only to the activities in the legislative branch. The table below includes information about the raw data I use from each case to calculate main independent variables.

Table 2.3 The content of raw data across the countries in the sample

Country	Raw Data Content
Belgium	Oral questions and interpellations
Denmark	Questions Hour
Spain	Oral Questions
United Kingdom	Prime Minister's Questions
United States of America	Congressional Hearings

In this study, I will use two commonly used measures of attention diversity. These two measures are the normalized Herfindahl-Hirschman Index and the normalized Shannon's H entropy. The normalized Herfindahl-Hirschman Index formula is given below

$$HHI = \frac{\sum_{i=1}^{N} {p_i}^2 - \frac{1}{N}}{1 - \frac{1}{N}}$$

where p_i is the share of attention allocated to issue topic *I,* and *N* is the total number of issue topics in the policy agenda space. In the CPA data there are 21 different major policy issue topics, therefore N equals to 21.[3] The values of HHI range from 1/N to 1, where 1/N corresponds to a scenario in which all issue topics are allocated equal amount of attention, and 1 corresponds to a scenario in which the whole attention is allocated to a single issue topic. The alternative measure, the Shannon's H entropy, is calculated by using the formula below

$$Shannon's\ H = \frac{-\sum_{i=1}^{n} p_i * \ln(p_i)}{\ln(N)}$$

[3] A list of the 21 policy issue topics could be found on the following link: https://bit.ly/2Sr750L

where p_i is the share of attention allocated to issue topic I, and N is the total number of issue topics in the policy agenda space. These two are widely used formulas to measure attention diversity in the policy issue attention literature (Boydstun et al, 2014). The HHI was originally developed in economics to measure market concentration, and the Shannon's H was originally developed to measure information entropy (Shannon, 1948). These two measures have been used by many studies in different fields to summarize the diversity of elements within a set of objects. In the policy issue attention literature and in this study, the HHI and Shannon's H formulas are applied to the attention allocation vector to measure the diversity of the attention allocation vector. Most studies use these two as alternative measurements of attention diversity (Breunig, 2011, Boydstun et al., 2014; Baumgartner and Jones, 2015). While they generate highly correlated measurements of diversity, the small difference between them is a result of their sensitivity to small changes in the distribution of the elements of a vector. Boydstun et al. (2014) show that the normalized Shannon's H entropy measure is better in terms of sensitivity to small changes in the distribution of attention across issue topics.

Another issue attention related variable I am going to include in my empirical models is the attention space size. It is basically the total number of elements in the attention space in a certain time period. I include this variable to control for the impact of the volume of policy making activity on the outcome. Another reason I include this variable is the relationship between attention space size and attention diversity. The size of the attention space is not constant over time, and the variation in its size is positively and significantly correlated with attention diversity. A model that does not control for attention space size may suffer from the omitted variable bias since the variation in attention diversity could be partly explained by the variation in attention space size, and the latter is likely to have a direct impact on the financial and real economic outcomes.

In choosing the time unit by which to measure the variables of interest, such as attention entropy and attention space size, there are a few important considerations that affect this choice. Firstly, time unit should be chosen such that there will be considerable variation in the sample. Secondly, the time frame should be chosen such that there will be sufficiently large number of observations from smaller time units to calculate the summary measurements – i.e. statistical properties such as frequency, central tendency and dispersion - more accurately. Thirdly, the time frame should be chosen such that it will make sense substantively. Finally, the time frame should be chosen such that the total number of observations in the sample will not be so small. There are a few time unit options when dealing with policy issue attention data. The first option is using week as the time unit. However, this option fails to satisfy the second condition because there is typically not sufficient number of policy making related events in a week to be able to calculate summary measures reliably. Another option is using year as the time frame. If daily or weekly data are available, using year as the time unit would mostly satisfy the first three conditions, but it may not satisfy the last condition when the time horizon is short and the number of cross sectional units is small. The last option is using month as the time unit. While it does not perfectly satisfy the all four conditions, it works better than week or year. In most months there is sufficiently large number of activities that are related to attention allocation stage of the policy making process, using months as the time unit will provide a larger sample size than using year as the time unit, a larger sample size will typically provide larger variation across observations, and since months are usually taken into account while organizing legislative calendars it makes more sense substantively. Similar concerns apply to the time unit choice for measuring stock market dynamics such as return volatility and trade volume. Given these, I will use month as the time unit.

In the aggregate level analyses, the left hand side variables are related to the dispersion of stock market indices' performances. A market index is a bundle created from a subset of stocks in a certain stock exchange(s) and its value is calculated as a weighted average of the values of stocks included in the bundle. Market indices are intended to be a proxy measurement of the performance of the entire stock market. Thus, to analyze how policy issue attention dynamics affect aggregate (market) level dynamics I will use market index data from the six developed countries for which issue attention and stock market data are available. In most countries there are multiple stock market indices with different methodologies to measure market performance. For my analysis, I selected the national indices from the Wall Street Journal's International Stock Indexes list.[4] The table below includes a list of the countries and the stock market index from each country that will be used in this study.

Table 2.4 The list of countries and major stock indices

Country	Stock Exchange	Market Index
Belgium	Euronext Brussels	BEL 20
Denmark	Nasdaq Copenhagen	OMXC 20
Spain	Bolsa de Madrid	IBEX 35
United Kingdom	London Stock Exchange	FTSE 100
United States of America	New York Stock Exchange, NASDAQ	S&P 500

[4] The list can be accessed on the following link: https://on.wsj.com/2E2FTMR

One of the left hand side variables is monthly historical volatility. Historical volatility is a measurement of the degree of variance in stock returns. It is also called realized volatility, because asset pricing models treat volatility as the stochastic dispersion parameter of the underlying data generating process of stock returns, which is usually assumed to be a geometric Brownian Motion process, and the observed variance over a certain period of time is considered a realization of stochastic volatility. Since volatility is a theoretical construct and not directly observable, we use realized volatility as an estimate of theoretical volatility. Earlier asset pricing models assume volatility is constant, but most contemporary asset pricing models assume it is a stochastic process like the process of returns, and the variation in historical volatility could be used as a proxy of the variation in stochastic volatility. Monthly historical volatility is calculated as the standard deviation of daily log returns. An important convention in financial statistics is using log ratio of prices to calculate return. Stock prices are always positive and not normally distributed. Using the log ratio of prices generates normally distributed return data. Another important convention in the studies of volatility and in the field of financial analysis is presenting volatility in annualized format. In this study I am using daily returns within a month to calculate monthly volatility. This generates an estimate of the dispersion of daily returns within a certain month. To annualize this estimate, we need to multiply it with the square root of the total number of business days in a certain year. It is assumed there are 252 business days in a year, therefore I multiply monthly volatilities with the square root of 252. The daily price data that I use to calculate log returns and volatility come from the Yahoo Finance database. I pull data from the Yahoo Finance API for the market indices listed in Table 4.

Another left hand side variable I am going to use for market level analysis is implied volatility. Unlike the historical volatility, the implied volatility is a forward looking measurement of dispersion. One of the most common examples of the implied volatility measure is the Volatility Index (VIX) created by the Chicago Board Options Exchange (CBOE). This index reflects the market's expectation of 30 day forward looking volatility. VIX measures implied volatility specifically for the Standard and Poors 500 Index, and similar indices are not available for all countries in my dataset. Due to data limitations I will use implied volatility model only for the US case.

The concept of implied volatility was originally developed from the Black-Scholes option pricing model. In this model one of the determinants of an option contract's price is expected volatility of the securities underlying the option contract (Stoll, 1969). The formula for implied volatility is derived by solving the option price equation for volatility. Volatility in the Black-Scholes model is a property of the market which is not directly observable, but an estimate of it could be obtained by using information about the price dynamics in option markets. The expression used to calculate the VIX index is given in the appendix. VIX index is also traded as a security in the options market, and its price reflects the market's expected volatility. To analyze the impact of policy issue attention dynamics on implied volatility I use monthly averages of the VIX index as the dependent variable. The values of the index are always positive and it has a similar distribution to the historical volatility. I pull historical price data for the VIX from the Yahoo Finance API.

To estimate the impact of policy issue attention dynamics on market level volatility, I use two estimation methods which are widely used for positive continuous data. The first method is OLS regression with logged dependent variable. Volatility data are positive and the distribution is similar to a lognormal distribution. Log transformation of raw volatility data generates normally distributed data. The second widely used method for estimating the conditional expectation of positive continuous data is a generalized linear model for gamma distributed dependent variable with a log link function. The shape of gamma distribution is quite similar to lognormal distribution, and some argue it can be an alternative to OLS with logged dependent variable. In this study, I use both estimation strategies and present results in the next section.

2.4 Results

In this section, I present empirical results for single country time series models and time series cross sectional models of aggregate stock return volatility. Table 2.5 and Table 2.6 show single country time series models that use the Shannon's H entropy as the measurement of attention diversity, and Table 2.7 and 2.8 show single country time series models that use the Herfindahl-Hirschman Index as the measurement of attention diversity. These two measures are negatively correlated, so I expect their coefficients to have opposite signs. All single country models include year and month fixed effects, but they are not reported in the results tables. Table 2.9 includes the results for the two time series cross sectional models. Both of them include time and country fixed effects. Delayed reaction to news is a common finding in the asset pricing literature, therefore I include up to three lags of independent variables, as well as the dependent variable.

If data are available, models include the Economic Policy Uncertainty Index (EPU) as a control variable. This index captures a particular dimension of the overall policy uncertainty, and empirical studies indicate it is a powerful predictor of stock volatility. I did not include lags of the EPU in the models for Spain and the UK because of the small sample size. I control for this variable, because EPU typically makes sudden jumps and volatility responds with similar jumps (Pastor, 2013; Liu & Zhang, 2015; Baker et al., 2015). EPU seems to be mainly capturing economic uncertainty caused by dramatic events.

Table 2.5 Issue attention dynamics and stock market volatility – GLM models (Attention diversity measured as attention entropy)

	Dependent variable:					
	Historical Volatility					VIX
	(Belgium)	(Denmark)	(Spain)	(UK)	(USA)	(USA)
Attention Entropy$_t$	0.401	0.989	-1.492	-0.556	0.347	0.137
	(0.491)	(0.878)	(0.972)	(0.917)	(0.309)	(0.125)
log(Attention Space Size$_t$)	-0.010	-0.043	0.338^{*}	0.137	0.034	0.003
	(0.083)	(0.075)	(0.189)	(0.150)	(0.049)	(0.019)
Attention Entropy$_{t-1}$	1.026^{*}	0.426	-0.256	0.891	0.055	-0.0004
	(0.575)	(0.948)	(0.899)	(0.825)	(0.276)	(0.133)
log(Attention Space Size$_{t-1}$)	-0.073	0.008	0.068	-0.107	-0.025	0.013
	(0.101)	(0.089)	(0.200)	(0.121)	(0.044)	(0.024)
Attention Entropy$_{t-2}$	-0.059	0.376	-0.132	-1.337^{**}	-0.433	-0.273^{**}
	(0.495)	(0.977)	(0.866)	(0.674)	(0.295)	(0.134)
log(Attention Space Size$_{t-2}$)	-0.054	-0.034	-0.035	0.285^{*}	0.027	0.017
	(0.102)	(0.072)	(0.176)	(0.147)	(0.046)	(0.020)
Attention Entropy$_{t-3}$	-0.392	2.217^{***}	0.179	-0.645	0.313	0.087
	(0.431)	(0.803)	(0.763)	(0.552)	(0.307)	(0.117)
log(Attention Space Size$_{t-3}$)	0.041	-0.034	-0.181	-0.361^{***}	-0.024	0.004
	(0.096)	(0.069)	(0.175)	(0.130)	(0.047)	(0.022)
EPU$_t$			0.002^{***}	0.005^{***}	0.009^{***}	0.004^{***}
			(0.001)	(0.001)	(0.001)	(0.001)
EPU$_{t-1}$					-0.004^{***}	-0.001
					(0.001)	(0.001)
EPU$_{t-2}$					0.003^{**}	-0.00005
					(0.001)	(0.001)
EPU$_{t-3}$					-0.002	-0.0003
					(0.001)	(0.0005)
Historical Volatility$_{t-1}$	0.020^{***}	0.014^{***}	-0.0004	0.011	0.015^{***}	
	(0.006)	(0.003)	(0.006)	(0.012)	(0.003)	
VIX$_{t-1}$						0.027^{***}
						(0.002)
Constant	1.086^{*}	-1.143	3.666^{***}	4.120^{***}	1.433^{***}	2.064^{***}
	(0.570)	(1.215)	(0.783)	(1.343)	(0.346)	(0.145)
Observations	149	235	64	79	308	297
Log Likelihood	-418.982	-680.050	-173.797	-202.238	-814.281	-629.988
Akaike Inf. Crit.	921.965	1,446.100	413.594	464.477	1,732.561	1,361.975

*p<0.1; **p<0.05; ***p<0.01

Table 2.6 Issue attention dynamics and stock market volatility – OLS with logged DV (Attention diversity measured as attention entropy)

	Dependent variable:					
	Historical Volatility					VIX
	(Belgium)	(Denmark)	(Spain)	(UK)	(USA)	(USA)
Attention Entropy$_t$	0.411	0.802	-1.553^{*}	-0.533	0.382	0.142
	(0.524)	(0.839)	(0.928)	(0.914)	(0.318)	(0.123)
log(Attention Space Size$_t$)	-0.022	-0.033	0.340^{*}	0.125	0.011	0.001
	(0.088)	(0.071)	(0.183)	(0.148)	(0.051)	(0.018)
Attention Entropy$_{t-1}$	1.011^{*}	0.587	-0.398	0.791	0.098	0.016
	(0.567)	(0.892)	(0.864)	(0.807)	(0.287)	(0.126)
log(Attention Space Size$_{t-1}$)	-0.073	0.024	0.093	-0.099	-0.020	0.009
	(0.098)	(0.083)	(0.189)	(0.117)	(0.044)	(0.022)
Attention Entropy$_{t-2}$	-0.005	0.434	-0.262	-1.377^{**}	-0.434	-0.265^{**}
	(0.512)	(0.932)	(0.880)	(0.653)	(0.294)	(0.129)
log(Attention Space Size$_{t-2}$)	-0.066	-0.058	-0.017	0.265^{*}	0.027	0.018
	(0.107)	(0.071)	(0.184)	(0.147)	(0.046)	(0.019)
Attention Entropy$_{t-3}$	-0.451	2.071^{**}	0.125	-0.591	0.421	0.082
	(0.430)	(0.809)	(0.738)	(0.555)	(0.333)	(0.111)
log(Attention Space Size$_{t-3}$)	0.053	-0.022	-0.174	-0.338^{**}	-0.032	0.004
	(0.095)	(0.067)	(0.170)	(0.134)	(0.049)	(0.021)
EPU$_t$			0.002^{***}	0.005^{***}	0.009^{***}	0.004^{***}
			(0.001)	(0.001)	(0.001)	(0.001)
EPU$_{t-1}$					-0.004^{***}	-0.001
					(0.001)	(0.001)
EPU$_{t-2}$					0.003^{**}	0.00003
					(0.001)	(0.001)
EPU$_{t-3}$					-0.002	-0.0003
					(0.001)	(0.0005)
Historical Volatility$_{t-1}$	0.021^{***}	0.014^{***}	-0.0003	0.010	0.014^{***}	
	(0.006)	(0.003)	(0.006)	(0.011)	(0.003)	
VIX$_{t-1}$						0.027^{***}
						(0.002)
Constant	1.134^{*}	-1.117	3.768^{***}	4.164^{***}	1.342^{***}	2.062^{***}
	(0.580)	(1.176)	(0.789)	(1.284)	(0.356)	(0.145)
Observations	149	235	64	79	308	297
R^2	0.663	0.606	0.825		0.733	0.902
Adjusted R^2	0.534	0.519	0.645		0.680	0.882
Log Likelihood				13.417		
Akaike Inf. Crit.				33.166		
Residual Std. Error	0.338 (df = 107)	0.305 (df = 192)	0.265 (df = 31)		0.271 (df = 256)	0.116 (df = 246)

Note: All models include up to three lags of the dependent variable, but only the first lags are shown in this table.All standard errors are robust standard errors. *p<0.1; **p<0.05; ***p<0.01

Results from some of the single country time series models weakly confirm my theoretical expectations. Higher values of attention entropy indicate greater diversity of policy issue attention, and higher values of the HHI indicate greater concentration of policy issue attention. In the majority of the columns, the coefficient of the second lag of the former is negative and statistically significant while the coefficient of the second lag of the latter is positive and statistically significant. In the cases of Belgium and Denmark, the statistically significant coefficient for entropy and HHI is not consistent with my theoretical expectations. These are the two cases for which EPU data are not available. Unfortunately, we do not have EPU data for Belgium and Denmark to test this proposition.

In the USA case, the HHI variable has a statistically significant effect on the historical volatility, and the size of the HHI variable's effect on the historical volatility is approximately 1.05 percentage points per one standard deviation change in the HHI variable. This is approximately half the size of the effect of the EPU variable. In the USA case, we observe a more consistent statistically significant second lag effect in the VIX models. The effect size in those models are respectively 1.03 percentage points for the entropy variable and 1.02 percentage points for the HHI variable. These effect sizes are slightly lower than the size of EPU's effect on the VIX. The size of the attention entropy variable's effect on the historical volatility is approximately 1.07 percentage points per one standard deviation change in the attention entropy variable in the case of the UK, and the effect size of the HHI variable in the case of the UK is approximately 1.1 percentage points per one standard deviation change in the HHI variable. These effect sizes are not large, but they are similar to the effect size of the EPU variable, which is approximately 1.27 percentage points per one standard deviation change.

Table 2.7 Issue attention dynamics and stock market volatility – GLM models (Attention diversity measured as Herfindahl-Hirschman index)

	Dependent variable:					
	Historical Volatility					VIX
	(Belgium)	(Denmark)	(Spain)	(UK)	(USA)	(USA)
HHI_t	-0.357	-3.036	0.959	0.960	-0.282	-0.117
	(0.440)	(2.015)	(0.860)	(1.113)	(0.364)	(0.139)
log(Attention Space Size_t)	-0.012	-0.027	0.259	0.135	0.062^{*}	0.013
	(0.076)	(0.070)	(0.196)	(0.117)	(0.037)	(0.014)
HHI_{t-1}	-0.844^{**}	0.255	-0.026	-1.115	0.101	0.052
	(0.411)	(2.465)	(0.840)	(0.923)	(0.301)	(0.138)
log(Attention Space Size_{t-1})	-0.035	0.023	0.024	-0.032	-0.013	0.016
	(0.087)	(0.084)	(0.216)	(0.091)	(0.036)	(0.018)
HHI_{t-2}	0.014	-0.821	-0.143	2.585^{***}	0.849^{***}	0.425^{***}
	(0.412)	(2.620)	(0.663)	(0.978)	(0.298)	(0.130)
log(Attention Space Size_{t-2})	-0.065	-0.030	-0.072	0.225	0.028	0.010
	(0.095)	(0.072)	(0.172)	(0.137)	(0.035)	(0.016)
HHI_{t-3}	0.124	-4.569^{**}	-0.007	1.169	-0.313	-0.068
	(0.276)	(2.201)	(0.673)	(0.860)	(0.432)	(0.115)
log(Attention Space Size_{t-3})	0.007	0.016	-0.144	-0.374^{***}	-0.003	0.010
	(0.073)	(0.071)	(0.178)	(0.109)	(0.040)	(0.017)
EPU_t			0.003^{***}	0.006^{***}	0.009^{***}	0.004^{***}
			(0.001)	(0.001)	(0.001)	(0.001)
EPU_{t-1}					-0.004^{***}	-0.001
					(0.001)	(0.001)
EPU_{t-2}					0.003^{**}	-0.00004
					(0.001)	(0.001)
EPU_{t-3}					-0.002	-0.0002
					(0.001)	(0.0005)
Historical Volatility_{t-1}	0.020^{***}				0.015^{***}	
	(0.006)				(0.003)	
VIX_{t-1}						0.027^{***}
						(0.002)
Constant	2.005^{**}	2.354^{***}	2.735	2.670^{***}	1.359^{***}	1.945^{***}
	(0.872)	(0.658)	(2.242)	(0.861)	(0.457)	(0.226)
Observations	149	235	64	79	308	297
Log Likelihood	-419.709	-692.945	-175.905	-201.822	-812.500	-628.676
Akaike Inf. Crit.	923.419	1,469.891	415.809	461.644	1,728.999	1,359.353

Note: All models include up to three lags of the dependent variable, but only the first lags are shown in this table. All standard errors are robust standard errors. *p<0.1; ** p<0.05; *** p<0.01

Table 2.8 Issue attention dynamics and stock market volatility – OLS with logeed DV (Attention diversity measured as Herfindahl-Hirschman index)

	Dependent variable:					
	Historical Volatility					VIX
	(1)	(2)	(3)	(4)	(5)	(6)
HHI_t	-0.348	-2.343	0.926	0.751	-0.323	-0.122
	(0.448)	(1.871)	(0.897)	(1.131)	(0.380)	(0.137)
$\log(\text{Attention Space Size}_t)$	-0.022	-0.028	0.247	0.104	0.040	0.012
	(0.077)	(0.066)	(0.205)	(0.121)	(0.039)	(0.014)
HHI_{t-1}	-0.840^{**}	0.342	0.076	-1.498	0.086	0.042
	(0.418)	(2.353)	(0.829)	(1.139)	(0.303)	(0.130)
$\log(\text{Attention Space Size}_{t-1})$	-0.042	0.049	0.039	-0.050	-0.004	0.013
	(0.084)	(0.082)	(0.215)	(0.093)	(0.036)	(0.017)
HHI_{t-2}	-0.033	-1.220	-0.029	2.594^{***}	0.861^{***}	0.424^{***}
	(0.429)	(2.538)	(0.687)	(0.950)	(0.303)	(0.126)
$\log(\text{Attention Space Size}_{t-2})$	-0.075	-0.051	-0.054	0.230^{*}	0.029	0.012
	(0.102)	(0.065)	(0.181)	(0.129)	(0.036)	(0.015)
HHI_{t-3}	0.135	-3.944^{*}	0.116	0.679	-0.451	-0.054
	(0.265)	(2.141)	(0.659)	(0.812)	(0.489)	(0.111)
$\log(\text{Attention Space Size}_{t-3})$	0.012	0.027	-0.114	-0.373^{***}	-0.006	0.011
	(0.072)	(0.064)	(0.175)	(0.125)	(0.042)	(0.017)
EPU_t			0.002^{***}	0.005^{***}	0.009^{***}	0.004^{***}
			(0.001)	(0.001)	(0.001)	(0.001)
EPU_{t-1}					-0.004^{***}	-0.001
					(0.001)	(0.001)
EPU_{t-2}					0.003^{**}	0.00005
					(0.001)	(0.001)
EPU_{t-3}					-0.002	-0.0002
					(0.001)	(0.0005)
$\text{Historical Volatility}_{t-1}$	0.021^{***}	0.014^{***}	0.002	0.011	0.015^{***}	
	(0.007)	(0.003)	(0.006)	(0.011)	(0.003)	
VIX_{t-1}						0.027^{***}
						(0.002)
Constant	2.090^{**}	2.223^{***}	2.462	2.813^{***}	1.386^{***}	1.949^{***}
	(0.831)	(0.597)	(2.144)	(0.856)	(0.464)	(0.220)
Observations	149	235	64	79	308	297
R^2	0.659	0.601	0.812	0.798	0.736	0.903
Adjusted R^2	0.528	0.513	0.618	0.679	0.684	0.883
Residual Std. Error	0.340 (df = 107)	0.307 (df = 192)	0.275 (df = 31)	0.248 (df = 49)	0.269 (df = 256)	0.116 (df = 246)

Note: All models include up to three lags of the dependent variable, but only the first lags are shown in this table. All standard errors are robust standard errors. *p<0.1; ** p<0.05; *** p<0.01

In Table 2.9, I present results for the time series cross sectional models which I test with data from three countries with EPU data. The first column uses entropy and the second column uses the HHI as the measurement of attention diversity. While the HHI model confirms my theoretical expectation, the entropy model generates contradictory results. In the entropy model, the contemporaneous effect of attention diversity on market volatility is positive and statistically significant, but the first lag of attention diversity has a negative and statistically significant effect. Since the absolute value of the positive coefficient is larger than the absolute value of the negative coefficient, the net effect of attention diversity according to this model is positive. This is a result that contradicts my theoretical expectation, but the results on the second column confirm my theoretical expectations.

Overall, models using the HHI measure feature greater statistical significance and the signs of the coefficients are more consistent across different cases. Since the HHI measure is less sensitive to small changes in attention allocation, the difference in the results suggests very small changes in attention allocation may not translate into changes in stock return volatility. In other words, volatility may not react to very small changes in the diversity of attention allocation.

The results also confirm the delayed reaction to news hypotheses. In all single country models, the significant attention diversity coefficients belong to lagged variables. However, the same does not apply to the EPU index. According to the results presented in this study, economic policy uncertainty has statistically significant and mostly contemporaneous impact on stock volatility. The reason why markets react to EPU faster than they react to attention diversity might be explained by the fact that changes in attention diversity tend to be more subtle. The nature of fluctuations in attention diversity may explain why the transmission of effect is slower.

Table 2.9 Issue attention dynamics and stock market volatility – Time series cross sectional models – OLS with fixed effects

	Dependent variable:	
	log(Historical Volatility)	
	(1)	(2)
EPU_t	0.003	0.003^{***}
	(0.001)	(0.001)
Attention $Entropy_t$	0.102^{***}	
HHI_t		-0.080
		(0.137)
Attention Space $Size_t$	0.019^{***}	0.025^{*}
	(0.039)	(0.014)
Attention $Entropy_{t-1}$	-0.056^{***}	
HHI_{t-1}		-0.054
		(0.130)
Attention Space $Size_{t-1}$	-0.001	-0.013
	(0.036)	(0.017)
Attention $Entropy_{t-2}$	-0.426	
HHI_{t-2}		0.516^{***}
		(0.126)
Attention Space $Size_{t-2}$	0.038	0.026^{*}
	(0.036)	(0.015)
Attention $Entropy_{t-3}$	0.203	
HHI_{t-3}		-0.096
		(0.111)
Attention Space $Size_{t-3}$	-0.072^{**}	-0.059^{***}
	(0.042)	(0.017)
Observations	462	462
R^2	0.641	0.642
Adjusted R^2	0.597	0.597

All standard errors are robust standard errors.
*p<0.1; ** p<0.05; *** p<0.01

2.5 Conclusion

In this paper I presented a simple model characterizing the process that translates information about policymakers' issue attention allocation into stock return volatility. The relationship this model predicts associates increasing concentration of attention allocation to increasing return volatility. This model is a largely simplified version of the learning models in Pastor & Veronesi (2013) and Pan et al.(2015), but it is sufficiently comprehensive to characterize the contribution of policy uncertainty emanating from issue attention allocation on the stock return volatility. Results presented in the previous section provide some empirical support to the proposition of the model. The theoretical model and empirical results only focus on the aggregate level relationship between issue attention dynamics and asset pricing dynamics. To achieve better understanding of the link between issue attention dynamics and stock market outcomes, we must also look at how other aspects of the attention allocation vector, such as the attention level for specific policy issues, the volatility of attention on an issue over time etc., affect investors' perception of policy uncertainty. Also, we need to investigate these relationships at industry level and firm level. Political economy research on policy uncertainty indicates the sensitivity to politics varies largely across industries and firms. This suggests the impact of the issue attention dynamics on the stock market outcomes might be different across industries and firms. To do industry and firm level analyses, the model in section three must be modified to allow variation of some components across industries, and to analyze the empirical implications we need stock market data at industry and firm levels.

Chapter 3: Stock Pricing Implications of Short-Term Policy Issue Attention Changes

3.1 Introduction

How does the extent of changes in policy agendas affect stock pricing dynamics? The internal dynamics of policy issue attention allocation processes largely determines what issues will be addressed by the policymakers, the timing of policy change, and the extent of policy change. The distribution of policy change in most political systems exhibit a pattern which suggests a punctuated change process. Long episodes of stability or incremental policy changes are occasionally followed by sudden and punctuated policy change. A similar pattern, to a varying degree across the stages and venues of the policy process, exists in the distribution of issue attention changes, and the policy agendas research shows that the punctuations in policy change is a function of punctuations in attention allocation processes. The distribution of attention changes tends to be concentrated around zero during episodes of policy stability, but before episodes of large policy change the attention change process tends to generate larger values, and usually in the tails of the distribution (Breunig and Koski, 2006; Breunig, 2011). If policy change is a function of issue attention change, the dynamics of issue attention allocation might have asset pricing implications.

In this chapter, I study the reaction of stock prices to daily changes in the media's attention to policy issues. I focus on the media attention, because the media is the venue that manages the largest flow of information from the policymakers to the general public, and to the investors. Attention is a necessary ingredient for policy change. The changes in media's attention allocation might contain signals about the state of the policy system – whether it is in the policy stasis state or a policy reform state. Larger changes in attention allocation might be interpreted as signals of an approaching policy reform state or a relatively larger policy change state. Larger changes might also signal the arrival of new issues to the policy agendas, or changing policy image within a policy domain (Jones and Baumgartner, 2005). Due to greater uncertainty that comes with a reform process, the arrival of new policy issues or changing policy image, I argue that the extent of change in daily attention allocation will be positively related to stock return volatility. I also expect to find a negative relationship between the extent of change in attention allocation and daily returns as there is strong empirical support for the negative association between short-term volatility and short-term returns (Harvey and Lange, 2015; Pastor and Veronesi, 2010).

I use daily closing prices of the S&P 500 Index and the New York Times front page article topics data to test my arguments. The data cover the period 1996 to 2006. I use an ARMA-EGARCH strategy to analyze the return and volatility effects of the extent of daily changes in issue attention. GARCH family of models are widely used to jointly model the mean and the variance of the return processes, and it is the most suitable strategy for my research problem. The results from these models largely support my theoretical expectations about the volatility and return effects of attention allocation changes. They show larger daily changes in attention allocation – greater attention instability – tend to increase the volatility (variance) of returns and tend to decrease the mean of returns.

Political economy studies that aim to explain how investors' policy change expectations evolve ignore the impact of agenda setting dynamics, and they mainly focus on partisan and institutional variables. While the partisan and institutionalist political economy approaches can capture a significant part of what changes in politics over long time frames, we need a new set of explanatory tools to capture what changes in politics over shorter time frames. Politics is not always as slow moving as the partisan and institutionalist approaches implicitly suggest. Politics can change from one day to another. One aspect along which there might sometimes be large daily fluctuations is political agenda setting processes. The policy agendas research in the last few decades have shown that attention dynamics are to a large extent independent from partisanship or institutional structures, and the dynamics of the attention allocation across policy issues can offer a better explanation of the timing of policy change. Policy actors have limited attention spaces, and they have to ignore some issues and prioritize others. These attention allocation decisions have consequences for the extent and the content of future policy changes.

The stock markets' information processing works more efficiently than the policy system's information processing. While the attention of policy actors may not change very quickly in response to changes in the information environment, the attention of markets to changes in the policy environment is faster. In this work, I study how the stock markets respond to daily changes in policy issue attention. It adds a new element to the theoretical toolkit of the political economy of asset pricing literature by developing and testing an agenda setting based theory of the political sources of variation in asset pricing dynamics.

This chapter proceeds as follows. In the second section, I present some stylized empirical facts about the changes in issue attention and discuss the potential explanations of the factors that might give rise to these stylized facts. In the third section, I present my theoretical expectations about the asset pricing implications of day-to-day issue attention changes. In the fourth section, I present the data I use to test the asset pricing effects, and I also discuss the empirical strategy to estimate the effects. In the fifth section, I present the results from empirical analyses, and discuss the implications. In the final section, I provide concluding remarks.

3.2 Distributional Characteristics of Issue Attention Changes

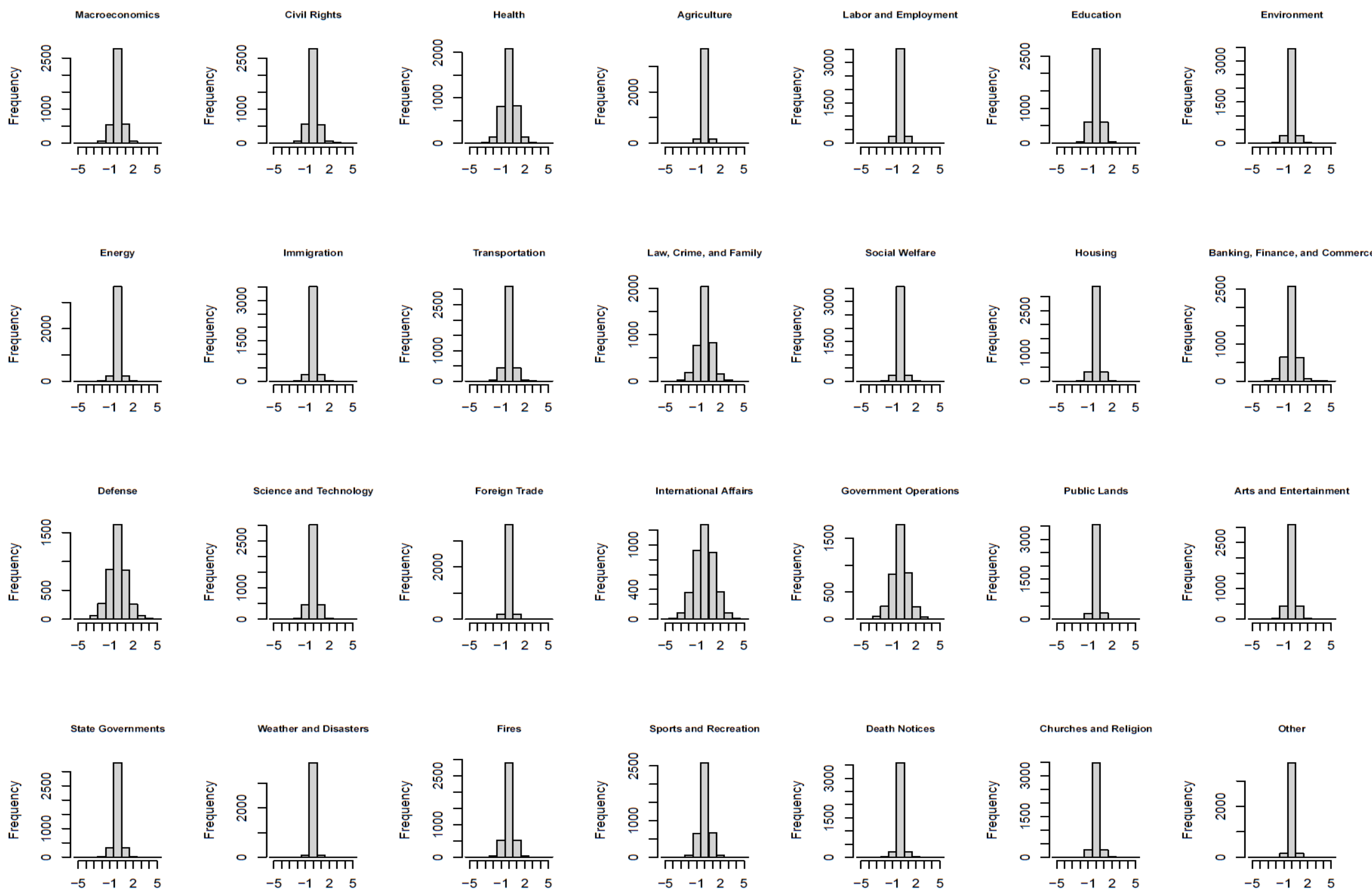
The leptokurtic distribution of changes in policy agendas is now one of the most established stylized facts in political science and public policy (Jones and Baumgartner, 2005; Baumgartner et al., 2009; Walgrave and Nuytemans, 2009; Boydstun, 2013). It has been the basis for a very large and growing literature that focuses on the dynamics of politics which cannot be captured by the more classical partisan or institutionalist approaches. The findings of the policy agendas researchers have also invalidated the incrementalist view of policy change which argues the signals from the environment – the impulses from the real world that might require policymaker response – which are assumed to be normally distributed, translate into policymaker response through a linear process that starts with problem identification and ends with policy implementation (Repetto and Steph; 2011). Linear translation of the signals from the environment causes incremental changes in issue attention and policy change, because the frequency distribution of real world impulses related a policy domain has a normal distribution centered at zero.

According to the policy agendas approach, the policy system is an information processing machine, but an inefficient one. The incrementalist view implicitly assumes policy actors have enough information processing capacity to absorb all the information coming from the environment and to update policies accordingly, but recent research in behavioral economics and political science suggest the opposite (Jones, 1999; Repetto and Steph, 2006). Due to cognitive and institutional constraints, the processing and absorption of information that flows from the environment is slow. The frictional forces cause inertia on the side of policy actors, therefore policy consequences of the changes in the environment usually do not emerge immediately, and sometimes the policy system does not respond at all. However, when the accumulated pressure of many impulses exceeds a threshold, the policy actors might respond quickly and in a punctuated manner.

The behavior of the policy systems I described above – the long episodes of no response or little response, and occasional punctuated policy maker response – underlies the two different policy change regimes I described in the first chapter. The first kind of policy state regime is policy stasis state. In this policy state regime, there is either no policy change or incremental policy change. The data points that populate the center areas of the leptokurtic policy change or attention change distributions are generated by a policy stasis state. This is the default policy change regime in all policy systems. The other policy change regime, the reform state, becomes active only occasionally. In that state, the policy system works differently, and during the transition from policy stasis state to a policy reform state, the changes in issue attention dimensions tend to be larger, and sometimes punctuated. The extent of punctuated response might differ in different levels of government, and it is relatively lower in media because of the more frequent updates of attention allocation.

Figure 3.1 shows the frequency distribution of daily changes in the New York Times frontpage attention allocation by issue topic over the 1996-2006 time period. Most attention changes happen in issue topics such as defense, government operations, international affairs, health, and law, crime and family, but stability or incremental change is the norm for these issue topics, as well. The other dimensions of the New York Times frontpage attention allocation vector are much more stable. There are also some dimensions which are categorized by Boydstun (2013) as nonpolicy topics, such as weather, sports and recreation, and fires. The level of attention these

Figure 3.1 : Daily attention changes by issue topic



issues get are usually very small and seasonal. They are not the main drivers of attention changes in the New York Times frontpage. These plots suggest when there is large overall change in attention allocation, it is usually driven by changes in the attention allocated to topics that might have higher potential impact on the performance of the firms.

Relatively larger changes in the media's issue attention allocation, even if they cannot be always defined as punctuated changes, might be interpreted by investors as signals of transition to a policy reform state, the arrival of new issues to the policy agenda, or the changing image of a policy issue(s). The signal interpretation of the markets might sometimes be wrong. Larger overall changes in media attention do not always translate into larger governmental response. But if there is historically a positive correlation between the extent of attention changes and the governmental response, as the findings of Breunig(2011), and Breunig and Koski (2006) suggest, then the investors' subjective probability of policy reform state or large policy change will be higher. On some days, the large overall attention changes might be a result of small attention changes in many dimensions rather than a large attention change scenario in which the new agenda has a more concentrated distribution. This scenario is also different from the normal attention change scenario in which there are change in a few dimensions. When this large overall change but small changes in many dimensions scenario occur, it might signal the shift from a normal policy agenda to a busy policy agenda with many new issues.

The relationship between media attention and the policymaker attention might be a two-way relationship. Sometimes the media tries to set the agenda of the policymakers by increasing their attention to an issue which receives little attention by policymakers or other policy actors, or by bringing a whole new issue to the attention of them. However, sometimes the policymakers' increasing attention to an issue might drive media attention. (Vleiegenthart et.al., 2016;

Walgrave et al., 2016; Boydstun, 2013) Regardless of the way the effect works, investors and the public mostly learn about the issue from the media. Thus, the changes in the media attention potentially contain information about the changes in policy making activity.

3.3 Attention Shocks and Asset Prices

The policy system is not efficient in the sense that the impulses from the environment do not always translate into policymaker response, and when there is a response, it is usually not immediate. A development in the environment from which the impulses originate, such as the economic environment or the international politics environment, must be either so urgent such that it cannot be easily ignored by the policymakers – e.g. a natural disaster – or it must generate sufficiently large attention in the public and media to find a place in the policymaker agenda. An example of an unignorable urgent event is the COVID19 pandemic which achieved an unignorable status by the spring of 2020. While some governments were quicker than others to respond, all governments across the world had to respond to the situation in some way. The other way an issue can get into the policymaker agenda works slower. In some cases, it might take years or decades in order for an issue to reach the policymaker agenda. Baumgartner and Jones (2005) explain this process with the friction analogy. A substance cannot move until the force applied to it exceed the counter force of the friction. In the example of the COVID-19 pandemic, the frictional force did not matter too much because of the urgency of the situation, but in most cases the frictional force dominates other forces and causes the stick-slip pattern in attention.

In the agenda setting processes, the frictional counterforce is a result of several different factors. Firstly, policymakers have limited time and limited information processing capacity. Even if the aggregation of many policymakers and bureaucratic organizations might increase the information processing capacity, the flow of information about policy-related real world impulses during a given time period is far greater than the information processing capacity of the whole policy system. Secondly, the policymakers have to follow certain rules and procedures which are encapsulated in the concept of institutions. The institutional forces can sometimes significantly limit the way policymakers can respond to an impulse from the environment. Finally, democratic politics require the representation of different preferences on policies. Public pressure or interest group pressure might sometimes cause friction, but this factor might also work in the opposite direction and trigger the burst of policymaker and media attention on a policy-related issue. The attention allocation choices, which can be encoded in the form of an attention allocation vector with dimensions defined by major policy topics, has the potential to reveal information about the equilibrium between the forces that affect the progression of policy issues onto the policymakers' agenda.

Markets process information more efficiently than the policy system (Fama 1970; Baumgartner and Jones, 1991). While there is significant debate in the finance literature regarding the extent and nature of efficiency, there is no uncertainty about the fact that the translation of the available new information into asset prices is faster than the translation of policy related information into policy change (Jones and Baumgartner, 2012, Robinson et al.; 2007). Daily changes in the media's attention allocation do not always predict the timing and extent of policy change, but they can potentially affect the market's expectations policy change. Bernhard and Leblang (2006) uses changes in partisan probabilities during election campaign periods to explain market volatility. They show that high-frequency changes in partisan probabilities are statistically related to price movements before an election. This relationship works through the mechanism of policy change expectations. Daily changes in the allocation of attention across policy issues might also affect policy change expectations. Thus, daily changes in attention allocation might have pricing implications, as changes in attention is necessary ingredient for policy change.

The extent of changes in attention allocation might contain information about the state of the policy system, arrival of new policy issues, or the changing image of a policy issue. As a large body of policy agendas research show larger changes in attention increase the likelihood of policy change, and the magnitude of policy change is positively correlated with the magnitude of change in attention. This rule especially applies to policymakers' attention, but the media, to some extent, mirrors the policymaker attention, and sometimes causes policymaker attention.

Large changes in media's attention allocation might be a manifestation or a signal of several different things: transition from policy stasis state to a policy reform state, the changing image of a policy issue, or the arrival of a busy policy agenda with many new issues. If a large attention change is a manifestation or a signal of transition to policy reform state, then the uncertainty about the impacts of the approaching reform will increase policy uncertainty. If it is a manifestation or a signal of the arrival of new issues to the agenda, then the increasing uncertainty about what issue the government will address in the future might increase policy uncertainty. In both scenarios, the policy change related uncertainty – policy change direction uncertainty or policy change impact uncertainty - will be higher compared to times when attention changes are more incremental -which is the norm in daily issue attention changes. Because of the reasons I discuss above, I expect larger changes in issue attention allocation will increase aggregate return volatility, which is a manifestation of total uncertainty or disagreement about the direction of the prices in the financial markets. I also expect that larger changes in daily issue attention allocation will decrease daily aggregate returns, because short term increases in volatility might negatively affect short term returns (Pastor and Veronesi, 2010; Harvey and Lange, 2018). The hypotheses below summarize my theoretical expectations.

Hypothesis 1: As the extent of changes in policy issue attention allocation increases, the volatility (variance) of the aggregate stock market returns will increase.

Hypothesis 2: As the extent of changes in policy issue attention allocation increases, the mean of the aggregate stock market returns will increase.

In the next section I describe the data and the empirical strategy I will use to test these hypotheses.

3.4 Data and Empirical Strategy

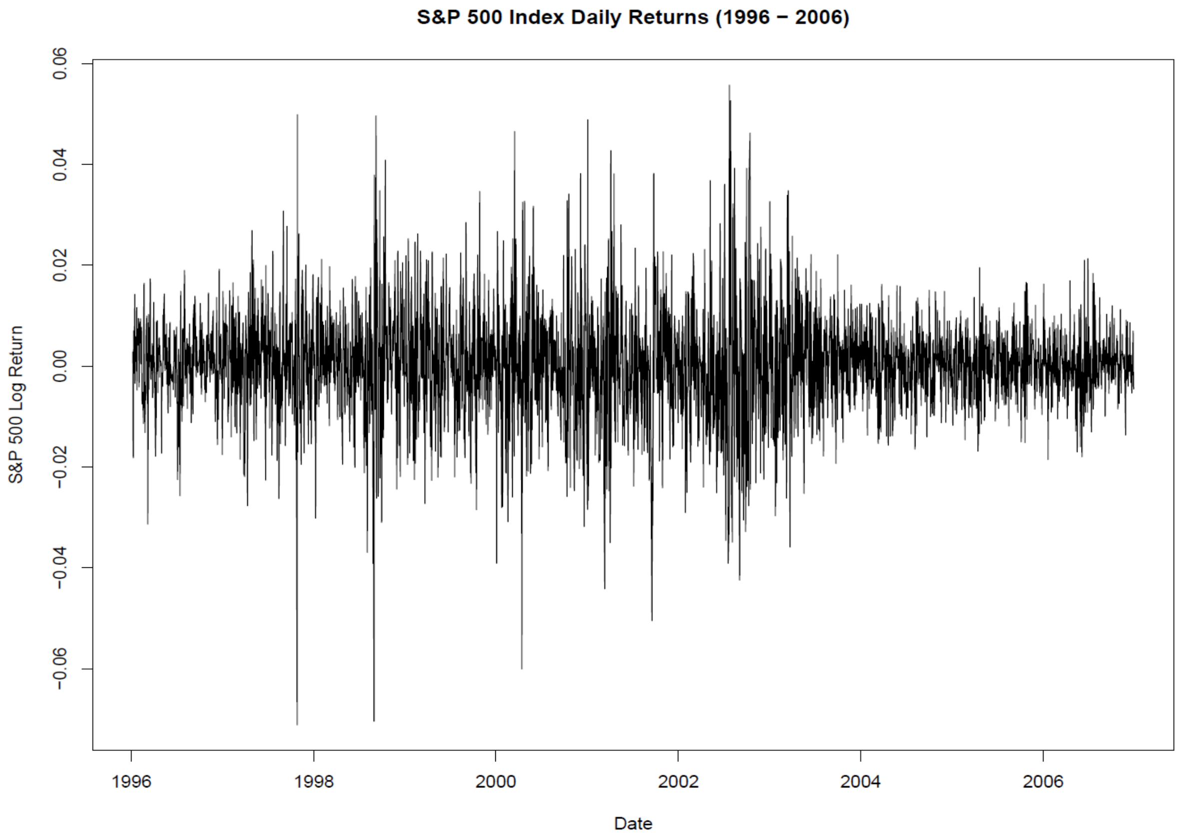
I test the main argument of this chapter using data on the daily prices of the Standard and Poor 500 Index (S&P 500) and the New York Times (NY Times) front page articles. S&P 500 is a market index whose return rate is widely used as a proxy for the aggregate stock market performance. The companies included in the index account for nearly 80% of the total market capitalization of publicly listed companies in the United States of America. I use daily log returns of the S&P 500 as the dependent variable of the mean equation of the EGARCH model in which the log variance (i.e. the volatility) of the log returns is modeled as a function of the past values of the return variance, past values of the disturbance term, and exogenous variables. The log return is defined as:

$$r_t = \ln(p_t) - \ln{(p_{t-1})}$$

where r_t is the daily log return at time t, p_t is the price of the asset at time t and p_{t-1} is the price of the asset at time $t-1$. In asset pricing research, log return is a widely used measure of change in stock prices, because it has some desirable properties which simple returns do not possess. Firstly, the distribution of log returns suffers less from heavy-tailedness which can sometimes be observed to a severe extent in simple returns. While log returns may not completely resolve this problem, it alleviates it. The GARCH family of models allow error distributions which have heavier tails than a normal distribution, such as the student's t distribution. However, the log returns are still the most widely used return measure in studies using a GARCH strategy. Secondly, log returns are additive, meaning that the return of an asset over n periods is the sum of returns in each subperiod (Tsay, 2005; Rockinger, Jondeau, and Poon, 2007). Price data used to calculate log returns come from the Yahoo Finance API. I use daily closing prices of the S&P 500 Index. In the United States, the stock markets are closed on weekends and certain holidays. Therefore, the sample only contains the dates on which the stock market was open. Figure 3.2 shows the log returns of the S&P 500 Index over the time period starting from January 1996 to the December 2006.

To measure the extent of daily changes in issue attention allocation, I use data on the NY Times frontpage articles (Boydstun, 2013). The raw front page articles dataset has more than 30,000 observations. Each observation corresponds to an article published on the front page of the NY Times during the period starting on January 1st 1996 and ending on December 31st 2006. I convert the article level raw data into a daily topic count matrix using the major topic information. The resulting daily frontpage attention allocation dataset has 4018 observations, but 2738 of these observations are used in the analysis because of the exclusion of dates on which the markets are closed. The major topic assignments were done by human coders, and they used the major topic classification scheme of the Comparative Agendas Project's (CAP) as the baseline scheme. They added some major topic categories that do not exist in the CAP's scheme,

Figure 3.2: Daily Log Returns of the S&P 500 Index over the sample period



such as sports, fires, culture, churches, death notices, human interest, and weather. However, an overwhelming majority of articles belong to the CAP major topic categories. In the CAP's topic classification scheme, each major topic has multiple subtopics. For example, the environment major topic category has eleven subtopic categories, and the macroeconomics major topic category has nine subtopics.[5] While using subtopics provide a more fine-grained way to measure issue topic category, since the number of subtopics is very large compared to the number of major topics, the resulting count vector will have many zeros and a large portion of nonzero values will equal to one. Using major topics reduces the sparsity of the attention allocation

[5] The subtopics of the environment major topic are as follows: general, drinking water, waste disposal, hazardous waste, air pollution, recycling, indoor hazards, species & forest, conservation, R&D, other. The subtopics of the macroeconomics major topics are as follows: general, interest rates, unemployment rate, monetary policy, national budget, tax code, industrial policy, price control, other.

vector, and makes it easier to capture relatively larger changes in attention allocation. Another reason why I prefer to use major topics is related to the trends in the policy agendas literature. Major topics are the most common way to measure attention allocation changes in the policy agendas research. Subtopic diversity is usually used when a study focuses on a specific policy domain and tries to capture the variation in attention to a very specific policy issue such as healthcare reform, which is a subtopic under the major topic category of health.

I use media attention data for several reasons. Firstly, it is the only venue of political agenda setting where attention allocation changes can be observed on a daily basis. This enables generating higher frequency measurements of attention changes in policy agendas. In other venues of political agenda setting, such as the legislative agenda or the executive agenda, we usually cannot observe changes in the policy agenda in a daily time frequency. Secondly, stocks move on news, and especially on news that might contain information about potential policy changes. Stock market investors learn about politics mainly through the consumption of news, and changes in the media agenda might be interpreted as signals of changing policymaker attention (Boydstun, 2013). Thirdly, media agenda can affect the agenda of the policymakers (Vleiegenthart et.al., 2016; Walgrave et al., 2016; Boydstun, 2013). A large number of studies in the policy agendas literature show that large positive changes in the attention of media on a certain issue tends to translate into positive policymaker attention change on the same issue and related issues. Finally, the front page of a newspaper is one of the best settings to analyze the implications of the scarcity of attention, which is the starting assumption of the policy agendas research. The size of the front page is not so flexible, and there are limits in terms of the extent to which the size of a front page article can be downsized. Boydstun (2013) reports that on most days, the number of articles on the front page of the New York Times equals to eight. Everyday, the editors of the frontpage face the decision to allocate this fixed space among the issues that compete for attention. Because of this fixed nature of the agenda space, a lot of issues have to be ignored. The stick – slip pattern we observe in legislative and executive agendas also apply to media agenda, but to a smaller extent.

Attention changes can happen in any of the 28 dimensions of the attention allocation vector. The attention allocation vector I defined in the first chapter can be used to characterize the daily distribution of New York Times frontpage articles by issue topic. The attention allocation vector was defined as:

$$A_t = \left[a_{1,t,}\ \cdots, a_{i,t}\right]$$

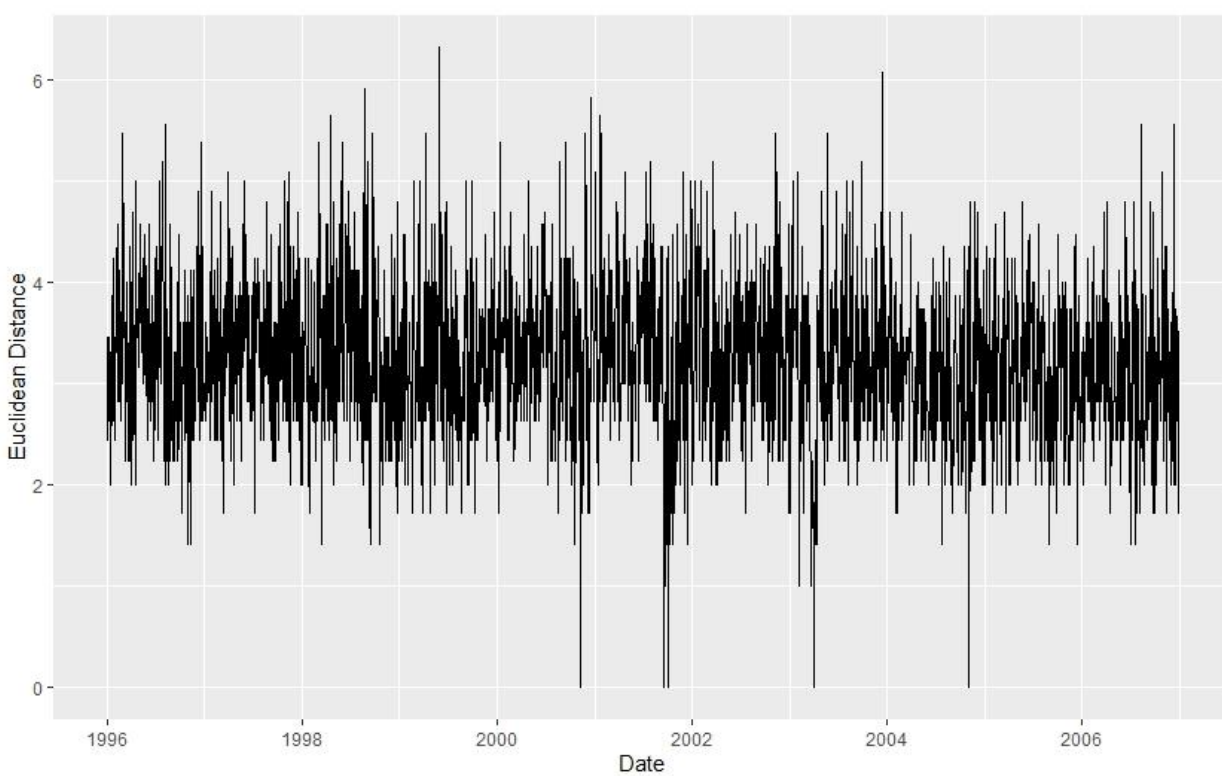
where $a_{i,t}$ is the number of articles on issue topic *i* on day *t*. I use the same topic scheme as Boydstun (2013), therefore, the New York Times frontpage attention allocation vector can be characterized as a 28-dimensional vector. My main hypothesis is related to the effect of daily overall change in attention allocation on the mean and variance of daily stock returns. I conceptualize the main independent variable as *attention dissimilarity*. To measure the extent of overall changes in attention allocation, we need to quantify the similarity/dissimilarity between the attention allocation vectors from two different time points.

I use several different metrics to measure the *attention dissimilarity* variable. I use this strategy to evaluate the results' sensitivity to the measurement strategy. The first metric is the Euclidean distance, which is a widely used multidimensional dissimilarity metric for high dimensional vector spaces. Euclidean distance is defined as:

$$Euclidean\ Distance = d(A_t, A_{t-1}) = \sqrt{\sum_{i=1}^{n}(a_{i,t} - a_{i,t-1})^2}$$

where $a_{i,t}$ is the number of articles on issue topic *i* on day *t*. The Euclidean distance aggregates pairwise differences between two vectors. The Euclidean distance metric has a lower bound of zero which corresponds to perfect similarity between two vectors, but the upper bound depends on the range of values each dimension can take on.

Figure 3.3: Euclidean distance values over the sample period

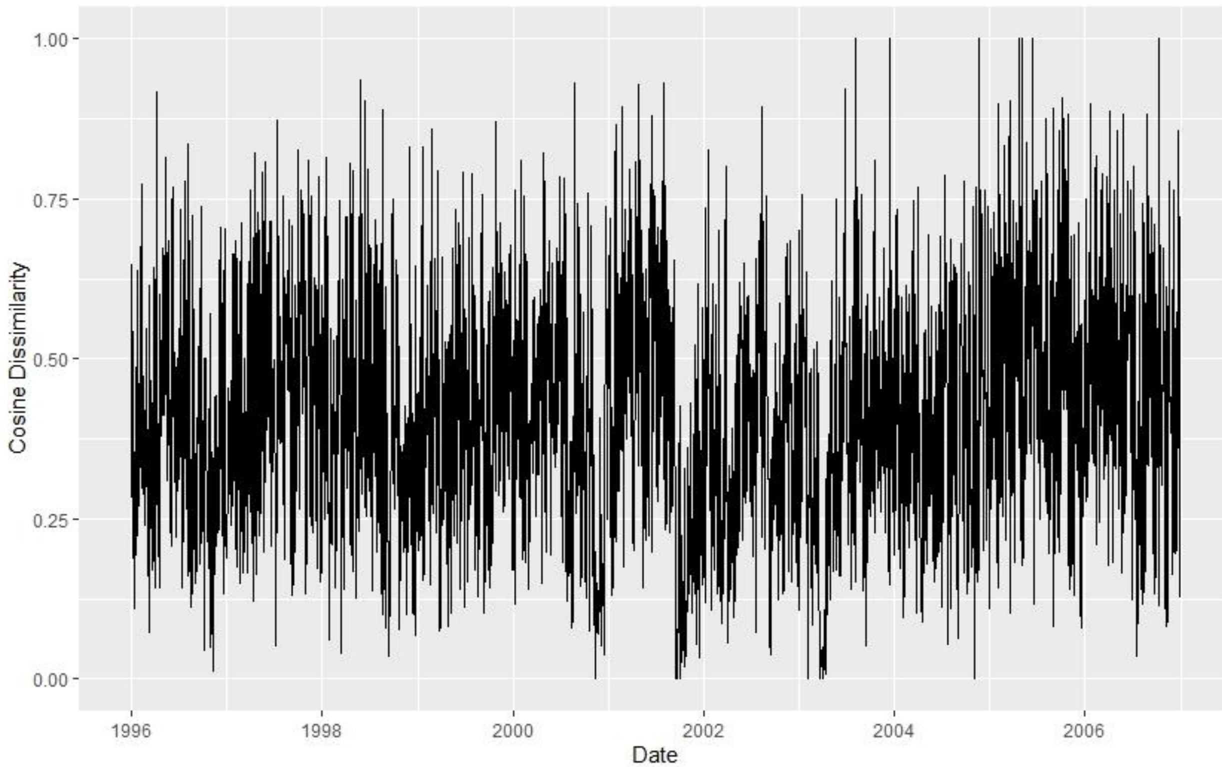


The second distance metric I use is the cosine dissimilarity which measures dissimilarity using the cosine of the angle between two vectors in d-dimensional space. The cosine dissimilarity metric uses the formula below

$$Cosine\ Dissimilarity = 1 - \cos(\theta) = 1 - \frac{A_t \cdot A_{t-1}}{\|A_t\|\ \|A_{t-1}\|} = 1 - \frac{\sum_{i=1}^{n} a_{i,t} a_{i,t-1}}{\sqrt{\sum_{i=1}^{n} a_{i,t}}\sqrt{\sum_{i=1}^{n} a_{i,t-1}}}$$

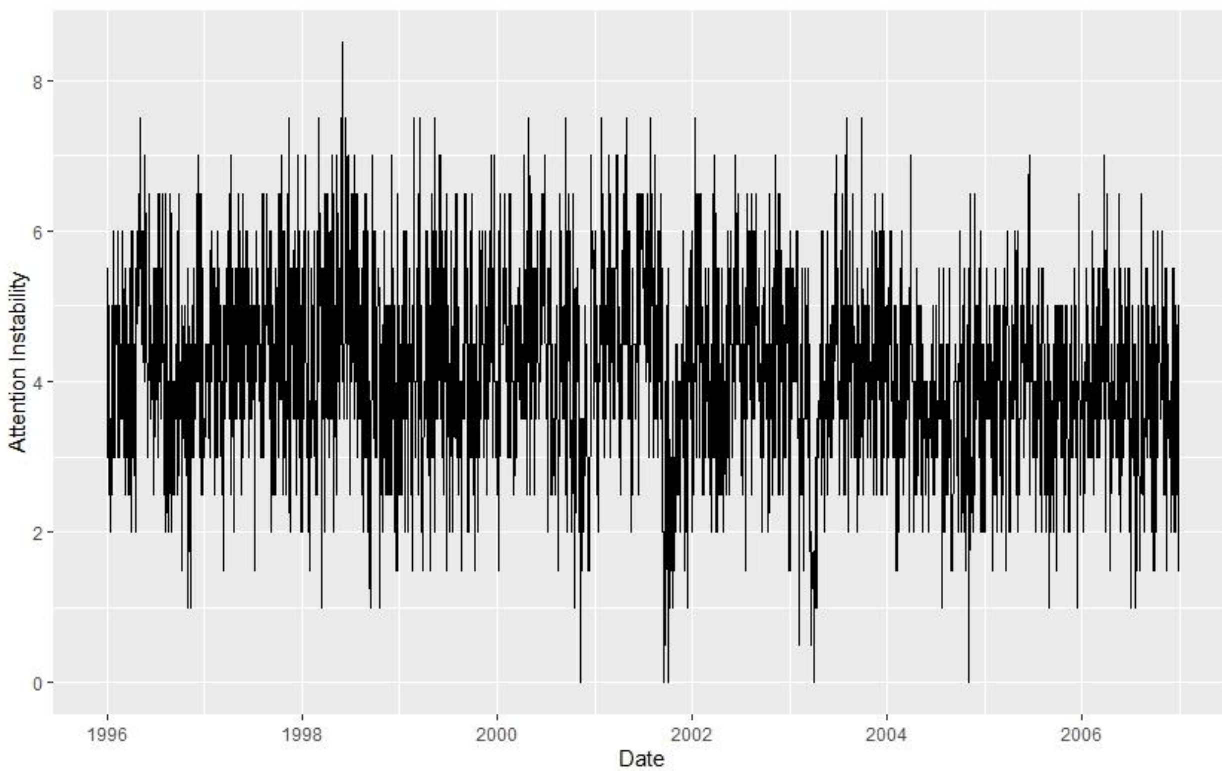
where $\cos(\theta)$ is the cosine of the angle between the attention allocation vectors of day *t* and day *t-1*. In algebraic terms, the cosine dissimilarity is basically one minus the ratio of the dot products of two vectors to the product of their magnitudes. Cosine dissimilarity is bounded in the range [0,1]. When two vectors have same values across all dimensions, the angle between them is zero degree and the cosine of that zero angle equals to one, and the cosine dissimilarity equals to zero. This scenario corresponds to a situation perfect similarity between two vectors. As the dissimilarity between two vectors increase, the cosine dissimilarity value will approach to one. When two vectors have no shared values, the cosine dissimilarity will be equal to one. Unlike the Euclidean distance, the cosine dissimilarity is not scale sensitive. Since the issue attention vector is a count vector and it is not theoretically bounded, the number of articles might affect the number of changes. When the number of frontpage articles increase (decrease) from time *t* to *t+1*, the number of dimensions that change their values or the mean change across dimensions might also increase (decrease). To eliminate this effect, we can normalize the vector, but cosine similarity does not require normalized data.

Figure 3.4: Cosine dissimilarity values over the sample period



These metrics are useful to capture the extent of overall changes in issue attention allocation, because when the media attention is in an incremental change state – i.e. the policy stasis state –, the magnitude of change in most dimensions – i.e. issue topics – will be zero, and in the dimensions which are not stable from time *t* to time *t+1*, the magnitude of change will be small. When there are larger shifts in attention, the magnitude of changes will be larger and the attention allocation vector at time *t* and time *t+1* will be less similar. The Euclidean distance value will be larger and the cosine similarity value will be smaller when the change is more punctuated. One disadvantage of the cosine similarity is that when total change is small but the set of issue topics with nonzero values in time *t* is largely different than the set of issue topics with nonzero values in time *t+1*, the cosine similarity score will be low. However, since the attention is sticky and there are usually a small number of issue topics that regularly get large attention, this scenario will not be so common. In most cases, low cosine similarity values will correspond to an abnormal attention change which is more punctuated than attention changes on an average day.

Figure 3.5: Attention instability values over the sample period



The third metric I use is the agenda instability metric developed by Sigelman and Buell (2004). It is defined as:

$$Attention\ Instability = \frac{\sum_{i=1}^{n} |a_t - a_{t-1}|}{2}$$

where where $a_{i,t}$ is the number of articles on issue topic *i* on day *t*. The three measures are highly correlated. The weakness of cosine similarity in terms of capturing the punctuatedness of attention changes is not a weakness of the attention instability measure, but its weakness is its scale sensitivity, which is not a weakness of the cosine similarity measure.

I use the daily version of the Economic Policy Uncertainty (EPU) index to control for the impact of economic policy related shocks on return and volatility. It is a news-based index which aims to capture uncertainty perception based on the mentions of keywords related to economic policy and uncertainty in the news media (Baker, Bloom and Davis, 2015). Therefore, EPU only focuses on uncertainty surrounding macroeconomic policy, and cannot capture the overall policy-related uncertainty. My main independent variable – i.e. the attention dissimilarity – is not policy domain specific. Another reason why I use the EPU as a control variable is the potential negative confounding relationship between attention shocks and economic policy uncertainty. During times of high Economic Policy Uncertainty, the policymakers and the media might have a concentrated focus on the issue(s) that is the source of sharp increase in economic policy uncertainty. The EPU Index makes sharp increases during political and economic crisis periods, even if the underlying event is not directly related to macroeconomic policy. When attention becomes overconcentrated and stable during the crisis period, the attention dissimilarity scores are very low. This complicates finding the expected relationship between attention instability and volatility. The EPU can explain high volatility during times of crises which tend to have low attention instability after the initial shift in attention.

I also control for daily trading volume of the S&P 500 Index, as a large literature shows they tend to co-move (Gallant, Rossi, and Tauchen 1992). Trading volume might increase periodically due to events like earnings announcement or the release of macroeconomic statistics. When trading volume increases due to an important announcement, it might also increase the short-term volatility due to processing of new information that arrives with the announcement. The trading volume variable measures the logarithm of the number of shares traded of the S&P 500 Index in a single day. Some studies use the trading volume as a metric that gauges total information flow to the markets (Andersen, 1996). The information flow from firms or other sources that have potential to affect firm performances might have return and volatility effects, and the trading volume variable can account for the variation in return and volatility caused by the fluctuations in the amount of information flow.

Another common control variable in return and volatility models is the yield rate of 10 year treasury bonds. Investing in treasury bonds is considered the least risky (or riskless) form of investment in the financial markets. Increasing (decreasing) yield rates might discourage (encourage) risk averse investors to invest in the stock markets, because stocks need to generate a higher return to justify the higher risk. Thus, the fluctuations in the treasury bond yield rates might have stock pricing implications. The treasury bond yield rate time series is not stationary, therefore I use the first differences of that series. I use the daily change in the 10 year treasury bonds as a control variable in both the mean and variance models of log returns.

I use an ARMA-EGARCH strategy to model the log returns and to test my hypotheses. The mean return processes is modeled using an ARMA(2,1) structure and the return volatility process is modeled using an EGARCH(1,1) structure. The GARCH family of models are flexible in terms of error distribution specification. Studies that analyze the statistical properties of the S&P 500 log returns suggest the student-t distribution is the best fit and it offers the best forecasting performance (Markowitz and Usmen, 1996; Hurst and Platen, 1997; Platen and Rendek, 2008, Fergusson and Platen, 2007). Log-returns alleviate the skewness problem, but may not completely resolve it. I use the *rugarch* R package developed by Ghalanos (2020) to estimate the models.

The ARMA(1,1) mean model is defined as:

$$r_t = \mu + \theta\varepsilon_{t-1} + \varphi r_{t-1} + \vartheta_i X_{i,t} + \varepsilon_t$$

$$\varepsilon_t \sim T(0, \sigma_t^2)$$

where r_t is the daily log return of the S&P 500 Index at time t, μ is the intercept, θ is the moving average coefficient, φ is the autoregressive coefficient, X_i is a set of exogenous variables, and ε_t is the error term. I use the same set of exogenous variables in the mean equation and the variance equation. For the variance equation, I use an EGARCH(1,1) model which is defined as:

$$\log(\sigma_t^2) = \omega + \alpha z_{t-1} + \gamma(|z_{t-1}| - E(|z_{t-1}|)) + \beta \ln(\sigma_{t-1}^2) + \rho_i X_{i,t}$$

where σ_t^2 is the variance of ε_t, z_t represents standardized residuals, and X_i is a set of exogenous variables. Since the dependent variable of the variance equation is logged variance, there is no restriction on ARCH and GARCH coefficient signs of the EGARCH model (Bollerslev, 1986; Nelson, 1991).

3.5 Results and Discussion

In this section, I present the results from ARMA-EGARCH models of the daily returns of the S&P 500 Index and discuss the implications of those results. Each of the three tables in this section shows the results for the models that use a different dissimilarity metric to capture the extent of daily changes in attention allocation. The Table 3.1 shows the results for models that use the Euclidean distance metric, Table 3.2 shows the results for models that use the Cosine dissimilarity metric, and Table 3.3 shows the results for models that use the attention instability metric of Sigelman and Buell (2004). The results from all these models largely support my hypothesis about the volatility and return impacts of issue attention allocation changes, but the evidence for the volatility hypothesis is more consistent across the models.

The third and fourth columns in each tables feature mean models that have an ARMA(2,1) structure. This selection was made using the Hyndman – Khandakar Algorithm (Hyndman and Khandakar, 2008) that recommends an ARIMA structure based on unit root tests, AIC statistic and the Log Likelihood.[6] While the ARMA(2,1) mean model is the preferred model based on the Hyndman – Khandakar Algorithm recommendation, it does not seem to be the best fit across all models I present in this section. For example, in Table 2, ARMA(2,2) models have better AIC and BIC scores than other ARMA specifications. However, some ARMA(2,2) models do not satisfy the stationarity conditions for AR(p) models. Another important consideration for ARMA(p,q) models is the invertbility condition of the MA(q) component. All models presented here satisfy the invertibility condition.[7] In the columns one and two of the results tables, I present models that use ARMA(1,1) structure for the mean equation, and in the columns five and six, I present models that use ARMA(2,2) structure for the mean equation. The models in the odd numbered columns assume the return process has student t distributed errors, and the models in

[6] The auto.arima function of the forecast package on the R platform implements this algorithm. This function recommended using ARIMA(2,0,1) structure for the daily log returns over the 1996-2006 period.

[7] The invertibility condition requires that in an MA(1) model, the absolute value of the moving average coefficient (θ) has to be smaller than one. In an MA(2) model the invertibility condition requires the following: $|\theta_2| < 1$, $\theta_1 + \theta_2 < 1$, $\theta_2 - \theta_1 < 1$. For the AR(p) component, the same rules apply to satisfy the stationarity condition.

even numbered columns assume the return process has normal distributed errors. The AIC-BIC statistics suggest the student t distribution is better fit for the return process. The sign and significance of the exogenous variables in volatility models are fairly stable across different ARMA specifications. All standard errors presented in the results tables are robust standard errors that are calculated based on the method of White (1982).

In the volatility models, I use an EGARCH(1,1) structure. Ziwot (2008) argues EGARCH(1,1) is generally the best fitting structure for the volatility equation. Unlike the standard GARCH model, the EGARCH model has the logarithm of variance on the left-hand side, which suggests the positivity of the variance does not depend on the sign of the coefficients. Another important feature of the EGARCH model is the ability to model asymmetric volatility effects of positive and negative innovations of the return process. The sign of the γ parameter tells us if there is asymmetric volatility effect. When it is zero, there is no asymmetric effect. When it is positive, it means positive shocks will generate more volatility than negative shocks, and it will be the opposite when it is negative. There is evidence for the asymmetric effect in the results presented here, but the sign of the coefficient is different than what most studies find. It is usually found that negative shocks generate greater volatility than positive shocks, but in the 1996-2006 period the sign of this effect was positive. This unexpected result might have to do with the time frame of the sample, which included events such as the boom and bust of the dotcom bubble.

To simplify the comparison of the effects, the exogenous variables of the ARMA-EGARCH models are standardized to have mean zero and standard deviation one. Each model features four exogenous variables that were discussed in the previous section: attention dissimilarity, economic policy uncertainty, log of trading volume, and the daily change in 10 year treasury bond rate. I use three alternative metrics to capture the extent of daily changes in policy issue

Table 3.1 ARMA-EGARCH models of S&P 500 daily returns – Euclidean distance metric

Mean Model	1	2	3	4	5	6
	ARMA(1,1)	ARMA(1,1)	ARMA(2,1)	ARMA(2,1)	ARMA(2,2)	ARMA(2,2)
Attention Dissimilarity	-0.00033^{*}	-0.00031	-0.00032^{*}	-0.00029	-0.00029^{*}	-0.00032^{*}
	(0.00016)	(0.00039)	(0.00016)	(0.00015)	(0.00014)	(0.00016)
EPU	-0.00003	-0.00008	-0.00000	-0.00008	0.00002	-0.00005
	(0.00019)	(0.00021)	(0.00023)	(0.00021)	(0.00019)	(0.00020)
Log(Trading Volume)	0.00018	-0.00016	-0.00019	-0.00015	-0.00018	0.00011
	(0.00024)	(0.00023)	(0.00012)	(0.00013)	(0.00012)	(0.00006)
Δ T-Bond Rate	-0.00051	-0.00036	-0.00049	-0.00034	-0.00049	-0.00037
	(0.00041)	(0.00050)	(0.00106)	(0.00041)	(0.00033)	(0.00037)
μ	-0.00066^{***}	0.00009	0.00031	0.00013	0.00026^{*}	-0.00091^{**}
	(0.00013)	(0.00019)	(0.00021)	(0.00016)	(0.00013)	(0.00033)
AR(1)	0.99846^{***}	-0.27496^{***}	0.62330^{***}	0.68176^{***}	1.80211^{***}	0.01609^{***}
	(0.00000)	(0.02497)	(0.01138)	(0.04190)	(0.00154)	(0.00171)
AR(1)			-0.02547	-0.02040	-0.98879^{***}	0.98212^{***}
			(0.01819)	(0.01550)	(0.00120)	(0.00000)
MA(1)	-0.99167^{***}	0.28485^{***}	-0.62980^{***}	-0.67624^{***}	-1.80737^{***}	-0.01666^{***}
	(0.00000)	(0.02000)	(0.01002)	(0.03744)	(0.00190)	(0.00400)
MA(2)					0.99074^{***}	-0.97211^{***}
					(0.00003)	(0.00000)
Variance Model	EGARCH(1,1)	EGARCH(1,1)	EGARCH(1,1)	EGARCH(1,1)	EGARCH(1,1)	EGARCH(1,1)
Attention Dissimilarity	0.01003	0.01452	0.01449^{*}	0.01459^{*}	0.01368^{*}	0.01220^{*}
	(0.00533)	(0.00889)	(0.00722)	(0.00685)	(0.00653)	(0.00578)
EPU	0.01199^{***}	0.01234^{**}	0.00978^{**}	0.01210^{**}	0.00975^{**}	0.01407^{***}
	(0.00273)	(0.00392)	(0.00360)	(0.00404)	(0.00367)	(0.00329)
Log(Trading Volume)	-0.00491^{*}	-0.00537	-0.00316	-0.00546	-0.00334	-0.00684^{**}
	(0.00216)	(0.00517)	(0.00325)	(0.00346)	(0.00310)	(0.00228)
Δ T-Bond Rate	-0.01296	-0.01435	-0.01587	-0.01525	-0.01646	-0.01330
	(0.00879)	(0.01164)	(0.00990)	(0.01124)	(0.00921)	(0.01032)
ω	-0.16548^{***}	-0.23805^{***}	-0.20660^{***}	-0.23529^{***}	-0.21217^{***}	-0.20502^{***}
	(0.00159)	(0.00274)	(0.00383)	(0.00314)	(0.00311)	(0.00200)
α	-0.13042^{***}	-0.12851^{***}	-0.11577^{***}	-0.12189^{***}	-0.12439^{***}	-0.13039^{***}
	(0.00791)	(0.01184)	(0.01430)	(0.01220)	(0.01117)	(0.01224)
β	0.98223^{***}	0.97409^{***}	0.97790^{***}	0.97441^{***}	0.97729^{***}	0.97772^{***}
	(0.00003)	(0.00003)	(0.00009)	(0.00003)	(0.00019)	(0.00003)
γ	0.06707^{***}	0.09367^{***}	0.08928^{***}	0.09463^{***}	0.08990^{***}	0.07303^{***}
	(0.00528)	(0.01045)	(0.00498)	(0.01077)	(0.00516)	(0.00605)
Shape	13.56164^{***}		12.66448^{***}		13.29928^{***}	
	(1.48964)		(3.17438)		(2.81844)	
Log likelihood	8830.92912	8811.17020	8829.75021	8811.52464	8834.72883	8816.04639
AIC	-6.43895	-6.42525	-6.43736	-6.42478	-6.44027	-6.42735
BIC	-6.40439	-6.39285	-6.40064	-6.39022	-6.40138	-6.39063

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 3.2 ARMA-EGARCH models of S&P 500 daily returns – Cosine dissimilarity metric

Mean Model	1	2	3	4	5	6
	ARMA(1,1)	ARMA(1,1)	ARMA(2,1)	ARMA(2,1)	ARMA(2,2)	ARMA(2,2)
Attention Dissimilarity	−0.00007	−0.00010	−0.00013	−0.00010	−0.00011	−0.00012
	(0.00011)	(0.00016)	(0.00017)	(0.00016)	(0.00022)	(0.00016)
EPU	0.00001	−0.00008	0.00000	−0.00009	−0.00001	−0.00010
	(0.00021)	(0.00020)	(0.00021)	(0.00020)	(0.00117)	(0.00020)
Log(Trading Volume)	0.00025*	−0.00011	−0.00014	−0.00011	−0.00011	−0.00011
	(0.00011)	(0.00011)	(0.00012)	(0.00011)	(0.00010)	(0.00008)
Δ T-Bond Rate	−0.00049	−0.00033	−0.00048	−0.00032	−0.00049	−0.00036
	(0.00039)	(0.00044)	(0.00039)	(0.00039)	(0.00091)	(0.00039)
μ	−0.00082*	0.00009	0.00032*	0.00013	0.00056***	0.00012
	(0.00041)	(0.00016)	(0.00014)	(0.00016)	(0.00000)	(0.00011)
AR(1)	0.99761***	−0.28828***	0.62712***	0.67613***	0.01876***	1.54300***
	(0.00001)	(0.00938)	(0.01085)	(0.02511)	(0.00058)	(0.00142)
AR(2)			−0.02464	−0.02018	0.98329***	−0.99343***
			(0.01883)	(0.01717)	(0.00000)	(0.00174)
MA(1)	−0.98786***	0.29668***	−0.63396***	−0.67069***	−0.02331***	−1.53610***
	(0.00000)	(0.01238)	(0.01300)	(0.02291)	(0.00001)	(0.00141)
MA(2)					−0.98059***	0.98638***
					(0.00000)	(0.00002)
Variance Model	EGARCH(1,1)	EGARCH(1,1)	EGARCH(1,1)	EGARCH(1,1)	EGARCH(1,1)	EGARCH(1,1)
Attention Dissimilarity	−0.00212	0.00126	−0.00025	0.00141	−0.00052	0.00155
	(0.00376)	(0.00602)	(0.00525)	(0.00596)	(0.00640)	(0.00582)
EPU	0.00693**	0.01013*	0.00642	0.01000*	0.00591	0.00988*
	(0.00266)	(0.00457)	(0.00431)	(0.00463)	(0.01405)	(0.00467)
Log(Trading Volume)	−0.00480***	−0.00660*	−0.00431	−0.00665*	−0.00342	−0.00662*
	(0.00127)	(0.00302)	(0.00286)	(0.00288)	(0.00258)	(0.00297)
Δ T-Bond Rate	−0.01292	−0.01408	−0.01558	−0.01484	−0.01450	−0.01298
	(0.00832)	(0.01107)	(0.00945)	(0.01120)	(0.00952)	(0.01132)
ω	−0.11985***	−0.22105***	−0.18320***	−0.21818***	−0.18549***	−0.21275***
	(0.00194)	(0.00311)	(0.00278)	(0.00328)	(0.00618)	(0.00269)
α	−0.12978***	−0.12788***	−0.11468***	−0.12168***	−0.12516***	−0.12493***
	(0.00853)	(0.01220)	(0.01223)	(0.01151)	(0.02861)	(0.01179)
β	0.98713***	0.97591***	0.98043***	0.97624***	0.98028***	0.97685***
	(0.00003)	(0.00004)	(0.00010)	(0.00015)	(0.00069)	(0.00009)
γ	0.05755***	0.09444***	0.08998***	0.09548***	0.09298***	0.09615***
	(0.00634)	(0.01110)	(0.00534)	(0.01004)	(0.01955)	(0.00203)
Shape	13.46470***		12.56423***		12.49939***	
	(2.48393)		(2.85878)		(2.71934)	
Log likelihood	8828.99423	8808.34522	8827.03196	8808.67592	8826.04988	8813.92255
AIC	−6.43754	−6.42319	−6.43538	−6.42270	−6.43393	−6.42580
BIC	−6.40298	−6.39078	−6.39865	−6.38813	−6.39504	−6.38908

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 3.3 ARMA-EGARCH models of S&P 500 daily returns – Attention instability metric

Mean Model	1	2	3	4	5	6
	ARMA(1,1)	ARMA(1,1)	ARMA(2,1)	ARMA(2,1)	ARMA(2,2)	ARMA(2,2)
Attention Dissimilarity	-0.00048^{***}	-0.00045^{**}	-0.00044^{**}	-0.00038	-0.00046^{**}	-0.00041
	(0.00010)	(0.00017)	(0.00015)	(0.00109)	(0.00015)	(0.00110)
EPU	-0.00006	-0.00009	-0.00002	-0.00009	-0.00000	-0.00011
	(0.00019)	(0.00019)	(0.00021)	(0.00192)	(0.00020)	(0.00522)
Log(Trading Volume)	0.00012^{*}	0.00008	-0.00022	-0.00018	-0.00022	-0.00018
	(0.00006)	(0.00013)	(0.00011)	(0.00059)	(0.00011)	(0.01851)
Δ T-Bond Rate	-0.00051	-0.00038	-0.00050	-0.00034	-0.00050	-0.00039
	(0.00031)	(0.00040)	(0.00046)	(0.00122)	(0.00038)	(0.02261)
μ	-0.00048^{**}	-0.00080^{***}	0.00032^{*}	0.00014	0.00030^{*}	0.00010
	(0.00018)	(0.00020)	(0.00016)	(0.00147)	(0.00015)	(0.00203)
AR(1)	0.99886^{***}	0.99913^{***}	0.62817^{***}	0.68335^{***}	-0.27062^{***}	1.54236^{***}
	(0.00001)	(0.00000)	(0.01107)	(0.03076)	(0.03900)	(0.00286)
AR(2)			-0.02623	-0.02077	0.69918^{***}	-0.99273^{***}
			(0.01951)	(0.08528)	(0.01520)	(0.00339)
MA(1)	-0.99342^{***}	-0.99466^{***}	-0.63559^{***}	-0.67837^{***}	0.24842^{***}	-1.53536^{***}
	(0.00000)	(0.00001)	(0.01136)	(0.02789)	(0.01474)	(0.00194)
MA(2)					-0.71527^{***}	0.98546^{***}
					(0.02325)	(0.00167)

Variance Model						
	EGARCH(1,1)	EGARCH(1,1)	EGARCH(1,1)	EGARCH(1,1)	EGARCH(1,1)	EGARCH(1,1)
Attention Dissimilarity	0.01471^{***}	0.01554^{***}	0.01836^{***}	0.01847^{*}	0.01842^{***}	0.01806
	(0.00441)	(0.00472)	(0.00542)	(0.00846)	(0.00540)	(0.05875)
EPU	0.01515^{***}	0.01650^{***}	0.01244^{**}	0.01458	0.01249^{**}	0.01443
	(0.00294)	(0.00334)	(0.00388)	(0.02586)	(0.00390)	(0.05459)
Log(Trading Volume)	-0.00442^{*}	-0.00622^{**}	-0.00233	-0.00463	-0.00255	-0.00471
	(0.00191)	(0.00193)	(0.00316)	(0.01228)	(0.00314)	(0.27281)
Δ T-Bond Rate	-0.01340	-0.01335	-0.01593	-0.01529	-0.01586	-0.01328
	(0.00904)	(0.01074)	(0.00959)	(0.01179)	(0.00970)	(0.04089)
ω	-0.19559^{***}	-0.22021^{***}	-0.22089^{***}	-0.24883^{***}	-0.22702^{***}	-0.24252^{***}
	(0.00158)	(0.00210)	(0.00280)	(0.02230)	(0.00271)	(0.01652)
α	-0.13059^{***}	-0.12948^{***}	-0.11486^{***}	-0.12072^{***}	-0.11868^{***}	-0.12474
	(0.00428)	(0.00873)	(0.01254)	(0.03078)	(0.01685)	(0.43880)
β	0.97902^{***}	0.97610^{***}	0.97638^{***}	0.97296^{***}	0.97570^{***}	0.97363^{***}
	(0.00001)	(0.00001)	(0.00007)	(0.00002)	(0.00006)	(0.00362)
γ	0.07140^{***}	0.07324^{***}	0.08837^{***}	0.09277^{***}	0.08902^{***}	0.09411^{**}
	(0.00559)	(0.00752)	(0.00484)	(0.00547)	(0.00633)	(0.03541)
Shape	13.48146^{***}		12.50630^{***}		12.68710^{***}	
	(3.25828)		(2.97938)		(3.08198)	
Log likelihood	8833.76656	8817.91262	8832.94162	8814.47315	8832.62008	8819.59248
AIC	-6.44103	-6.43018	-6.43969	-6.42693	-6.43873	-6.42994
BIC	-6.40646	-6.39777	-6.40297	-6.39237	-6.39984	-6.39322

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

attention. The evidence presented in all the model specifications mostly support the hypothesis that the extent of changes in overall issue attention allocation will have a positive effect on volatility of daily returns, and negative effect on the mean of daily returns. In models where I use the attention instability metric or the Euclidean distance metric to measure the extent of attention allocation changes, the volatility effect is positive in all columns and statistically significant in almost all of them. The size of the volatility effect of the Euclidean distance and attention instability variables are similar to the effect size of the EPU variable. There is no supporting evidence in models where I use the cosine dissimilarity metric. As I mentioned in the previous section, the cosine dissimilarity metric is more sensitive to the number of dimensions that change their value, and the Euclidean distance metric and the attention instability metric are more sensitive to the size of changes, rather than the number of dimensions that change. The results suggest the kind of large attention change that the Euclidean distance metric or the attention stability metric are more capable to capture than the cosine dissimilarity metric is more important for asset pricing impacts of attention allocation changes.

As argued by Pastor and Veronesi (2010) and Harvey and Lange (2018), increases in short-term volatility will usually drive stock prices down in the short term. They call this the news impact, and it is expected to be the opposite of the long-term effect of volatility on stock prices. In the long-term, higher volatility may increase average returns, but in the short term volatility tends to have the opposite effect. This suggests, higher daily changes in issue attention allocation might negatively affect daily stock returns. The results presented here mostly support this expectation. The sign of the attention dissimilarity coefficients in the mean models are mostly the opposite of their volatility effect signs. The evidence for the negative return effect is actually a little bit more consistent than the evidence for the positive volatility effect. Similar to the volatility results, the cosine dissimilarity models do not provide supporting evidence for the mean return effect. The size of the return effect for the Euclidean distance and the attention instability variables are similar, and they are approximately one percentage points in simple returns per one standard deviation change in attention dissimilarity.

Consistent with previous findings in the finance literature (Pastor and Veronesi, 2013), the economic policy uncertainty variable (EPU) has a positive association with the volatility of returns. The evidence for the volume effect on volatility is mixed. The sign of the volume variable is generally not in line with my theoretical expectation and the previous findings in the finance literature. The sign of the treasury bond rates' effect on returns are different than the theoretical expectation. In sum, short-term changes in policy issue attention can have asset pricing implications. Larger daily changes in issue attention allocation in the media are positively related to the variance of aggregate stock returns, and negatively related to the mean of aggregate stock returns.

3.6 Conclusion

In this chapter, I focused on the asset pricing implications of short-term changes in policy issue attention. I argued that larger daily changes in media's issue attention will increase the volatility of aggregate market returns and decrease the mean of aggregate market returns. By using data on the New York Times Front Page articles, I measure the extent of daily changes in attention allocation. The measures I used aim to capture overall changes in high dimensional vectors. The results obtained from the ARMA-EGARCH analyses of the daily returns of the S&P 500 Index over the 1996 and 2006 period are mostly in line with my theoretical expectations.

A limitation of the analysis presented in this chapter is the duration of the time period analyzed. To obtain more generalizable results, we need to extend the length of the sample. Financial time series usually feature structural breaks which sometimes might cause the decoupling of relationships between variables. A recent example of that is the decoupling of the relationship between the Economic Policy Uncertainty Index and the VIX Index during the first year of Donald Trump’s presidency (Pastor and Veronesi, 2017). To obtain more generalizable results and to explore time dependencies between issue attention changes and stock pricing dynamics, we need to focus on a longer time period. Future work should also focus on asset pricing implications of short-term attention allocation changes in novel agenda setting arenas such as the social media platforms which today manage a large portion of total information flow about politics.

Chapter 4: Tax Reform, Noisy Politics and Stock Pricing Dynamics

4.1 Introduction

A corporate tax cut is always an exciting news for financial markets. Lower corporate tax rates mean higher expected future cash flow. Because of that relationship between tax rates and cash flow, news about tax reform can move the markets. News about a tax reform typically start arriving much earlier than the formal legislative process begins. In this chapter, I study how the salience of tax reform issue affect stock returns and volatility, and how this effect might be conditioned by the salience of other policy reform issues that compete for the attention of policy makers. I specifically focus on the 2017 tax reform process in the United States, which introduced large corporate and individual tax cuts. I expect increasing salience of tax reform issue will cause stock returns to go up and stock volatility to go down. I also expect the magnitude of these effects will be conditioned by the salience of competing policy reform issues which are not related to tax reform. I also study the asset pricing implications of the overall salience of high-salience political issues and events that can be described as noisy politics. I expect an increase in noisy politics will increase stock return volatility. Another stock market related outcome I study is the trading volume. I expect the trading volume will increase with greater attention to noisy politics. Greater attention to noisy politics means greater information flow about noisy politics, which should drive more buying and selling activity in the stock markets.

Some of these propositions may sound contradictory to what I argued in the first chapter about the impact of reform processes on stock market movements. In the model I presented in the first chapter, a reform process increases dividend uncertainty and causes greater return volatility. Because of higher uncertainty about the possibility and the potential impact of a typical policy reform than an incremental policy change, a policy reform process tends to increase volatility and might decrease returns in stock markets. However, the 2017 tax policy reform process significantly deviated from the average policy reform process in terms of the likelihood of reform and impact uncertainty. Because of that nature of 2017 tax reform process, the translation of attention changes into stock market return and volatility was different than a typical reform process.

A foundational assumption of agenda setting theories is the limitedness of attention space. A policy reform process typically occupies a large space in the agendas of policy makers. Given the limitedness of the attention space, policy reform processes tend to crowd out other policy issues from the policy agenda (Jennings et al., 2011; Fernández-i-Marín et al., 2019). In the first year of Donald Trump's presidency, there were two main policy reform attempts. One of them was the healthcare reform which eventually failed in the United States Senate. The other policy reform attempt was the tax reform process, which passed through the legislative process and was signed into law towards the end of the President Donald Trump's first year in office. From the beginning of his presidency, the healthcare reform and tax reform were perceived to be competing issues by the news media and market actors. A Financial Times article that was published in 2017, after the failure of the first attempt to pass a healthcare reform bill, reported the following quote by David Donabedian, chief investment officer at the Atlantic Trust:

> “This increases the likelihood that you are going to a get a tax-cut package perhaps sooner than anticipated simply because of the political necessity.” [8]

This statement was quite representative of the prevailing sentiment in the markets in late March 2017 (Collier, 2017). However, the healthcare reform process was not over, and it continued competing for attention until its failure in July 2017, and to a lesser extent after July 2017. In this chapter, I study the impact of attention to tax reform and healthcare reform on the aggregate stock returns and volatility. Using Google Trends data to measure the salience of policy reform issues, I find that increasing salience of tax reform issue positively affected stock returns and negatively affected return volatility. I also find evidence that these effects were moderated by the salience of the healthcare reform issue. During times in which attention to healthcare reform was abnormally high, the positive return effect and the negative volatility effect tended to be smaller. I also analyze the impact of noisy politics on the return volatility and the trading volume. In these analyses, I find that increasing attention to noisy politics positively affected trading volume, but I could not find consistent evidence for the volatility effect. These findings confirm that stock pricing dynamics are affected by the attention to policy reform processes and noisy politics.

This chapter proceeds as follows. In the second section I give background information about issue attention dynamics during the first year of Donald Trump’s presidency. In the third section, I discuss how issue salience might affect asset pricing outcomes and trading activity. In the the fourth section, I describe the data and the empirical strategy. In the fifth section I present and discuss results, and in the final section I provide concluding remarks.

[8] See https://www.ft.com/content/76298cb2-10d7-11e7-a88c-50ba212dce4d

4.2 Background

During the campaign period of the 2016 Presidential Election in the United States, one of the most salient policy issue topics was tax policy. The presidential candidate Donald Trump proposed large cuts in corporate and individual tax rates.[9] Donald Trump's victory was surprising given that polls and election markets assigned a much larger probability to the victory of the Democratic candidate Hillary Clinton. Because of the surprising result and the expectation of large tax cuts under Donald Trump's presidency, the short term reaction of the stock market was a sizable upward move.[10] However, the pricing of the tax reform was not finished after the election, because there was still uncertainty regarding the realization of a tax cut.

After his inauguration on January 20, 2017, President Trump made it clear that tax reform and healthcare reform will be the top priorities of the new administration. However, due to limited attention space they were not able to focus on both reform projects at the same time. Healthcare reform proposals received more attention in the first few months of his presidency. At the beginning of his presidency he issued an executive order which did not introduce any remarkable policy change but intended to set the future policy direction (Jost, 2017). In the first few months of 2017, the issue of tax reform was competing for attention, but after a short period in which both issues received abnormal attention, the issue of healthcare reform received considerably higher attention from the policymakers and the public. The tax reform could not achieve priority status until September 2017. In late July 2017, it became clear that the healthcare reform was going to fail, and the policymakers' and the public's attention started shifting more towards the issue of tax reform.

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[9] See https://www.wsj.com/articles/donald-trump-lays-out-more-details-of-economic-plans-1473955537
[10] See https://money.cnn.com/2016/11/09/investing/dow-jones-trump-wins-election/index.html

Another important characteristic of the first year of Donald Trump's presidency was the number of high-salience political issues and events. The first year of the Trump presidency was not an ordinary year in terms of noisy politics. There were many other attention-grabbing events and issues that occupied significant attention space in public agenda and policymaker agenda. In a study of public salience of political issues and events during the first year of the Trump presidency, West (2018) reports:

> "From the standpoint of politics and public policy, 2017 was an eventful year. Trump was inaugurated on Jan. 20. There was a historic women's march on Washington, D.C. on Jan. 21 that attracted millions of participants. The president delivered his first address to Congress on Feb. 28. Neil Gorsuch was confirmed to the Supreme Court on April 7. FBI Director James Comey was fired on May 9. President Trump sent his infamous "covfefe" tweet on May 31. The Senate failed to repeal the Affordable Care Act on July 28. Protests turned violent in Charlottesville, Va., on Aug. 17. An American terrorist in Las Vegas killed dozens of people on Oct. 1. Former Trump campaign manager Paul Manafort was indicted on Oct. 30. Democrats won major victories in Virginia and New Jersey on Nov. 7. Former Trump national security adviser Michael Flynn pled guilty on Dec. 3. Alabama Democrat Doug Jones won an unexpected seat in the Senate on Dec. 12. The Senate passed Trump's tax cut bill and repealed Obamacare's individual health mandate on Dec. 19."

Some of these were issues or events that caused jumps in public attention multiple times throughout the year of 2017, and others caused only single and transitory jumps in public attention. All these developments potentially contributed to the congestion of public and policymaker attention spaces, and might have had asset pricing implications.

While the tax reform issue was one of the top issue in the agenda during the election campaign process and one of the top issues in the early months of the Trump presidency, it did not get concentrated attention until late 2017. On November 2, a tax reform bill was introduced in the House of Representatives that started the formal legislative process for tax reform. The bill faced little friction in the legislative branch of the United States Government, and on December 22 the tax reform bill was signed into law by President Donald Trump.

How did stock markets react to changes in the information flow about policy reform issues and the public's attention allocation during this reform process? In the next section, I review the related literature and develop testable hypotheses to analyze the link between issue salience dynamics and stock market dynamics after the 2016 presidential election and during the first year of Donald Trump's presidency.

4.3 Issue Salience and Asset Pricing Dynamics

A big contribution of the policy agendas literature to the study of the public policy process has been the introduction of the idea that attention is limited. It sounds like an obvious fact, but most models of public policy process and political decision making implicitly assume political agents always have sufficient attention space available to attend to all issues they are interested in (Simon, 1955). Departing from the assumption that individuals are boundedly rational and have limited attention space, policy agendas research shows that big policy changes are preceded by sharp changes in the policymakers', the media's, and the public's attention allocation.

Research on the implications of attention dynamics has grown remarkably in the recent asset pricing literature, as well. The seminal study of Da et al. (2011) on the implications of attention to firms' stock tickers on Google searches indicate that attention shocks cause abnormal pricing outcomes. They challenge traditional asset pricing models' assumption that new information is immediately incorporated into prices, and find that attention dynamics through the mechanism of information acquisition affect the speed of price reaction to new information. Similarly, Ben-Rephael et al. (2018) show that investor attention, which they conceptualize as demand for information, can predict the accrual of risk premium better than the supply of information, which is driven by events like earnings announcements or news releases. These studies suggest that attention is an important driving force of the incorporation of information into asset prices.

Because of uncertainty about future cash flow, the prices are determined by expectations about future cash flows. Future cash flow of a firm can be affected by various idiosyncratic and market level conditions. Some public policy decisions might dramatically impact the future cash flow of a firm. While there are many policy decisions that might affect future cash flows, one of the most important ones is a tax policy change. There is little uncertainty about the positive impact of a reduction in tax rates on expected future cash flows. Donald Trump's tax reform proposal included declines in both corporate tax rates and personal tax rates. Both of these policy changes were expected to positively affect the future cash flows. The decline in corporate tax rate increases the net profit of firms. The decline in personal tax rate can also positively affect future cash flows through its affect on consumption. In the 2017 tax reform process, there was almost no disagreement about the positive impact of tax reform, but there was significant uncertainty about the timing of policy change. In a typical reform process, there is generally large uncertainty about both the timing and the potential impact of the policy reform.

The political economy literature on asset pricing focuses on the political factors that affect stock return and volatility through their impact on the expectations of future cash flows. One of the most popular arguments in this literature is related to the link between the partisan orientation of a government and stock prices. The conventional argument about partisanship and stock market dynamics is that right wing governments positively affect stock prices due to their more business-friendly policy decisions. Most empirical studies who investigate this link confirm the conventional argument (Roberts, 1990; Leblang and Mukherjee, 2005; Bernhard and Leblang, 2006; Fowler, 2006; Sattler, 2013; Bechtel, 2009). A supporting example is the reaction of the major stock market indexes in the United States after the 2016 Presidential election. After the surprising election victory of the Republican candidate Donald Trump, the stock market indexes initially reacted negatively, but after a short decline there was a long-term upward trend began. While the partisan theories of asset pricing dynamics can explain the initial positive reaction after the 2016 presidential election, they cannot explain the pricing dynamics after that point, because there was no change in partisan expectations and the efficient market hypothesis suggests that at the moment the partisan orientation of the new president became clear expected impact of partisanship on future cash flows was translated into stock prices. Since there was not a change in the partisan orientation of the president and the government after the elected, the changes in the stock prices in the post-election period cannot be explained well by partisanship related variables.

I argue that the fluctuations in the salience of the tax reform issue can explain the movements in stock prices in the post-election period. After the election, the information flow about the content and timing of tax reform intensified. However, as the attention and asset pricing literatures' findings suggest the information is incorporated into prices when the investors pay attention to the information flow, or when they demand information. The salience of the tax reform issue in the post-election period can help explain the evolution of tax reform expectations and the pricing action until it became clear that Donald Trump's tax cut pledges were turning into reality. Increasing salience of tax reform issue within a context of a strong and business friendly government will be interpreted as the progression of tax reform proposal, and I expect increasing salience will positively affect mean returns and will negative affect volatility due to the resolution of uncertainty regarding the timing of policy change.

I also argue that the effect on tax cut expectations might be smaller if the attention to information flow about healthcare reform is also abnormally high, because investors' belief that the level of attention concentration necessary to pass policy reform will be achieved is going to be smaller.

Issue salience dynamics might also affect trading activity in the markets. However, I do not expect the salience of a specific issue can explain the trading activity during the period I am focusing on. Overall salience of political and policy issues might be a more useful explanatory tool to develop a more general explanation of issue salience and trading activity relationship. I borrow the concept of noisy politics from Culpepper (2011) to describe the overall salience of high-salience political issues. There are many political issues that do not attract significant public or media attention, but issues such as tax reform, healthcare reform, impeachment of a president or the appointment of a Supreme Court Judge generally get high public and media attention. These kinds of high salience issues might also affect stock prices, but the direction of the effect on the mean return and volatility might significantly vary by issue. However, the overall salience of issues that are part of the noisy politics space – the issue space that consists of high-salience political issues – can explain the volume of buying and selling activity in the markets. Increasing rate of information about noisy politics might drive trading activity if the attention to noisy politics increase the flow of new information about future economic performance. I argue that increasing overall salience of noisy politics issues will increase trading volume.

I summarize my theoretical expectation with the set of hypotheses below:

Hypothesis 1.1: As the salience tax reform increases, stock market returns will increase.

Hypothesis 1.2: The positive impact of tax reform salience on stock returns will get smaller as the salience of healthcare reform increases.

Hypothesis 2.1: As the salience of tax reform increases, return volatility will decrease.

Hypothesis 2.2: The magnitude of the negative impact of the salience of tax reform on return volatility will get smaller as the salience of healthcare reform increases.

Hypothesis 3.1 As the attention to information flow about noisy politics increases, the trading volume will increase.

Hypothesis 4.1 As the attention to information flow about noisy politics increases, the trading volume will increase.

In the next section, I discuss the data and the empirical strategy I use to test these hypotheses.

4.4 Data and Empirical Strategy

I use Google Trends data to measure the salience of tax reform issue, healthcare reform issue and noisy politics – i.e. overall attention to high salience, attention-grabbing political and policy related issues. Google Trends data measure internet search activity within a certain territory and time period, which is usually used as a proxy for public attention or salience of issue topics. The trajectory of attention to these issues over the period under study confirms the leptokurtic distribution assumption of the punctuated equilibrium theory, which argues policy issue attention bursts after long periods of stasis. In an effort to characterize punctuated equilibrium patterns in the media's attention allocation, Boydstun et al (2014) find that the media's reaction to political developments follow a similar stick-slip pattern observed in the policymakers' attention allocation. Using Google Trends data, they also find that attention surges in media translates into attention surges in public. Because of that, Google Trends data can generally approximate media and policymaker attention to an issue or event.

In this chapter I will focus on the post-election and the first year after of Donald Trump's presidency for several reasons. Firstly, there were two major reform processes during his first year in office. Tax reform and healthcare reform were in Donald Trump's agenda during the election campaign process, and after he took office, he signalled that these issues will be his priority in the first year. Secondly, focusing on the post-election period and the first year of his presidency allows us to eliminate concerns about potential confounding effects of election uncertainty which is an important driving force of expectations about policy change (Bernhard and Leblang, 2006). Finally, 2017 was a year of relative economic stability and it suggests there was probably no structural breaks in the behavior of stock markets which are typically caused by major economic crises such as the 2008 global financial crisis and the burst of the dotcom bubble in 2000.

The first year of Trump's presidency was extraordinary in terms of the frequency of attention-grabbing issues and events. Culpepper (2011) describes these kinds of issues and events as noisy politics. According to Culpepper (2011), tax policy is a noisy politics issue, because when it is in the agenda of policy makers, it will also have high public salience. On the other hand, there are some issues which get significant policymaker attention, but they have low public salience. According to Culpepper (2011), the issue of corporate control regulation is one such issue that sometimes get significant policymaker attention, but it rarely gets high public attention. In the first year of Trump's presidency there were many issues and events that had high public salience. To create a noisy politics measure, I use Google Trends data on the keywords related to the issues and events mentioned by West (2018). Table 4.1 includes the list of keywords that I use to create the noisy politics salience index. There are two sets of keywords in this table. The smaller one is a subset of the larger one. The large set of keywords have at least one keyword related to each event and issue in West (2018). I use two sets of keywords, because Google Trends provides relative search activity data, and when there is large difference between the highest data value in the sample and the rest of the sample, some small data values are suppressed to zero, which causes loss of important information in some variables. The keywords related to tax reform and healthcare reform suffer from this problem, because some events mentioned in West (2018) received extreme attention at the time they happened and these high search activity values cause the suppression of variation in other variables. In the small set of keywords, I only included keywords that are directly related to a policy decision of the government, because the search activity on other keywords that are related to a person or an event tend to get extreme attention within a very short time frame and they tend to get very little attention outside this time frame. Due to the relative and bounded nature of the Google Trends data, the extreme search activity on keywords such as “Las Vegas shooting” or “James Comey” suppresses variation in policy reform related keywords, which are primarily important for this study. For the analysis of assetp pricing implications of tax reform salience and healthcare reform salience, I run a separate Google Trends query which only includes the keywords related to tax reform and healthcare reform, so that the variation in tax reform salience and healthcare reform salience is not suppressed.

I use Da et al’s (2011) abnormal attention measure to create the salience measures for tax reform and healthcare reform, and also to create the noisy politics index. I use abnormal attention measure, because only new information matters for the financial markets. Da et al. (2011) name this measure as the Abnormal Search Volume Index (ASVI) and it measures abnormal attention to a single issue within a certain time frame. ASVI is calculated using the formula

$$ASVI_{i,t} = \log(SVI_{i,t}) - \log\,[Med(SVI_{i,t-1}, \ldots, SVI_{i,t-8}\,)]$$

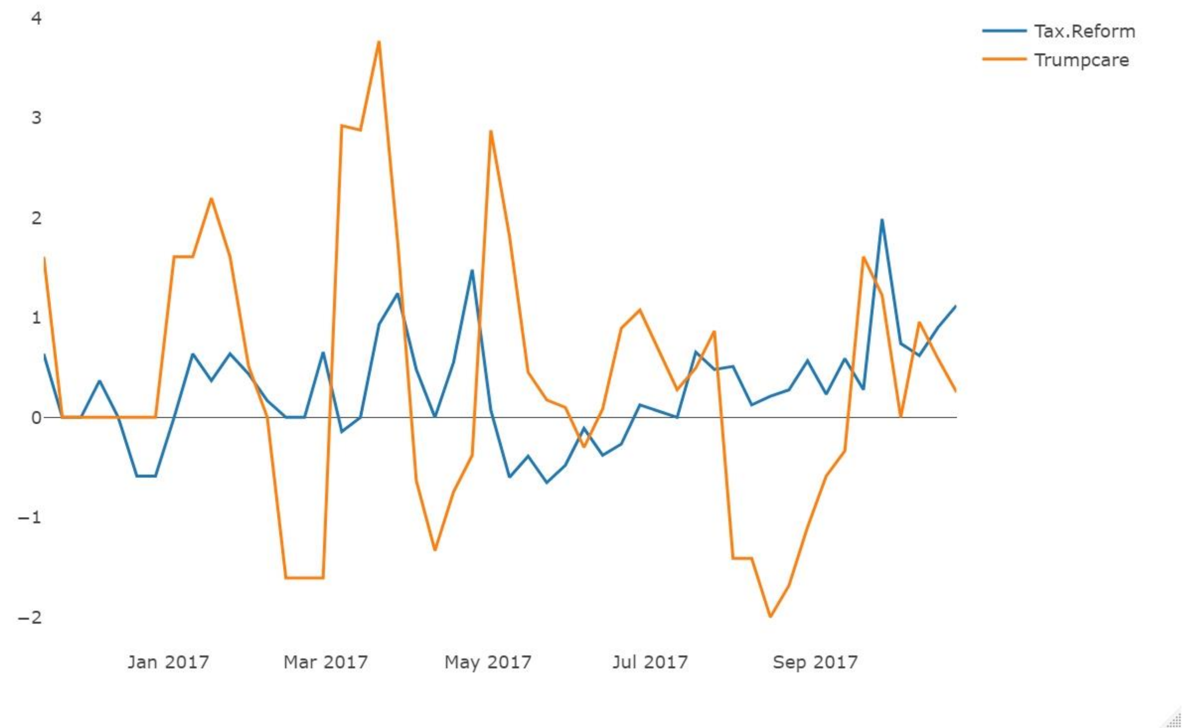
where $SVI_{i,t}$ is raw Google Trends value for keyword *i* in week *t,* and *Med* is the median value of SVI_i during the eight week time period from *t-8* to *t-1.*

Table 4.1: Keywords used to construct the noisy politics index (NPI)

Large Keyword Set	Small Keyword Set
• Trump inauguration • Women's March • State of the Union • Neil Gorsuch • James Comey • Trumpcare • Affordable Care Act • Charlottesville • Paul Manafort • Michael Flynn • Tax Reform • Travel Ban • Executive Order • Impeachment • Las Vegas Shooting	• Trumpcare[11] • Affordable Care Act • Tax Reform • Travel Ban • Impeachment

[11] Among the several most popular keywords for Donald Trump's healthcare reform plan, the "trumpcare" keyword was the most popular keyword in Google searches. The keyword "healthcare reform" received very little attention. Another related keyword was "trump healthcare" which received slightly less attention and it was highly correlated with the keyword "trumpcare".

Figure 4.1: Tax reform salience and healthcare reform salience (11/09/2016 - 12/21/2017)



Using the single keyword abnormal attention measure above, I create a noisy politics index (NPI) that aggregates abnormal attention to issues and events listed in West (2008). The formula I use to calculate NPI is

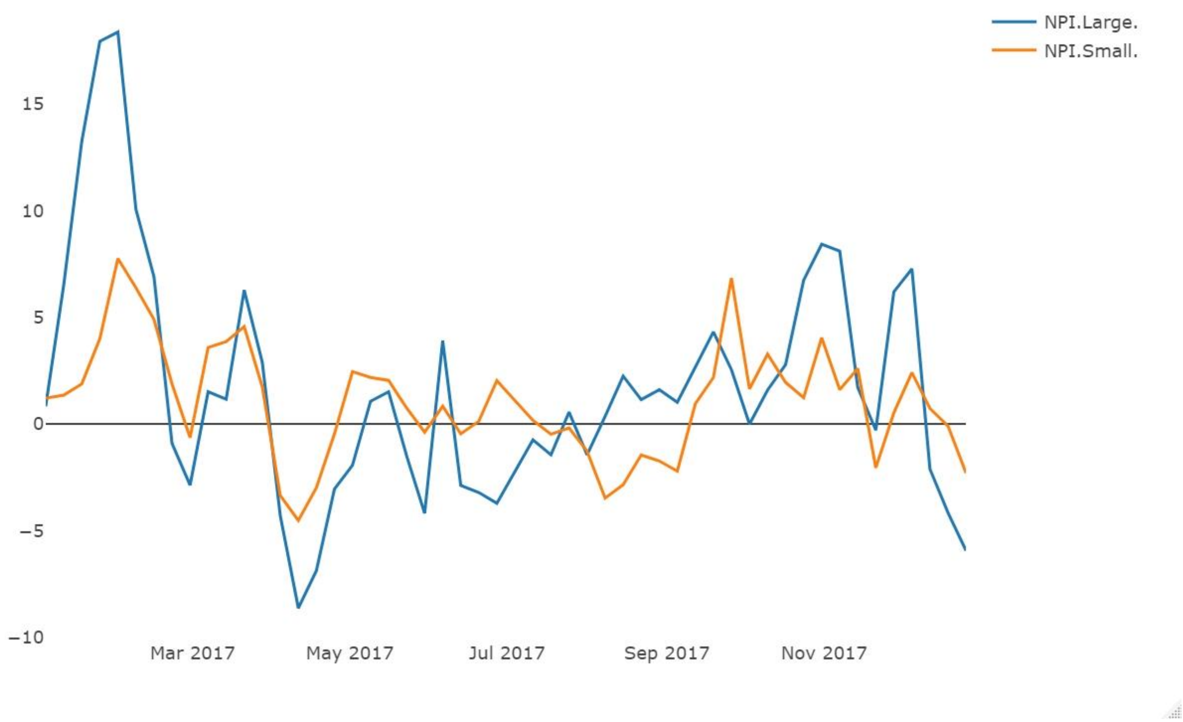
$$NPI_t = \sum_{i=1}^{n} ASVI_{i,t}$$

where *i* is an issue or event that exists in the noisy politics space and $ASVI_{i,t}$ is the measure of abnormal attention to *i* in week *t.* I use the *gtrendR*[12] package to pull data from the Google Trends API. The raw Google Trends (SVI) data provide weekly measure of relative search

[12]https://cran.r-project.org/package=gtrendsR

activity on a set of keywords. The highest value SVI can take is 100, and it is assigned to the keyword-week pair that has the highest search volume within the selected time frame. I select the time period between , September 1, 2016 and December 31, 2017. Among the keywords listed in Table 1, “Las Vegas shooting” was the keyword with the highest SVI value within the specified time period. Among the keywords listed in the small keyword set in Table 1, “tax reform” was the keyword that had a maximum SVI value of 100. All other SVI values are scaled using the top keyword in the set of keywords as the reference. The Google Trends API does not allow pulling SVI data for more than five keywords in a single query. There are 16 keywords in the large set of keywords and five keywords in the small set. To ensure that SVI measures do not change across different queries, we need to first determine the keyword with top SVI and use it as the reference keyword in all queries. To identify the top keyword within a set of keywords and within the selected time period, I developed an algorithm that identifies the top keyword by doing pairwise comparisons within the set of keywords. Using the top keyword identified by the algorithm as the reference keyword, I pulled data on the 16 keywords listed in Table 1 by doing multiple queries and merged the data from different queries using the top keyword as the reference. The raw data obtained through this procedure indicate search activity volume in the United States for the selected keywords. Then, using the raw Google Trends Data, I calculate ASVI for each keywords, and then using the ASVI values I calculate the NPI score. Figure 2 shows the NPI values over the period under study. The NPI measures created using the two different keyword sets are highly correlated ($\rho = 0.667$), which suggests the variation in noisy politics were mostly driven by the more policy relevant issues which are listed in the small keyword set.

Figure 4.2: Noisy Politics Index over the time period between 1/1/2017 and 12/31/2017



I use Standard & Poors 500 (S&P 500) Index daily price data to measure aggregate stock market returns and I use the trading volume of the S&P 500 Index to approximate the variation in market level trading volume. I also use the Chicago Board of Exchange's Volatility Index (VIX) which is forward looking index that aims to capture one month ahead expectations about S&P 500 volatility. The daily stock market data comes from the Yahoo Finance database. Figure 4.3 shows the S&P 500 daily return data over the period between November 9, 2016 and December 31, 2017.

Figure 4.3: Daily log returns of the S&P 500 Index over the 11/09/2016 – 12/31/2017 period

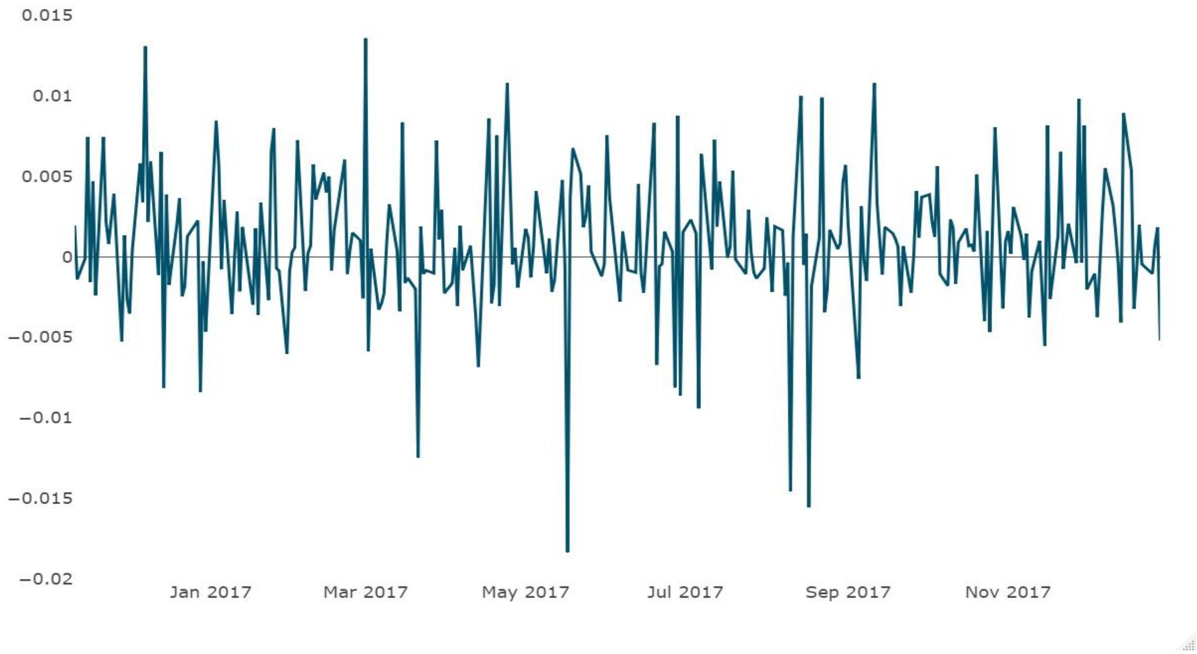
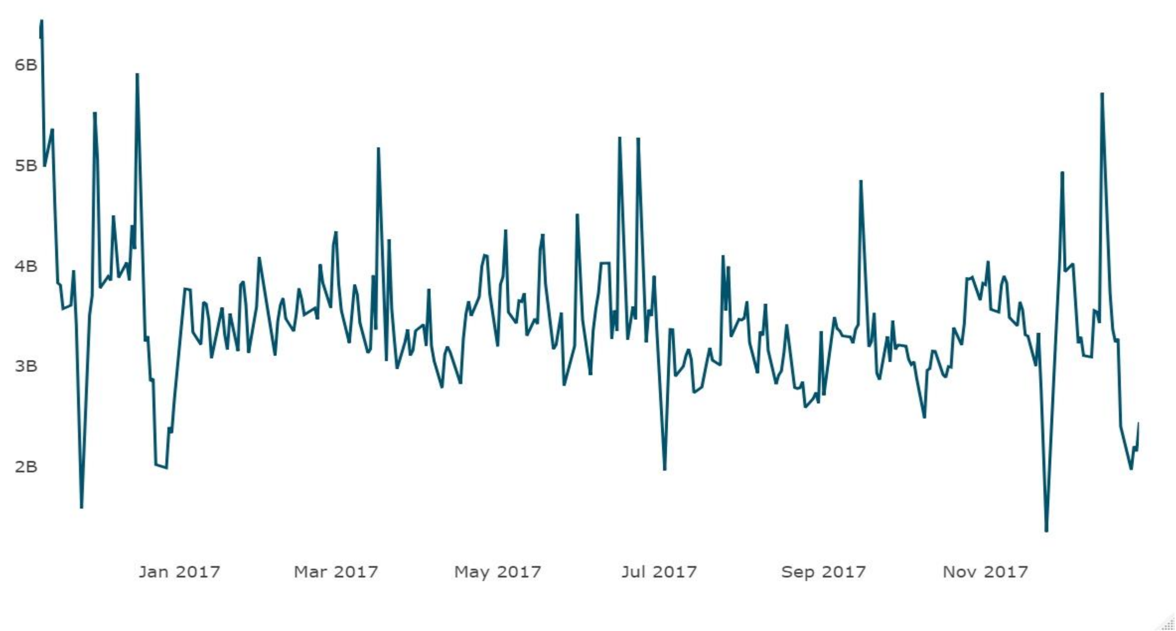


Figure 4.4: Daily trading volume of the S&P 500 Index over the 11/09/2016 – 12/31/2017 period



To estimate the effect of tax reform salience, health care reform salience, and noisy politics on the mean and volatility of stock market returns, I use an Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model (Nelson, 1991). The EGARCH model is special type of the GARCH family of volatility models in which positive and negative innovations of the return process can have differential effect on the volatility process. The original GARCH model of Bollerslev (1986) assumes there is no difference between the volatility consequences of negative and positive innovations, which suggests only the absolute magnitude of the innovations matter, but not their signs. The EGARCH model relaxes this assumption and usually achieves greater forecasting performance, because volatility reaction to negative shocks tend to be larger than the volatility reactions to positive shocks. (Leblang and Mukherjee, 2004).

An ARMA - EGARCH model includes a conditional mean model and a conditional volatility model. The conditional mean of stock returns in an EGARCH(1,1) model can be written as:

$$r_t = \mu + \varepsilon_t , \qquad \varepsilon_t \sim N(0, \sigma_t^2)$$

where r_t is the log return at time *t*, μ is a constant, and ε_t is and error term or an innovation term which has a normal with mean 0 and variance σ_t^2. In GARCH family of models, the normal distribution assumption can be relaxed. Some studies argue that student t distribution is a better fit for the stock returns due to heavy-tailedness commonly observed in return series (Markowitz and Usmen, 1996; Hurst and Platen, 1997; Platen and Sidorowicz, 2007, Fergusson and Platen, 2007). I modify this baseline model slightly by adding ARMA(1,1) terms, and also the external regressors which I use to test my hypotheses.

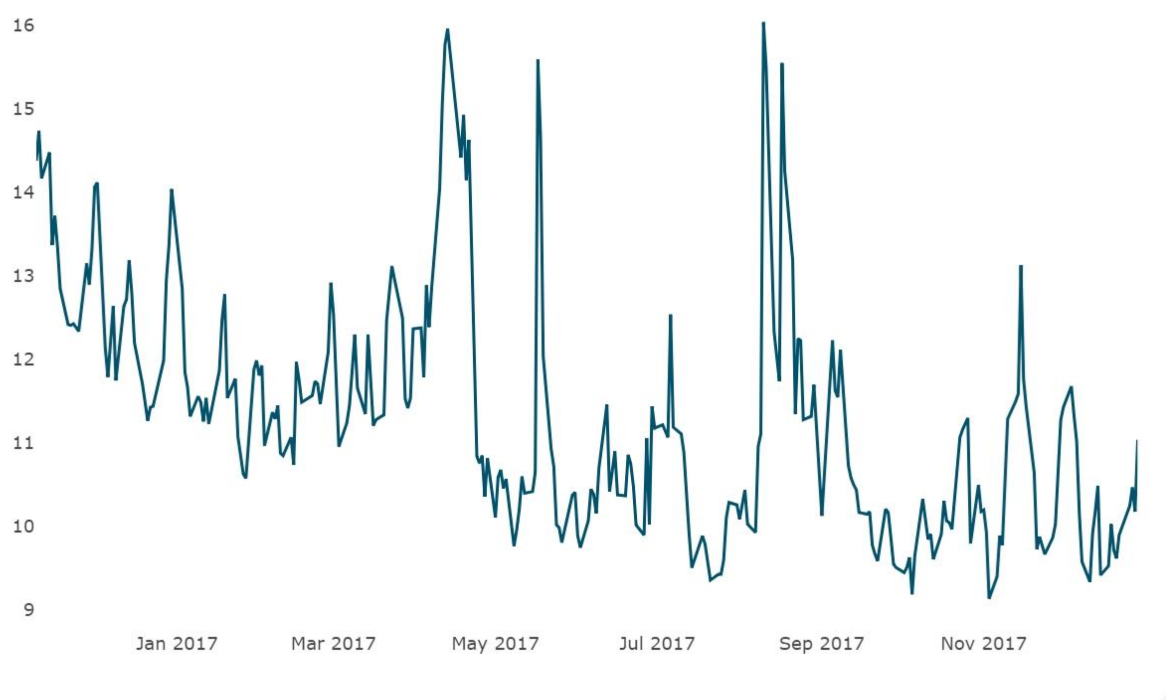
The volatility model of EGARCH can be written as:

$$\ln(\sigma_t^2) = \omega + \alpha z_{t-1} + \gamma\big(|z_{t-1}| - E(|z_{t-1}|)\big) + \beta \ln(\sigma_{t-1}^2)$$

where z_t represents standardized innovations and $E(|z_t|)$ is the expectation of standardized innovations. I add the external regressors to this baseline EGARCH volatility model.

I also use the VIX index to analyze volatility effects of issue salience related variables. I use this strategy, because the GARCH strategy may suffer from estimation instability when the sample size is not large enough. To prevent estimation issues I keep the GARCH as simple as possible.

Figure 4.5: Daily closing value of the VIX over the 11/09/2016 – 12/31/2017 period



To achieve this, I did not include any control variables, such as the trading volume which is a common control variable in volatility models. I use the VIX models as additional analyses of the volatility effects and to test the sensitivity of issue salience related variables to adding control variables. I use the models below for VIX and trading volume analyses:

$$Log(VIX_t) = \alpha + \varphi VIX_{t-1} + \beta_i X_{i,t} + \varepsilon_t$$

$$Log(Volume_t) = \alpha + \varphi Volume_{t-1} + \beta_i X_{i,t} + \varepsilon_t$$

where VIX_t is the value of the CBOE Volatility Index on day *t*, $Volume_t$ is the trading volume of the S&P 500 Index on day *t*, α is the intercept, φ is the AR(1) coefficient, and β_i is the vector that contains the coefficients of the exogenous variables X_i, and ε_t is a normally distributed error term.

4.5 Results and Discussion

In this section, I present and discuss the results of the ARMA-EGARCH models of S&P 500 Index daily returns, OLS models of the CBOE Volatility Index (VIX), and OLS models of daily trading volume of the S&P 500 Index. The tables from 4.2 to 4.5 present the results of the ARMA-EGARCH models that provide estimates of the relationship between salience of specific policy reform issues and the mean and variance of daily aggregate stock market returns. Table 4.6 and Table 4.7 present the results of ARMA-EGARCH models that include the Noisy Politics Index as the exogenous variable in the mean equation and the variance equation. The Table 4.8 presents the results of the OLS models of the CBOE Volatility Index. The Table 4.9 presents the results of the OLS models that I used to analyze the trading volume effects of noisy politics. The results from the ARMA – EGARCH and OLS models largely support my theoretical expectations about the volatility effects of tax reform issue salience, but the evidence for mean return effects is weaker. The evidence for the trading volume effects of noisy politics, which intends to capture the volume of political information flow to the markets, is strong, but the evidence for the volatility effects of noisy politics is weak.

The ARMA-EGARCH models are used to jointly estimate the mean and variance of stock market returns. Based on the suggestion of the Hyndman – Khandakar algorithm (Hyndman and Khandakar, 2008) I decided to use an ARMA(1,0) structure in the mean models of the S&P 500 Index Daily Log Returns. This suggests, the return process has an autoregressive component, but no moving average component. I also present the results of models that use ARMA(1,1) structure to compare the fit of similar ARMA structures. The variance equations in all EGARCH tables have EGARCH(1,1) structure. Ziwot (2018) argues for most return series EGARCH(1,1) is the best fitting model structure. Since daily stock market returns generally exhibit fat-tailedness, some researchers argue that an EGARCH model with student t distributed errors is a more appropriate choice than an EGARCH model with normally distributed errors. However, most studies do not pay attention to the distribution specification, and they assume normally distributed errors. In the ARMA-EGARCH tables, I present normal distribution specifications in the odd numbered columns, and I present student t distribution specifications in the even numbered columns. Based on the log likelihood, AIC, and BIC scores, the student t distribution seems to be the better choice in most cases.

The models in Table 4.2 through 4.5 present the results of ARMA-EGARCH models that I use to estimate the volatility and mean return effects of the salience of tax reform issue and the salience of the healthcare reform issue after the 2016 presidential election. The results in Table 4.2 and Table 4.3 are from the period between November 9, 2016 and November 2, 2017. This is the

Table 4.2 ARMA-EGARCH models of S&P 500 index daily returns – (11/09/2016 - 11/01/2017)

Mean Model				
	1	2	3	4
	ARMA(1,0)	ARMA(1,0)	ARMA(1,1)	ARMA(1,1)
Tax Reform Salience	0.00042^{***}	0.00022	0.00039^{***}	0.00021
	(0.00011)	(0.00022)	(0.00008)	(0.00021)
Healthcare Reform Salience	-0.00035^{***}	-0.00026	-0.00035^{*}	-0.00023
	(0.00008)	(0.00024)	(0.00014)	(0.00023)
AR(1)	-0.12423^{***}	-0.10468^{*}	-0.50133^{***}	-0.42594^{***}
	(0.02719)	(0.04586)	(0.01805)	(0.02826)
MA(1)			0.39200^{***}	0.32642^{***}
			(0.01636)	(0.02657)
μ	0.00067^{***}	0.00069^{**}	0.00064^{***}	0.00067^{***}
	(0.00017)	(0.00024)	(0.00008)	(0.00016)

Variance Model				
	1	2	3	4
Tax Reform Salience	-0.09046^{*}	-0.08170^{**}	-0.08354^{*}	-0.07382^{**}
	(0.03678)	(0.02942)	(0.03355)	(0.02605)
Healthcare Reform Salience	-0.05792^{*}	-0.09280^{**}	-0.05680^{*}	-0.08293^{**}
	(0.02594)	(0.03446)	(0.02312)	(0.02916)
ω	-2.90705^{***}	-3.21989^{***}	-2.77947^{***}	-2.89491^{***}
	(0.01381)	(0.01876)	(0.02187)	(0.02758)
α	-0.06638	-0.06342	-0.07935	-0.07774
	(0.03701)	(0.07106)	(0.05262)	(0.06575)
β	0.73699^{***}	0.70664^{***}	0.74860^{***}	0.73646^{***}
	(0.00004)	(0.00026)	(0.00002)	(0.00051)
γ	-0.21572^{*}	-0.16701	-0.23098^{***}	-0.17624
	(0.10326)	(0.14526)	(0.00359)	(0.12434)
Shape		4.62824^{***}		4.75499^{***}
		(0.49642)		(0.55534)
Log likelihood	1007.28905	1016.14523	1007.57014	1016.25655
AIC	-8.07522	-8.13883	-8.06939	-8.13163
BIC	-7.93313	-7.98254	-7.91311	-7.96114

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 4.3 ARMA-EGARCH models of S&P 500 index daily returns – Interaction Models – (11/09/2016 – 11/01/2017)

Mean Model				
	1	2	3	4
	ARMA(1,0)	ARMA(1,0)	ARMA(1,1)	ARMA(1,1)
Tax Reform Salience	0.00052***	0.00015	0.00051***	0.00012
	(0.00007)	(0.00032)	(0.00008)	(0.00026)
Healthcare Reform Salience	−0.00010	−0.00044	−0.00011**	−0.00041
	(0.00006)	(0.00031)	(0.00004)	(0.00039)
Tax Reform X Healthcare	−0.00020	0.00019	−0.00022*	0.00021
	(0.00011)	(0.00023)	(0.00009)	(0.00018)
AR(1)	−0.12615***	−0.10945**	−0.67825***	−0.36526***
	(0.01320)	(0.03990)	(0.01817)	(0.02750)
MA(1)			0.56073***	0.26482***
			(0.01370)	(0.03060)

Variance Model				
	1	2	3	4
Tax Reform Salience	−0.04414*	−0.12730	−0.03409	−0.09254*
	(0.02106)	(0.08886)	(0.01971)	(0.03803)
Healthcare Reform Salience	−0.01312	−0.18266	−0.00919	−0.11822*
	(0.02466)	(0.16922)	(0.01568)	(0.04862)
Tax Reform X Healthcare	−0.04760	0.04436	−0.05781***	0.01828
	(0.03196)	(0.13253)	(0.01475)	(0.05838)
μ	0.00070***	0.00070	0.00065***	0.00068
	(0.00006)	(0.00037)	(0.00006)	(0.00083)
ω	−1.81314***	−4.78463*	−1.73670***	−3.46845***
	(0.01327)	(2.01646)	(0.00116)	(0.02423)
α	−0.06556	−0.01349	−0.07261*	−0.06528
	(0.04041)	(0.19071)	(0.03658)	(0.09141)
β	0.83608***	0.56304**	0.84308***	0.68361***
	(0.00000)	(0.21431)	(0.00002)	(0.00077)
γ	−0.16507***	−0.22682	−0.20243***	−0.19468
	(0.00518)	(0.24330)	(0.03281)	(0.18162)
Shape		4.19815		4.35229***
		(6.09236)		(0.90972)
Log likelihood	1008.17879	1016.62440	1009.40613	1016.63997
AIC	−8.06623	−8.12651	−8.06807	−8.11854
BIC	−7.89573	−7.94181	−7.88336	−7.91963

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

time period between the presidential election day (11/08/2016) and the day when tax reform bill was introduced in the US House of Representatives(11/02/2017). The results in Table 4.4 and Table 4.5 are from a different time period, which has an end date of December 21, 2017, the day before the tax reform bill was signed into law by the President Donald Trump (12/22/2017). I use these two different time periods to see if the estimates change when the sample includes the days after the formal legislative process began in the US House Representatives. The results in those four tables suggest that the estimates of the volatility and mean return effects of tax reform salience and healthcare reform salience are not sensitive to the choice of sample period. The volatility effect of the tax reform issue salience is the most consistent finding across all the results in tables 4.2 through 4.5. During times when the salience of tax reform issue was abnormally high, the volatility of aggregate market return tended to be lower. The effect size varies significantly across models, but in all models the sign of the effect is consistently negative. Contrary to my theoretical expectation, the volatility effect of the healthcare reform salience is negative in most models, but the evidence is not as consistent as the evidence for the volatility effect of tax reform salience. In Table 4.3 and Table 4.5, I present results of models that include the interaction between tax reform salience and healthcare reform salience. My theoretical expectation was to find a positive interaction coefficient due to agenda congestion effect, but there is no support for this argument in the results.

The evidence on the mean return effects of tax reform salience and healthcare reform salience largely supports my theoretical expectations. Due to the strong positive effect of tax reform on expected cash flows, I expect increasing salience of tax reform will positively affect aggregate market returns. There is supporting evidence for this expectation in most models, but the statistical significance is sensitive to error distribution choice. I also expected to find negative mean return effect of the salience of the healthcare reform due its more uncertain and less desirable effects on future cash flows. The sign of the health care reform salience coefficient is negative in all models and it is statistically significant in most models, but the statistical significance is sensitive to error distribution choice. In the interaction models (Table 2 and Table 4), the sign of the tax reform and healthcare reform interaction coefficient is mostly negative, but it is not statistically significant in most models.

GARCH family of models may suffer from estimation instability in small samples. Hwang and Pereira (2004) argue the minimum sample size for GARCH(1,1) models should be around 500 for preventing convergence issues and get stable estimates of the ARCH and GARCH parameters. In my analysis, the sample size is small due to the length of the time period I focus on. The sample size is slightly above 200 in my models, which is significantly lower than the 500 threshold. As an additional test, I estimate OLS models of the CBOE Volatility Index with tax reform salience and healthcare reform salience variables on the right-hand-side. In the EGARCH models, to make models less complex and to prevent estimation issues – i.e. convergence problem which is relatively common for GARCH models, I did not include control variables such as trading volume or 10 year treasury bond rates. I could include these controls in the OLS models of the VIX index. The results in Table 7 provide strong support for the negative volatility effect of the tax reform salience, and also for the positive conditioning effect the healthcare reform salience, but there is no support for the independent effect of tax reform salience. The size of negative effect of tax reform salience on the expected volatility is approximately one percentage point for one standard deviation change in tax reform salience. In sum, there is strong evidence for the volatility reducing effect of tax reform salience in both

Table 4.4 ARMA-EGARCH models of S&P 500 index daily returns – (11/09/2016 - 12/21/2017)

Mean Model

	1	2	3	4
	ARMA(1,0)	ARMA(1,0)	ARMA(1,1)	ARMA(1,1)
Tax Reform Salience	0.00035^{***}	0.00014	0.00032^{***}	0.00013
	(0.00008)	(0.00010)	(0.00006)	(0.00020)
Healthcare Reform Salience	-0.00038^{*}	−0.00027	-0.00038^{*}	−0.00033
	(0.00017)	(0.00016)	(0.00018)	(0.00022)
AR(1)	-0.12598^{***}	-0.11122^{***}	-0.50545^{***}	0.73245
	(0.02920)	(0.03154)	(0.02485)	(0.77130)
MA(1)			0.39359^{***}	−0.82547
			(0.01991)	(0.65401)
μ	0.00071^{***}	0.00071^{***}	0.00069^{***}	0.00078^{***}
	(0.00016)	(0.00017)	(0.00010)	(0.00019)

Variance Model

	1	2	3	4
Tax Reform Salience	-0.08441^{**}	-0.06344^{**}	-0.07934^{**}	-0.07494^{*}
	(0.02918)	(0.02356)	(0.02870)	(0.03166)
Healthcare Reform Salience	-0.05800^{*}	-0.08008^{**}	-0.05684^{**}	-0.10922^{**}
	(0.02332)	(0.02511)	(0.02179)	(0.03647)
ω	-2.91398^{***}	-2.86032^{***}	-2.81096^{***}	-3.58943^{***}
	(0.01688)	(0.01977)	(0.01081)	(0.18246)
α	−0.07215	−0.08312	−0.08490	−0.09129
	(0.03969)	(0.08812)	(0.05380)	(0.06279)
β	0.73676^{***}	0.74010^{***}	0.74614^{***}	0.67341^{***}
	(0.00002)	(0.00178)	(0.00004)	(0.01379)
γ	-0.20828^{**}	−0.14710	−0.22240	−0.12125
	(0.06773)	(0.17039)	(0.12443)	(0.14040)
Shape		5.13348^{***}		4.81865^{***}
		(1.11515)		(1.43004)
Log likelihood	1153.44525	1161.13833	1153.69525	1161.71858
AIC	−8.10954	−8.15701	−8.10422	−8.15403
BIC	−7.98040	−8.01495	−7.96216	−7.99906

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 4.5 ARMA-EGARCH models of S&P 500 index daily returns – Interaction Models – (11/09/2016 - 12/21/2017)

Mean Model	1	2	3	4
	ARMA(1,0)	ARMA(1,0)	ARMA(1,1)	ARMA(1,1)
Tax Reform Salience	0.00043^{***}	0.00009^{*}	0.00044^{***}	0.00002
	(0.00010)	(0.00004)	(0.00007)	(0.00014)
Healthcare Reform Salience	-0.00022^{*}	-0.00039^{*}	-0.00016^{***}	-0.00038
	(0.00011)	(0.00019)	(0.00002)	(0.00028)
Tax Reform X Healthcare	-0.00017	0.00015	-0.00022^{***}	0.00008
	(0.00015)	(0.00011)	(0.00003)	(0.00032)
AR(1)	-0.12752^{***}	-0.10872^{**}	-0.61811^{***}	0.88013^{***}
	(0.03217)	(0.04089)	(0.01252)	(0.02383)
MA(1)			0.50624^{***}	-0.95238^{***}
			(0.01095)	(0.00002)
μ	0.00073^{***}	0.00070^{***}	0.00072^{***}	0.00076^{***}
	(0.00019)	(0.00013)	(0.00005)	(0.00010)

Variance Model	1	2	3	4
Tax Reform Salience	-0.06437^{**}	-0.07097^{**}	-0.05607^{***}	-0.11060^{*}
	(0.02010)	(0.02722)	(0.01197)	(0.04728)
Healthcare Reform Salience	-0.02960	-0.10021^{*}	-0.02368	-0.21557^{**}
	(0.02706)	(0.04379)	(0.02207)	(0.06878)
Tax Reform X Healthcare	-0.03206	0.01278	-0.04088	0.05798
	(0.03256)	(0.04285)	(0.02564)	(0.06236)
ω	-2.30815^{***}	-3.12971^{***}	-2.14089^{***}	-4.96079^{***}
	(0.01544)	(0.01786)	(0.00074)	(0.13672)
α	-0.06923	-0.08269	-0.07743^{**}	-0.05817
	(0.04562)	(0.06763)	(0.02407)	(0.07667)
β	0.79171^{***}	0.71527^{***}	0.80699^{***}	0.54686^{***}
	(0.00001)	(0.00023)	(0.00001)	(0.01351)
γ	-0.19027^{***}	-0.15945	-0.21390^{***}	-0.12258
	(0.00384)	(0.13885)	(0.05932)	(0.13974)
Shape		4.81689^{***}		4.14850^{***}
		(0.52859)		(1.14839)
Log likelihood	1154.19000	1161.35890	1154.98581	1162.57711
AIC	-8.10064	-8.14439	-8.09919	-8.14594
BIC	-7.94566	-7.97650	-7.93130	-7.96513

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 4.6 Noisy Politics and daily stock pricing dynamics – NPI large keyword set

Mean Model

	1	2	3	4
	ARMA(1,0)	ARMA(1,0)	ARMA(1,1)	ARMA(1,1)
NPI	0.00004	-0.00013^{***}	0.00010^{***}	0.00002^{*}
	(0.00053)	(0.00000)	(0.00001)	(0.00001)
AR(1)	−0.14701	-0.14630^{***}	0.31147^{***}	0.72420^{***}
	(0.15554)	(0.00368)	(0.00566)	(0.00007)
MA(1)			-0.47915^{***}	-0.81357^{***}
			(0.00793)	(0.00001)
μ	0.00029	0.00033^{***}	0.00050^{***}	0.00043^{***}
	(0.01022)	(0.00000)	(0.00003)	(0.00000)

Variance Model

	1	2	3	4
NPI	0.01314	0.01866^{***}	0.01278	0.02639^{***}
	(0.41227)	(0.00024)	(0.00717)	(0.00163)
ω	−1.68243	-0.88375^{***}	-1.63152^{***}	-0.75836^{***}
	(34.06050)	(0.00087)	(0.00001)	(0.00002)
α	−0.18001	-0.10556^{***}	-0.16207^{***}	-0.15983^{***}
	(5.17021)	(0.00021)	(0.04251)	(0.00002)
β	0.84870	0.91885^{***}	0.85369^{***}	0.92992^{***}
	(18.55650)	(0.00294)	(0.00000)	(0.00091)
γ	−0.39188	-0.26033^{***}	-0.30206^{***}	-0.21492^{***}
	(50.62997)	(0.00167)	(0.00679)	(0.00037)
Shape		4.23185^{***}		3.95551^{***}
		(0.00159)		(0.00091)
Log likelihood	1036.99829	1045.79736	1033.24594	1047.57215
AIC	−8.19919	−8.26133	−8.16132	−8.26751
BIC	−8.08682	−8.13492	−8.03491	−8.12705

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

EGARCH and OLS models of volatility, and no support for the volatility effect of healthcare reform salience.

Noisy politics and asset pricing dynamics is another relationship I analyze in this chapter. In Table 5 and Table 6, I present ARMA-EGARCH models that feature NPI index as the exogenous variable in the mean and variance equations. I expect to find that the noisy politics will positively affect volatility because of the increasing uncertainty with greater political activity. The NPI index is not issue-specific, but it tries to measure the overall salience of all attention-grabbing political issues. Therefore, I do not have mean return effect expectation about the NPI Index. The EGARCH models in Table 5 and Table 6 provide support to my volatility effect argument, but the results from the OLS models of the VIX do not provide support to my positive volatility effect expectation.

My main argument about the noisy politics' effect on markets is related to trading activity in the stock markets. The noisy politics index (NPI) intends to capture the total information flow about politics, and I expect increasing information flow about politics will increase trading activity. In Table 8, I present OLS models of the S&P 500 Index daily trading volume. The trading volume variable is stationary. The results in this table provide strong support to my theoretical expectation. NPI positively affects trading volume, and it does not depend on the keyword choice.

Table 4.7 Noisy Politics and daily stock pricing dynamics – NPI small keyword set

Mean Model				
	1	2	3	4
	ARMA(1,0)	ARMA(1,0)	ARMA(1,1)	ARMA(1,1)
NPI	0.00011^{***}	0.00012^{***}	0.00030^{***}	0.00010^{***}
	(0.00000)	(0.00001)	(0.00000)	(0.00002)
AR(1)	-0.10070^{***}	-0.11674^{***}	0.40174^{***}	0.55077^{***}
	(0.00128)	(0.00341)	(0.00175)	(0.00050)
MA(1)			-0.52497^{***}	-0.67282^{***}
			(0.00218)	(0.00064)
μ	0.00026^{***}	0.00045^{***}	0.00036^{***}	0.00050^{***}
	(0.00000)	(0.00000)	(0.00000)	(0.00000)

Variance Model				
	1	2	3	4
NPI	0.02197^{***}	0.02349^{***}	0.01518^{***}	0.02637^{***}
	(0.00004)	(0.00001)	(0.00003)	(0.00009)
ω	-1.22727^{***}	-0.75399^{***}	-1.50099^{***}	-0.98348^{***}
	(0.00314)	(0.00050)	(0.00279)	(0.00031)
α	-0.18412^{***}	-0.16919^{***}	-0.15122^{***}	-0.14719^{***}
	(0.00019)	(0.00013)	(0.00053)	(0.00069)
β	0.88929^{***}	0.93056^{***}	0.86510^{***}	0.91029^{***}
	(0.00507)	(0.00112)	(0.00189)	(0.00040)
γ	-0.31700^{***}	-0.23192^{***}	-0.37096^{***}	-0.27742^{***}
	(0.00044)	(0.00000)	(0.00049)	(0.00008)
Shape		3.89864^{***}		4.69147^{***}
		(0.00396)		(0.00464)
Log likelihood	1038.21393	1044.27728	1038.46222	1047.54240
AIC	-8.20888	-8.24922	-8.20289	-8.26727
BIC	-8.09651	-8.12281	-8.07648	-8.12681

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 4.8 : Policy reform salience, noisy politics, and expected volatility

	Dependent variable:							
	Log(VIX)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tax Reform Salience	−0.011*	−0.013**	−0.011*	−0.012**				
	(0.006)	(0.007)	(0.006)	(0.006)				
Healthcare Reform Salience	−0.003	−0.007	−0.001	−0.006				
	(0.003)	(0.005)	(0.003)	(0.005)				
NPI					0.00003	−0.002		
					(0.001)	(0.002)		
NPI Ex. Tax							0.0001	−0.002
							(0.001)	(0.002)
VIX_{t-1}	0.068***	0.067***	0.069***	0.068***	0.068***	0.067***	0.068***	0.068***
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Δ T-Bond Rate	−0.307**	−0.304**	−0.302**	−0.303**	−0.431***	−0.423***	−0.431***	−0.428***
	(0.138)	(0.136)	(0.130)	(0.128)	(0.153)	(0.150)	(0.153)	(0.152)
Log(Trading Volume)	0.049*	0.062**	0.046*	0.058**	0.036	0.047*	0.035	0.045
	(0.028)	(0.031)	(0.025)	(0.027)	(0.027)	(0.028)	(0.027)	(0.028)
Tax Reform x Healthcare Reform		0.012*		0.011*				
		(0.007)		(0.006)				
Constant	0.588	0.301	0.626	0.385	0.854	0.629	0.864	0.674
	(0.592)	(0.651)	(0.531)	(0.581)	(0.584)	(0.608)	(0.578)	(0.602)
Observations	246	246	281	281	250	250	250	250
R^2	0.716	0.720	0.725	0.729	0.686	0.688	0.686	0.687
Adjusted R^2	0.710	0.713	0.720	0.723	0.680	0.683	0.681	0.682
Residual Std. Error	0.065 (df = 240)	0.065 (df = 239)	0.064 (df = 275)	0.064 (df = 274)	0.065 (df = 245)	0.064 (df = 245)	0.065 (df = 245)	0.064 (df = 245)

Note: All standard errors are robust standard errors. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 4.9 Noisy politics and trading volume

	Dependent variable:	
	Log(Trading Volume)	
	(Large Keyword Set)	(Small Keyword Set)
NPI	0.004^{***}	0.010^{***}
	(0.001)	(0.003)
Trading Volume_{t-1}	0.000^{***}	0.000^{***}
	(0.000)	(0.000)
Absolute Return_t	6.482^{**}	6.829^{***}
	(2.640)	(2.533)
Monday	-0.059^{*}	-0.060^{*}
	(0.035)	(0.034)
Tuesday	0.048	0.046
	(0.035)	(0.034)
Wednesday	0.050	0.049
	(0.033)	(0.032)
Thursday	0.035	0.034
	(0.032)	(0.031)
Constant	21.418^{***}	21.440^{***}
	(0.094)	(0.093)
Observations	250	250
R^2	0.299	0.310
Adjusted R^2	0.279	0.290
Residual Std. Error (df = 242)	0.132	0.131
Note:		*p<0.1; **p<0.05; ***p<0.01

4.6 Conclusion

In this chapter, I focused on the asset pricing implications of issue salience dynamics in the United States during the period that began with the presidential election in November 2016 and ended at the end of the year 2017. I specifically focused on the tax reform issue salience, healthcare reforms issue salience, and the overall salience of all attention-grabbing political issues during that period – i.e. the noisy politics. The findings I presented in the previous section largely supports my theoretical expectations about the mean return and volatility effects of tax reform salience, and my expectations about the trading volume effect of noisy politics. My other theoretical expectations have weaker empirical support. Overall, the results suggest that issue salience dynamics might be among the driving forces of the rate of pricing action in stock markets.

An original contribution of this chapter is the Noisy Politics Index (NPI), which aggregates the salience of high-salience political issues. This index can be used as a proxy for the information flow about important political issues, and in this chapter I showed that it has significant effect on trading activity, because greater information flow means greater buying and selling activity. The NPI Index can be generalized to other time periods, but the keyword selection will be a challenging issue for longer time frames. Since I focused on a short time period, it was easier to create a keyword list that can be useful to capture issue attention fluctuations. To generalize the NPI Index, we may need to employ automated keyword extraction tools that can reliably extract relevant keywords for events and issues from newspaper articles and other mediums. The Noisy Politics Index can also be useful for other political science and public policy work. It captures an important aspect of politics and public policy making processes. Most policy agendas research and other political science research that study issue attention and salience dynamics have issue-specific focus. However, the noisy politics index can be useful to study more general effect of attention and salience in politics.

Chapter 5: Conclusions

The nexus between the policy process and the stock market has been a popular research topic for decades. With increasing availability of data on the policy process, the interest on this topic has surged significantly, especially in the field of finance. However, an important limitation of this growing literature is the narrow understanding of politics. This dissertation is an attempt provide a political science perspective to the issue of policy and markets. With this goal in mind, in this dissertation I addressed the question how issue attention allocation by policy actors affect stock pricing dynamics. Policy actors, which include elected politicians, policy professionals, the media, and some other members of the broader society, have limited attention space. The number of issues that compete for attention is far greater than what the attention space of policy actors can handle. The policy agendas literature in political science investigates the implications of the attention constraints faced by policy actors. One of the major findings of the policy agendas research is the parallelism between the distribution of attention by issue topic and the distribution of policy change by issue topic. Both distributions feature high-peakedness and heavy-tailedness, which are manifestations of the stick-slip pattern in attention changes and policy changes, and the studies show that attention changes and policy changes generally move in the same direction. Based on this evidence, I argued the stock markets will react to changes in issue attention allocation because attention allocation changes provide information about the timing and extent of policy changes.

5.1 Summary of Arguments and Findings

In this dissertation, I studied the issue attention allocation and markets relationship at the aggregate level using data on legislative attention, media attention, and public attention. In the second chapter, I presented evidence for the volatility reducing effect of attention diversity in legislative agendas. Policy agendas research show the policy system operates in two different states. The policy system usually operates in the policy stasis state in which there is no policy change or there is incremental policy change. Occasionally, the policy system operates in policy reform state in which the extent of policy change is significantly larger. Attention diversity is a property of attention allocation processes that inform investors about the state of the policy system. Legislative attention diversity tends to be low during times a policy reform is in the agenda; thus, I expect the market's expectation of a big policy change will be higher when attention diversity across topic categories is lower. Since the impact uncertainty of a policy reform is typically higher than the impact uncertainty of incremental policy change or no policy change, I argued the aggregate return volatility will increase as the attention diversity decreases. The results from analyses of monthly legislative attention diversity and monthly aggregate return volatility in five developed democracies largely supported my hypothesis.

In the third chapter, I focused on short-term changes in issue attention allocation. Policy agendas at the government level do not change so much in the short term, but the media's policy agenda could change. To analyze stock market reaction to short-term issue attention changes, I used data on the New York Times front page articles to capture short-term changes in policy agendas. While the variation in media attention does not perfectly capture the variation in policymaker agenda, the investors' get most of their information about politics from the media and the media has power to influence policymaker agendas. Because of that the media agenda is important in its own right and also it can be a proxy for policymaker agenda. Using dissimilarity metrics such as Euclidean distance and attention instability to measure the extent of daily attention changes, I showed larger changes in daily issue attention leads to greater short-term volatility and lower short-term returns in the S&P 500 Index.

In the fourth chapter, I focused on the post-2016 presidential election period and the first year of Donald Trump's presidency in the United States of America. During that time period, there were two major policy reform issues in the former President Donald Trump's policy agenda, which were tax reform and healthcare reform. I argued that the stock market will react to the salience of these reform issues. Using Google Trends data to measure the salience of those policy reform topics, I found higher salience of tax reform issue led to greater returns and lower volatility in the S&P 500 Index. The evidence for the healthcare reform issue is weaker, but I found that the salience of healthcare reform affects how markets react to the salience of tax reform. In that chapter, I also analyzed the asset pricing implications of noisy politics, which I defined as the overall salience of the high-salience political issues. Noisy politics, the side of the politics to which people pay most attention, is a process that affects the volume of political information flow into the markets. I argues the greater overall attention to noisy politics issues the greater will be the political information flow. Using Google Trends data on keywords related to major political events and issues during the first year of Donald Trump's presidency and an aggregation strategy that aims to capture the total attention to those issues at a certain time point, I found noisy politics, during the time period under study, led to greater trading volume and greater volatility in the S&P 500 Index.

The findings of this dissertation showed the dynamics of the attention allocation processes have asset pricing implications. However, there are some limitations of the results I presented in this study. Firstly, some variation in issue attention might be driven by movements of the stock market. Especially in societies where the stock market is perceived as a gauge of overall economic performance, stock market movements might cause politician, median and public reaction to policy related issues. My research does not address this endogeneity potential. Secondly, the reaction of markets to issue attention changes might be time changing. Factors such as the composition of government and changes in the credibility of media and politicians might affect how the market will react to issue attention allocation dynamics. However, this is a minor issue since I do not focus on a very long time period in most of my analyses. Thirdly, the way market categorizes policy issue topics might be different than the way Comparative Agendas Project (CAP) researchers categorize policy issue topics. The CAP coding scheme is a very detailed and sophisticated way to categorize policy issues, but the markets' understanding of the policy issue topic space might be significantly different than the CAP's policy issue topic space characterization. This coding related issue is a minor issue for the results presented in the fourth chapter since they do not rely on the CAP coding scheme.

5.2 Future Research

In this section I discuss the ways future research can build on and improve the contributions of this dissertation. First, this dissertation focused on the aggregate effects – i.e. the overall market level effects – of issue attention dynamics, but a focus on firm level or industry level effects might help drawing a more detailed picture of the nexus between issue attention dynamics and market movements. It is highly likely that some firms and industries are more sensitive to public policy decisions. Future research on that nexus must analyze cross-industry and cross-firm variation in terms of pricing reaction to issue attention allocation dynamics. Second, the data availability issues limits the temporal generalizability of the results. This is especially the case in the third and four chapters where the time period under study is relatively short. In the fourth chapter, I developed a noisy politics index, but I only used data from the first year of Trump's presidency. In the development of this index, the selection of keywords are so important and I used a human generated reliable source that listed the most important policy related issues and events during the first year of Donald Trump's presidency. To generalize this index to other time periods, we need list keywords associated with attention-grabbing and important policy related issues and events. Automated keyword extraction methods might be useful to generate a list of keywords that can be used to measure noisy politics over a longer time period. Increasing availability of data and computational techniques to process the data will be useful for future studies that aim to extend the noisy politics index measurement period. Last, in this study I argued that attention allocation changes will lead to stock market reaction, because of the potential impact of attention changes on investors' expectations of policy change. I did not provide empirical evidence for the issue attention dynamics and policy change expectations link. Future research should also focus on the mechanisms that transmit the effects on stock markets. An experimental research strategy will be very useful to study the issue attention dynamics and policy change expectations link.

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