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# POLICY UNCERTAINTY AND OPERATING WORKING CAPITAL BEHAVIOR

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## ABSTRACT

This paper empirically investigates the relationship between policy uncertainty, as measured by the Economic Policy Uncertainty Index, and net operating working capital, defined as the sum of accounts receivable and inventory net of accounts payable, at the firm-level. Through a series of regressions incorporating 100,556 firm years between January 1st, 1990 and December 31st, 2014, it finds strong statistical evidence that policy uncertainty and net operating working capital share a strong inverse relationship. This inverse relationship is particularly evident among firms operating in industries with low industry-level asset tangibility, high industry-level heterogeneity, and high industry-level Lerner Index.

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# Chapter 1

## Introduction

Risk and return influence decisions in every realm of life. Most are familiar with this concept in terms of finance – investors purchase the stock of a financially risky firm expecting to obtain larger returns than they would receive from a financially sound firm. Likewise, if an investor values a reliable stream of income over greater returns, he or she will invest in the bond of a blue-chip firm – or even the government – instead of the bond of a nearly insolvent firm. However, even in more mundane decisions, the risk and return dynamic remains. When a driver decides to break the speed limit, he or she implicitly values the return of speeding (perhaps getting home sooner) more than the potential risk (getting pulled over). In all of these decisions, however, there is a third factor at play: uncertainty. The uncertainty of any situation can cloud a risk and return assessment. An investor may believe a particular firm's equity poses little risk and provides adequate return, but if a looming lawsuit threatens to substantially impair the firm's finances, the uncertainty of the situation renders the investor's evaluation questionable.

Perhaps the biggest source of uncertainty for firms comes from government policy. With the power to tax and regulate all citizens and businesses, governments can theoretically alter the risk and return dynamic almost instantaneously. In anticipation of these alterations, people and firms respond with a heightened sense of uncertainty. The researchers Scott Baker, Nicholas Bloom, and Steven Davis (2015) have developed Economic Policy Uncertainty indexes (EPU) in an attempt to measure this uncertainty. Their indexes look for certain combinations of words, such as "economic", "uncertain", and "White House" in leading American, Canadian, Dutch,

European, Indian, Japanese, Korean, and Russian newspapers (Baker, Bloom, & Davis, 2015). Data for all of the indexes can be found at the website, www.policyuncertainty.com. For the purposes of this paper, EPU refers to the index measuring monthly U.S. policy uncertainty since January, 1985. Unsurprisingly, this index tends to spike around wars, elections, and terrorist attacks (Baker, Bloom, & Davis, 2015). Uncertainty rises when major political events transpire.

This paper seeks to build on research examining the relationship between policy uncertainty and capital investment decisions by applying similar concepts to operating working capital decisions as measured by the working capital requirement (WCR) – defined as the sum of accounts receivable and inventories net of accounts payable. In particular, I look into the effect policy uncertainty has on firm-level net operating working capital behavior by empirically investigating two major questions. First, I examine how policy uncertainty affects firm-level WCR behavior as a whole. Second, I explore how different industry product markets and industry asset profiles affect firm-level WCR responses to policy uncertainty. As a secondary interest, I also observe how policy uncertainty affects the components of WCR. To achieve this, I examine the correlation between the EPU and WCR among 100,556 firm years between January 1st, 1990 and December 31st, 2014.

The remainder of this paper is organized as follows. Chapter 2 reviews previous work in the area of economic policy uncertainty. Chapter 3 provides an overview of WCR and the EPU as well as my hypothesis about their relationship. Chapter 4 describes the data and methods I used to conduct this research. Chapter 5 presents and analyzes the results of my empirical work. Chapter 6 offers my conclusions reached from the data.

# Chapter 2

## Literature Review

The typical investor operates under the assumption that a given investment cannot be reversed (Bernanke, 1983). Additionally, over time, new information about the returns of an investment arrives (Bernanke, 1983). Given these two assumptions, Bernanke (1983) concludes that uncertainty delays investment because an investment should only occur "when the costs of deferring the project exceed the expected value of information gained by waiting." Thus, events with uncertain long-run implications increase the returns of waiting for new information and have the potential to create investment cycles (Bernanke, 1983). Moreover, in some scenarios, it may even make sense to invest in a small net present value project rather than a large net present value project (Bernanke, 1983).

Bernanke's work seems to contradict the net present value (NPV) model, in which investors should undertake a project if its NPV exceeds zero. As Robert McDonald and Daniel Siegel (1986) explain, this is because a simple NPV analysis fails to properly account for the option of waiting. In situations in which an investor must choose between two mutually exclusive, positive NPV projects, the investor rationally chooses the project with the higher NPV. When an investor has seemingly only one positive NPV project to invest in, he or she should recognize that the actual decision is more complicated. In this scenario, just like the one before it, the investor has a choice between mutually exclusive projects – investing in the project today, or investing in the project in the future (McDonald & Siegel, 1986).

Firms appear to consider uncertainty when investing. Baker, Bloom, and Davis (2015) find evidence that firms with greater exposure to government purchases respond with reduced investment and hiring. In recent years, policy uncertainty has registered high enough in the EPU to materially depress investment in industries with high government purchases (Baker, Bloom, and Davis, 2015). These industries, including defense, healthcare, and construction "are important enough for policy uncertainty to matter at the aggregate level" (Baker, Bloom, and Davis). Once uncertainty is resolved, however, an investing boom occurs, as firms look to undertake previously tabled projects (Stokey, 2014).

Lower levels of investment also correlate strongly with partisan conflict. Whereas the EPU broadly measures uncertainty so that any politically relevant event that may create doubts about future policy decisions registers within the index, Marina Azzimonti's (2015) Partisan Conflict Index (PCI) merely measures partisan conflict. The PCI somewhat correlates with the EPU; for instance, presidential elections create spikes in both indexes (Azzimonti, 2015). However, Azzimonti (2015) finds many instances in which events that create spikes in the EPU actually reduce the PCI below its typical baseline. The divergence between the two models mainly occurs concerning national security events such as 9/11 and the Iraq War (Azzimonti, 2015). Despite its differences from the EPU, the PCI still yields similar results in terms of investment decisions. Interestingly, even when economic policy uncertainty is low, if partisan conflict is high, investment levels will be adversely effected (Azzimonti, 2015). In this situation, the likelihood of unfavorable low-probability events, or tail risks, increases (Azzimonti, 2015). Overall, Azzimonti (2015) estimates that a "10% increase in the [PCI] is associated with a 3.4% decline in aggregate private investment in the U.S."

Elections are among the most routinely partisan events as well as a recurring source of policy uncertainty. Unsurprisingly then, just as they hedge against other risks, firms seek to mitigate the risks of policy uncertainty surrounding elections by influencing the contests. Akey and Lewellen (2015) investigate this by focusing on firms' campaign contributions during U.S. congressional election cycles (Akey & Lewellen, 2015). In particular, they examine firms that actively contributed money to candidates in close elections; then, they separate the selected firms into "policy-sensitive" and "policy-neutral" buckets (Akey & Lewellen, 2015). The study deems firms to have received a "lucky" shock for each supported candidate that won, and an "unlucky" shock for each supported candidate that lost (Akey & Lewellen, 2015).

Akey and Lewellen's (2015) work yields four main findings. First, holding policy sensitivity fixed, firms experiencing "lucky" political shocks subsequently reduce risk-taking and see an increase in operational performance and firm value (Akey & Lewellen, 2015). "Unlucky" shocks are associated with nearly symmetric results, but with the opposite sign. Second, "policy-sensitive" firms react more sharply to political shocks than "policy-neutral" firms, making the marginal value of political donations higher for "policy-sensitive" firms (Akey & Lewellen, 2015). Third, political donations do not perfectly hedge policy uncertainty (Akey & Lewellen, 2015). Even "lucky" "policy-sensitive" firms saw reductions in investment and increases in volatility following elections, albeit at a less dramatic rate than "unlucky" firms (Akey & Lewellen, 2015). Finally, "lucky" and "unlucky" shocks seem to have enduring effects on the risk taking of firms (Akey & Lewellen, 2015).

Other research extends beyond the U.S. to examine the economic effects of elections in foreign countries. In their research of national elections in 48 different countries between 1980 and 2005, Brandon Julio and Youngsuk Yook (2012) find that even after controlling for

economic conditions, firms reduced investment by 4.8% in election years. In general, the closer the election, the more pronounced the decline in investment (Julio & Yook, 2012). Furthermore, countries with less stable governments, fewer checks and balances, and high levels of government spending as a percentage of GDP were more likely to see firms reduce investment levels by a larger amount (Julio & Yook, 2012). When an incumbent deemed "market friendly" by the World Bank faced re-election, investment again tended to drop more than in comparable scenarios where the World Bank had not deemed the incumbent "market friendly" (Julio & Yook, 2012). All of these results again point to heightened uncertainty driving pauses in investments. However, like Nancy Stokey (2014), Julio and Yook (2012) found that in the year following elections, once the uncertainty had dissipated, firms responded with increased investment – albeit at a less dramatic rate of increase than the prior decrease (Julio & Yook, 2012).

In addition to decreased investment, Julio and Yook (2012) found that firms increased their cash to assets ratio by 4.3% in election years. This percentage is similar to the percentage decline in investment, suggesting that firms choose to increase their working capital with the funds they withhold from investment (Julio & Yook, 2012). This finding is consistent with Opler, Pinkowitz, Stultz, and Williamson's (1999) research that concludes that firms with greater cash flow uncertainty will choose to hold more cash as a precautionary procedure protecting against greater future cash outlays. Opler, et al. (1999) also hypothesize that management likes holding excess cash in times of uncertainty so that when a "firm runs into difficulties", management can use the excess to "avoid making required changes."

Between 1980 and 2006, Bates Kahle, and Stultz (2009) found that U.S. firms increased their cash to asset ratios by an average of 0.46% annually. In 1980, the average cash to assets

ratio was 10.5%. By 2006, the ratio had increased to 23.2% (Bates, Kahle, & Stultz, 2009). As the researchers point out, this considerable increase occurred despite the proliferation of financial investment products over the examined period – theoretically giving firms better opportunities to invest their cash (Bates, Kahle, & Stultz, 2009). Bates, Kahle, and Stultz (2009) conclude that reluctance to repatriate foreign profits, reduced and more efficient inventories, and increases in research and development explain much of the growth in cash holdings. However, they also found that increases in cash flow volatilities played a significant role for the increase. When separating firms into two sets of quintiles based on size and volatility, Bates, Kahle, and Stultz (2009) observed that while all five quintiles of both factors saw increased cash to asset ratios, the smallest and most volatile quintiles saw the largest increases (Bates, Kahle, & Stultz, 2009). The most volatile quintile's cash to asset ratio increased 300% compared to less than 50% for the least volatile quintile (Bates, Kahle, & Stultz, 2009).

Given how greatly political uncertainty can affect the investment decisions of individual firms, it is unsurprising that uncertainty correlates with various macroeconomic factors. In assessing the U.S. recession between 2007 and 2009, James Stock and Mark Watson (2012) conclude that along with the financial shocks of liquidity and risk, uncertainty shocks were most responsible for producing the recession and the subsequent drops in GDP and employment. Uncertainty shocks can explain around 3% of GDP drops and rebounds (Bloom, Floetotto, Jaimovich, Saporta-Eksten, & Terry, 2012). Additionally, when Standard & Poor's downgraded the U.S. Treasury's credit rating for the first time ever in 2011, the organization cited political uncertainty among its primary reasons for the reduction (Pastor & Veronesi, 2013). There is also evidence that political uncertainty affects the stock market. In tight presidential election contests, both the market's volatility and returns rise in the several months preceding the election

(Born & Li, 2006). However, when an incumbent is virtually assured of re-election, returns and volatility are “virtually indistinguishable from nonelection periods” (Born & Li, 2006).

# Chapter 3

# Hypothesis Development

## A. Working Capital Requirement and its Components

The WCR is defined as the sum of accounts receivable and inventory net of accounts payable. Thus, a positive WCR indicates a net-asset position that a firm must finance while a negative WCR indicates a net liability position that provides a firm with financing. Below, I discuss the three components of the WCR, including the significance of each to a firm as well as trend charts for each component. Then, I discuss WCR as a whole, including an explanation of financing implications and the firm characteristics shown to influence WCR. I also provide a trend chart for WCR.

### 1. Accounts Receivable

Accounts receivable refers to the claim a firm has on money owed by customers in exchange for goods or services provided. In other words, a firm generates accounts receivable when it delivers a good or service but has not yet received payment for that good or service. For most firms, receivables are necessary to support adequate sales levels. By allowing customers to pay at least a portion of the sales price at a later date, firms can attract more customers and generate additional revenue. Assuming that firms can then collect the accounts receivable as promised, the extra sales will lead to additional profits and cash flows.

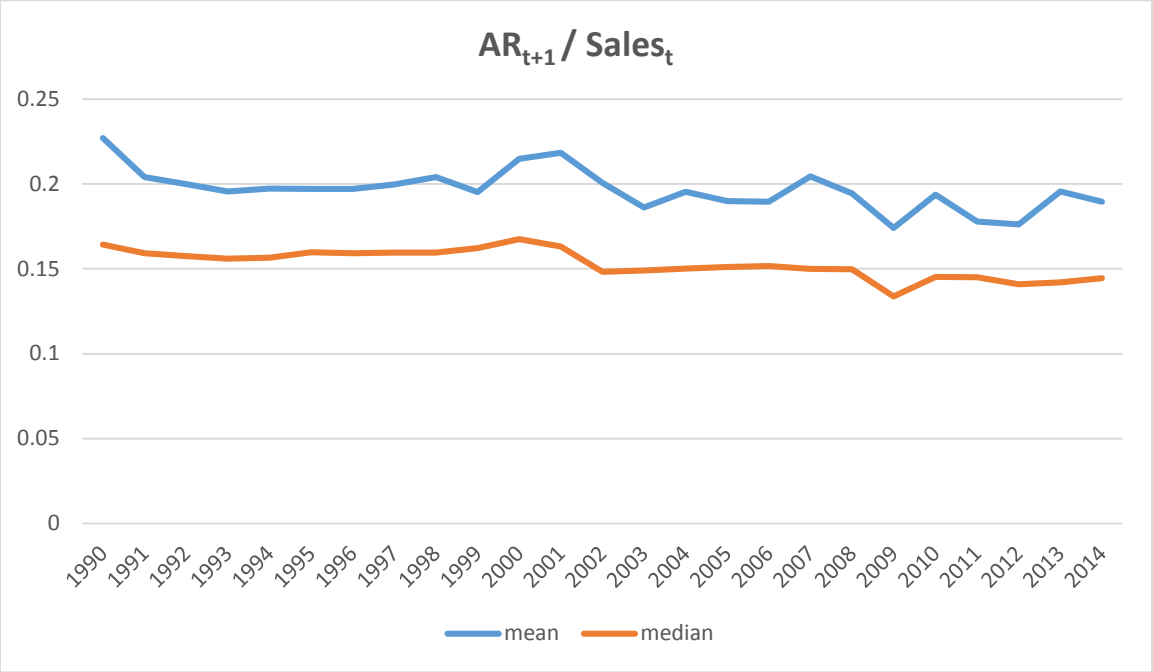
Because accounts receivable essentially represents a loan to a customer, firms want to collect on accounts receivable quickly. The longer it takes a firm to convert its accounts receivable into cash, the longer that cash remains unavailable for investment. The ratio days sales outstanding (DSO) measures accounts receivable collection efficiency by calculating the number of days it takes a firm to convert credit sales into cash. To calculate DSO, a firm's average accounts receivable over a period (beginning of period accounts receivable plus end of period accounts receivable divided by two) is divided by credit sales over that period. The resulting number is then multiplied by the number of days in the period (365 if annual, 90 if quarterly). The DSO formula is shown below:

$$DSO = \frac{Average\ AR}{Credit\ Sales} \times Days\ in\ Period$$

In general, firms want to maintain as low of a DSO as possible without restricting sales. A high ratio could indicate mismanagement or difficulties collecting on accounts receivable.

Below, Figure 1 charts the mean and median accounts receivable to lagged sales ratio of the firms used in my samples over the sample period 1990-2014. Neither measure varies much over the life of the sample, indicating no significant trends have taken place with accounts receivable.

**Figure 1: Accounts Receivable to Lagged Sales: 1990-2014**




## 2. Inventory

Inventory refers to the assets a firm holds with the intention of selling. The types of inventory can vary depending on the nature of the firm. For merchandisers, inventory simply represents the goods a firm purchases and then resells to customers. For manufacturers, inventory refers to the raw materials, work-in-progress goods, and finished goods that the manufacturer will eventually sell. Service firms typically have low inventory levels. Regardless of its type, inventory is generally one of the most important assets a firm holds because it represents one of the primary ways a firm generates revenue.

Although inventory is crucial to a firm's success, holding too much inventory can have negative effects. As with accounts receivable, inventory ties up resources – every dollar held in inventory represents a dollar that the firm could have invested elsewhere. Additionally, large

inventories are subject to obsolescence, spoilage, and associated storage costs. Still, not holding enough inventory also poses a risk to firms. If a firm runs out of inventory, known as a stockout, it will be unable to generate additional revenue until it restocks its inventory. In an ideal world, firms would hold exactly the same amount of inventory as they sell. In practice, firms tend to error on the side of caution and devote the required resources to holding excess inventory.

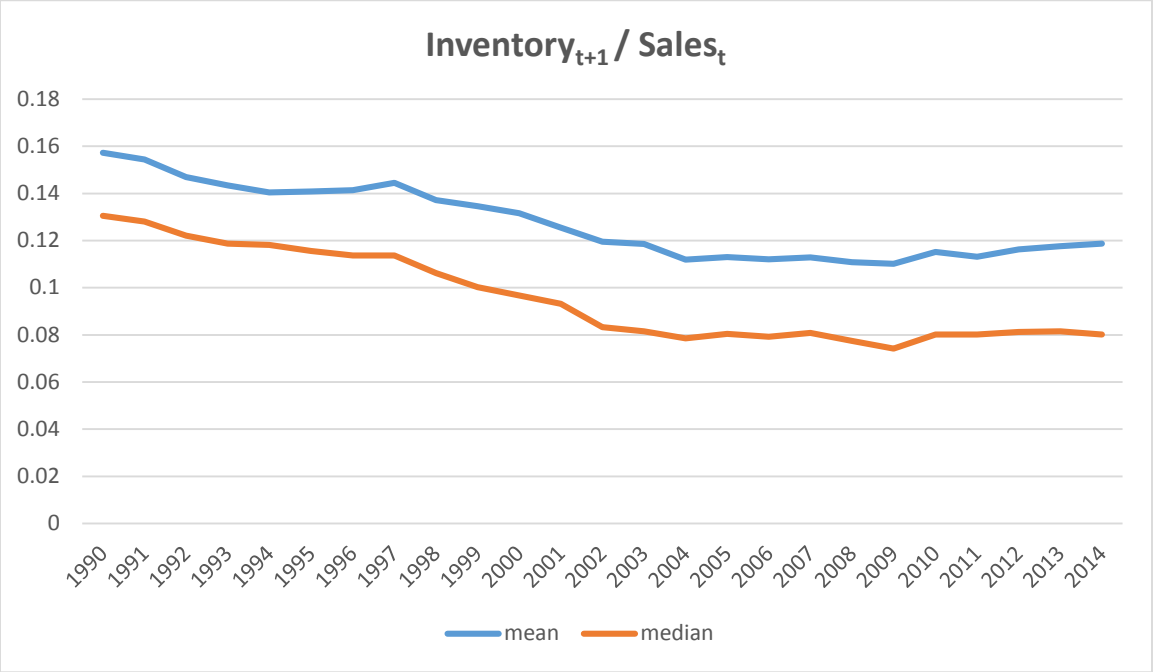
The ratio days inventory outstanding (DIO) measures a firm's efficiency in managing inventory by calculating the number of days it holds its inventory before selling. To calculate the DIO, a firm's average inventory over a period (beginning of period inventory plus end of period inventory divided by two) is divided by cost of goods sold. The resulting number is then multiplied by the number of days in the period (365 if annual, 90 if quarterly). The DIO formula is shown below:

$$DIO = \frac{Average\ Inventory}{Cost\ of\ Goods\ Sold} \times Days\ in\ Period$$

In general, firms want to maintain as low of a DIO as possible without experiencing stockouts. A high DIO could indicate poor management or obsolete inventory.

Below, Figure 2 charts the mean and median inventory to lagged sales ratio of the firms used in my samples over the sample period 1990-2014. Both the mean and median ratios decline substantially between 1990 and 2004; since then, the inventory to lagged sales ratio has remained mostly constant. The steady decline is likely attributable to two main factors. First, many firms identified the value of increased inventory efficiencies and emphasized supply chain systems during the period. Second, the period captures the internet boom and other technological advances that have given rise to firms with little inventory, such as software developers.

**Figure 2: Inventory to Lagged Sales: 1990-2014**




### 3. Accounts Payable

Accounts payable refers to the obligation a firm has to pay short-term debts to creditors. Essentially, it is the other side of an accounts receivable transaction – one firm's payable is another firms receivable. Accounts payables most frequently arise during the purchase of inventory and rarely involve interest. A firm can often receive a discount on its payable by paying early, however.

Because accounts payable essentially represents a loan from a supplier, firms want to keep accounts payables outstanding for as long as possible. The longer a firm takes to settle its accounts payable, the longer it can invest that cash in something else. The ratio days payables outstanding (DPO) measures accounts payable payment efficiency by calculating the number of days it takes a firm to pay its short-term credit purchases. To calculate DPO, a firm's average

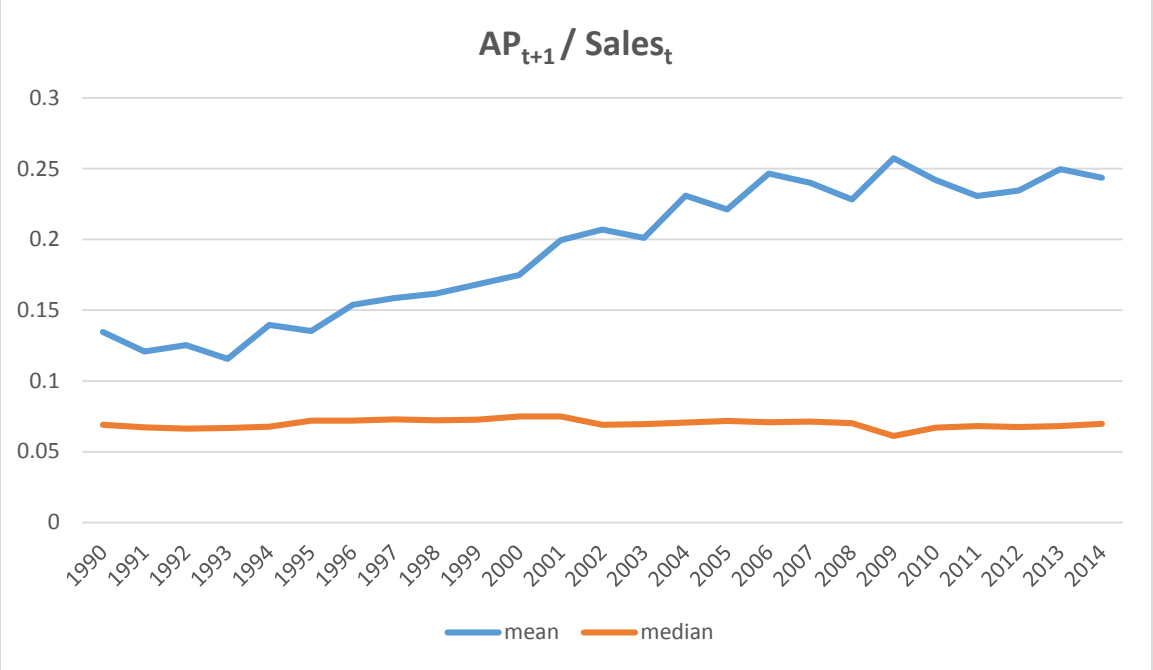
accounts payable over a period (beginning of period accounts payable plus end of period accounts payable divided by two) is divided by cost of goods sold over that period. The resulting number is then multiplied by the number of days in the period (365 if annual, 90 if quarterly). The DPO formula is shown below:

$$DPO = \frac{Average\ AP}{Cost\ of\ Goods\ Sold} \times Days\ in\ Period$$

In general, a firm wants to maintain as high of a DPO as possible without defaulting. A low DPO could indicate limited market power.

Below, Figure 3 charts the mean and median accounts payable to lagged sales ratio of the firms used in my samples over the sample period 1990-2014. The median ratio stays constant for the entire period while the mean ratio steadily and substantially increases. This indicates that some firms have significantly increased accounts payables but that most firms held their accounts payables steady over the period.

**Figure 3: Accounts Payable to Lagged Sales: 1990-2014**



**4. Working Capital Requirement**

WCR represents the operating portion of working capital. As mentioned above, the WCR is defined as the sum of accounts receivable and inventory net of accounts payable. Between 1996 and 2006, WCR made up approximately 23% of firms' capital structures (Hill, Kelly, & Highfield, 2010). Because a positive WCR requires greater accounts receivable and inventory than accounts payable, it must be financed either from the firm's own free cash flow or through external financing of some kind (Hill, Kelly, & Highfield, 2010). Therefore, a positive WCR implies either opportunity costs or explicit financing costs (Hill, Kelly, & Highfield, 2010). Because a negative WCR requires greater accounts payable than accounts receivable and inventory, it provides financing that a firm can use to fund long-term assets (Hill, Kelly, & Highfield, 2010).

Given the differing financing implications of positive and negative WCR's, it follows that a firm would want to maintain as low of a WCR as possible. This point is further illustrated when looking at the cash conversion cycle (CCC). The CCC is defined as DSO plus DIO minus DPO. The CCC formula is shown below:

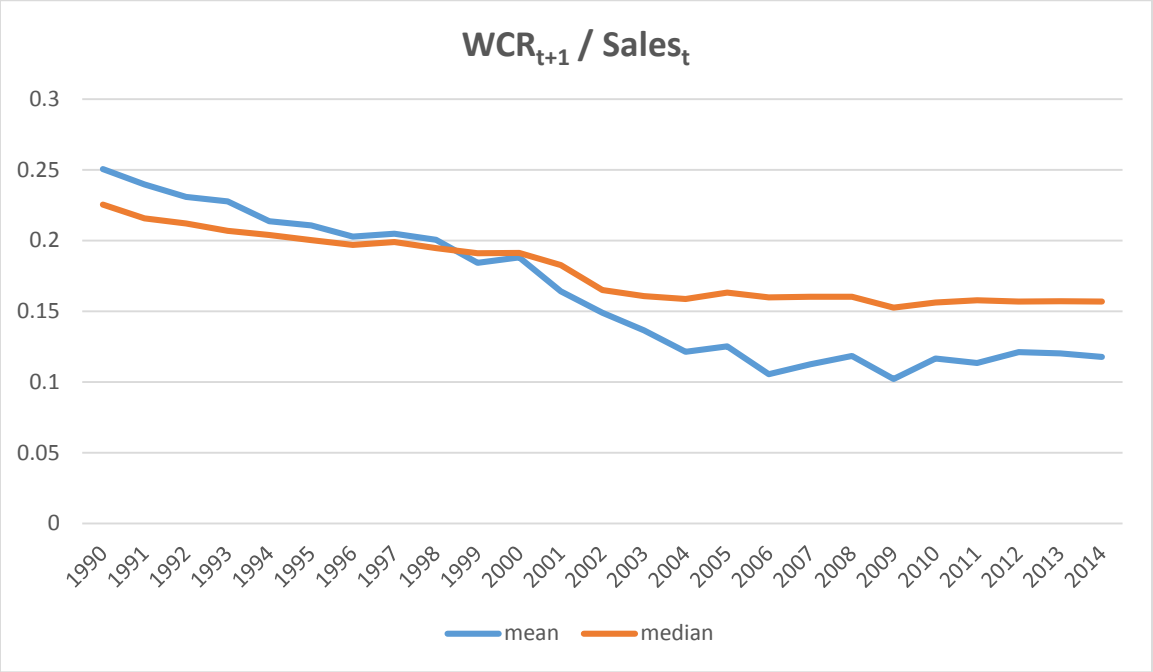
$$CCC = DSO + DIO - DPO$$

Firms want to maintain low CCC's. This aligns with the ideal financial strategies of the individual components of WCR as discussed above. By quickly converting credit sales to cash, a firm will maintain a low DSO. By quickly selling inventory, a firm will maintain a low DIO. And by maximizing the time it takes to settle payables, a firm will maintain a high DPO. It then makes sense that research has found that increases in net operating working capital (and thus the CCC) negatively relate to fixed-investment, profitability, and risk-adjusted returns (e.g. Fazzari & Peterson, 1993; Shin & Soenen, 1998; Deloof, 2003).

What may not seem intuitive, however, is the fact that nearly all firms maintain positive WCR's. Hill, Kelly, and Highfield (2010) find that just 520 out of 3,343 firms experienced even one year with a negative WCR between 1996 and 2006. Just 6.8% of firm year observations in their study returned negative WCR's. What's more, of the positive WCR firm years, the average WCR was 21.8% of sales – a significant percentage (Hill, Kelly, & Highfield, 2010). This is likely because maintaining a positive WCR is a safer strategy than maintaining a negative WCR. A negative WCR creates temporary financing for a firm but also puts it in a precarious position where it must repay its payables with fewer liquid assets on the books. Therefore, while a negative WCR may arise because of a firm's superior working capital management, it is more likely that the firm has been forced to take a negative WCR position because of financial distress or difficulties obtaining internal and external financing (Hill, Kelly, & Highfield, 2010).

Below, Figure 4 charts the mean and median WCR to lagged sales ratio of the firms used in my samples over the sample period 1990-2014. Both the mean and median ratios significantly decline throughout the period. Inventory reduction, as discussed above, drives both of the ratios declines. The mean WCR to lagged sales additionally decreases because as mentioned above the mean accounts payable to lagged sales ratio drastically increases but the median accounts payable to lagged sales ratio does not.

**Figure 4: WCR to Lagged Sales: 1990-2014**




## 5. Firm Specific Factors Impacting WCR

Hill, Kelly, and Highfield (2010) examine how operating conditions and the ability to finance operating working capital influence WCR. Specifically, they focus on the operating conditions of sales growth, contribution margin, and sales volatility as well as indicators of the ability to finance operating working capital such as operating cash flow, asymmetric information and the costs of external financing, capital market access, market power, and financial distress (Hill, Kelly, & Highfield, 2010). Sales growth is measured as the percent change in sales during the previous year. Contribution margin is measured by the proxy lagged gross profit margin, or the ratio of sales minus cost of goods sold divided by sales. Sales volatility is measured as the ratio of the standard deviation of sales to net assets. Operating cash flow is measured as lagged operating income plus depreciation minus taxes, scaled by net assets. Asymmetric information

and the costs of external financing are measured by the proxy of lagged market-to-book ratio. Capital market access is measured by the proxy of lagged market value of equity. Market power is measured as the ratio of lagged annual firm sales to the industry's lagged annual sum of sales. Financial distress is measured by whether the firm has difficulty making interest payments and is overleveraged.

Hill, Kelly, and Highfield (2010) use the following empirical model to determine the direction and extent to which each factor listed above correlates with WCR:

$$WCR_{i,t} = \beta_0 + \beta_1 Growth_{i,t-1} + \beta_2 GPM_{i,t-1} + \beta_3 SaleVAR_{i,t} + \beta_4 OCF_{i,t-1} \beta_5 M/B_{i,t-1} + \beta_6 Size_{i,t-1} + \beta_7 MktShare_{i,t-1} + \beta_8 Distress_{i,t-1} + \beta_j Controls_{i,t} + \varepsilon_i$$

After running this regression, Hill, Kelly, and Highfield (2010) determine that WCR negatively correlates with sales growth, sales volatility, market-to-book ratio, and financial distress while it positively correlates with operating cash flow and size. WCR and gross profit margin show no correlation while a weak negative correlation exists between WCR and market share (Hill, Kelly, & Highfield, 2010).

## B. Economic Policy Uncertainty

The EPU measures policy-related economic uncertainty from January 1st, 1985 to present day by tracking the number of articles using specific terms in the following ten leading U.S. newspapers: *USA Today, Miami Herald, Chicago Tribune, Washington Post, Los Angeles Times, Boston Globe, San Francisco Chronicle, Dallas Morning News, New York Times*, and the *Wall Street Journal* (Baker, Bloom, & Davis, 2015). To meet Baker, Bloom, and Davis's (2015) criteria, an article must contain at least one mention of 'uncertain', at least one mention of

'economic', and at least one mention of the policy-related terms 'Congress', 'deficit', 'Federal Reserve', 'legislation', 'regulation', or 'White House'. Variations such as 'uncertainty ', 'economy' and 'the Fed' also meet the criteria (Baker, Bloom, and Davis, 2015).

To protect against concerns about newspaper reliability, accuracy, and bias, Baker, Bloom, and Davis (2015) evaluate the EPU in five ways. First, they compare the results of the EPU to other measures of economic uncertainty, such as implied stock market volatility. Second, they compare the results of the EPU to other measures of policy uncertainty, such as how often the Federal Reserve mentions policy uncertainty in its beige books. Third, they compare EPU movements based just on the results of right-leaning and left-leaning newspapers to examine whether the political slant of a newspaper alters the EPU. Fourth, they conduct a human audit of 12,000 randomly selected newspaper articles in which the auditors assess whether the article meets the terminology criteria. Fifth, they examine whether commercial data providers such as Bloomberg and Reuters use the EPU, indicating that the index provides valuable decision-making information. Baker, Bloom, and Davis (2015) conclude that the EPU satisfactorily meets all five evaluations.

Figure 1 depicts the monthly movement of the EPU between January 1st, 1990 and December 31st, 2014. The index moves around a baseline of 100, dropping to 57.2 in February, 2007 and spiking at 245.1 in August, 2011.

**Figure 5: Monthly Economic Policy Uncertainty Index: 1990-2014**

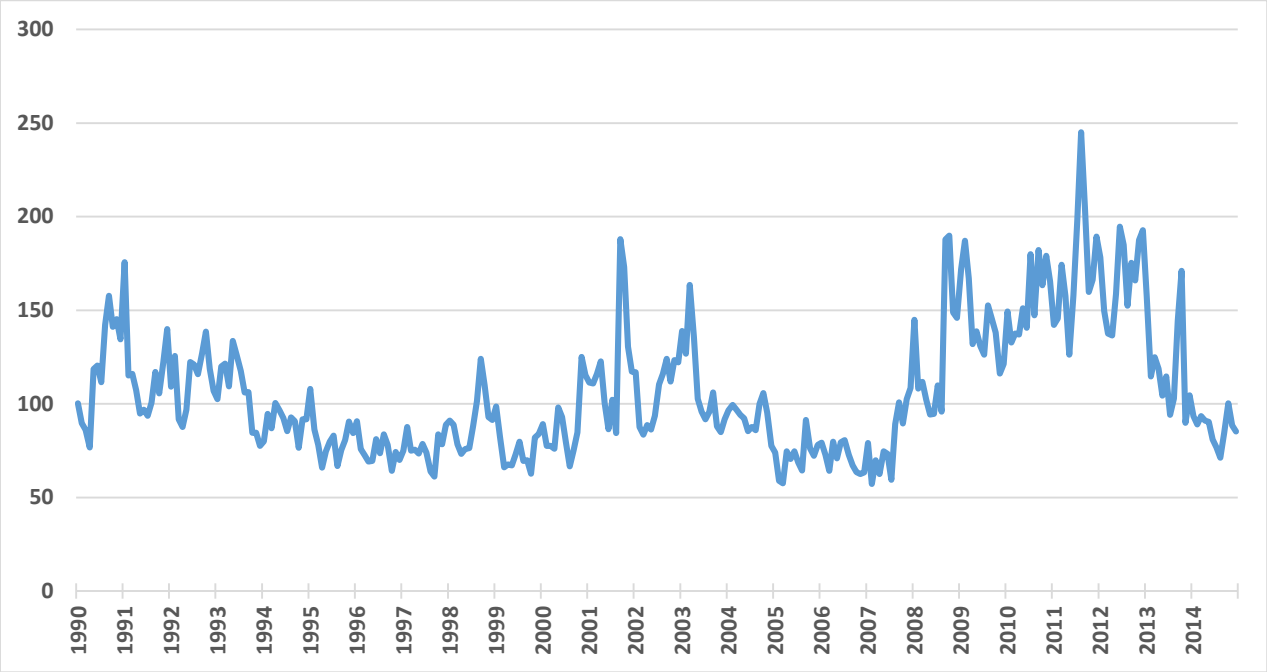
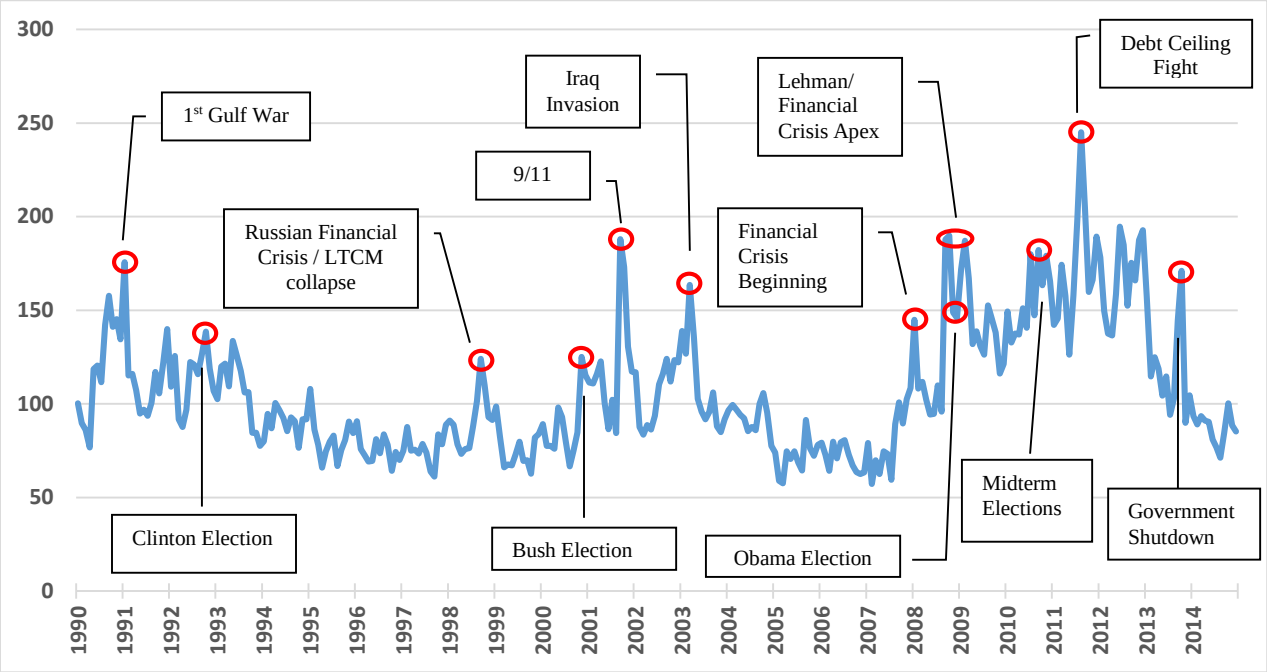



Figure 2 highlights the events driving particular spikes in the EPU. Elections, wars, and significant financial events, such as the financial crisis, all play major roles in spiking the index. Interestingly, the election of President Obama in 2008 briefly reduced the EPU by over 23%, likely because many Americans saw him as better able to resolve the financial crisis than his predecessor, President George W. Bush. Shortly after President Obama assumed office, however, the EPU again spiked as the financial crisis deepened.

**Figure 6: Highlighted Monthly Economic Policy Uncertainty Index: 1990-2014**




Clearly, the period before the financial crisis elicited less uncertainty. In the 216 months between January 1st, 1990 and December 31st, 2007, the EPU averaged around 90, with a mean of 93.5 and a median of 88.8. A few events still spiked the index during this period, but in most cases, the uncertainty quickly subsided. For one long stretch following the 1994 midterm elections through the dawn of the new millennium, the EPU remained almost exclusively below the 100 baseline, only briefly rising to 124.0 after two foreign financial crises – in Asia and Russia – helped bring about the collapse of celebrated U.S. hedge fund Long Term Capital Management (LTCM). This stability reconciles with the 1990's reputation as a time of superior peace, prosperity, and technological advances in the U.S. The EPU also remained well below 100 following the re-election of President Bush until the final months of 2007 – another extended period with a stable relative lack of uncertainty. Interestingly, this stability does not

seem to reconcile as well with the general political climate of the time, which was marred by deep partisan divisions over war and national security.

Beginning with the outset of the financial crisis in 2008 and continuing through the highly partisan fights over economic and regulatory policies throughout the Obama presidency, the EPU registers much higher uncertainty. In the 84 months between January 1st, 2008 and December 31st, 2014, the EPU averaged around 140, with a mean of 139.2 and a median of 141.4. The average EPU measurement between 2008-2014 was nearly two standard deviations above the average between 1990-2007. The largest index spike also occurred during this period, reaching 245.1 during the intense debt ceiling negations in August, 2011. In fact, the EPU did not dip below 100 during the Obama Presidency until July, 2013. It then immediately spiked again in September and October, 2013 in response to the Federal Government shutdown.

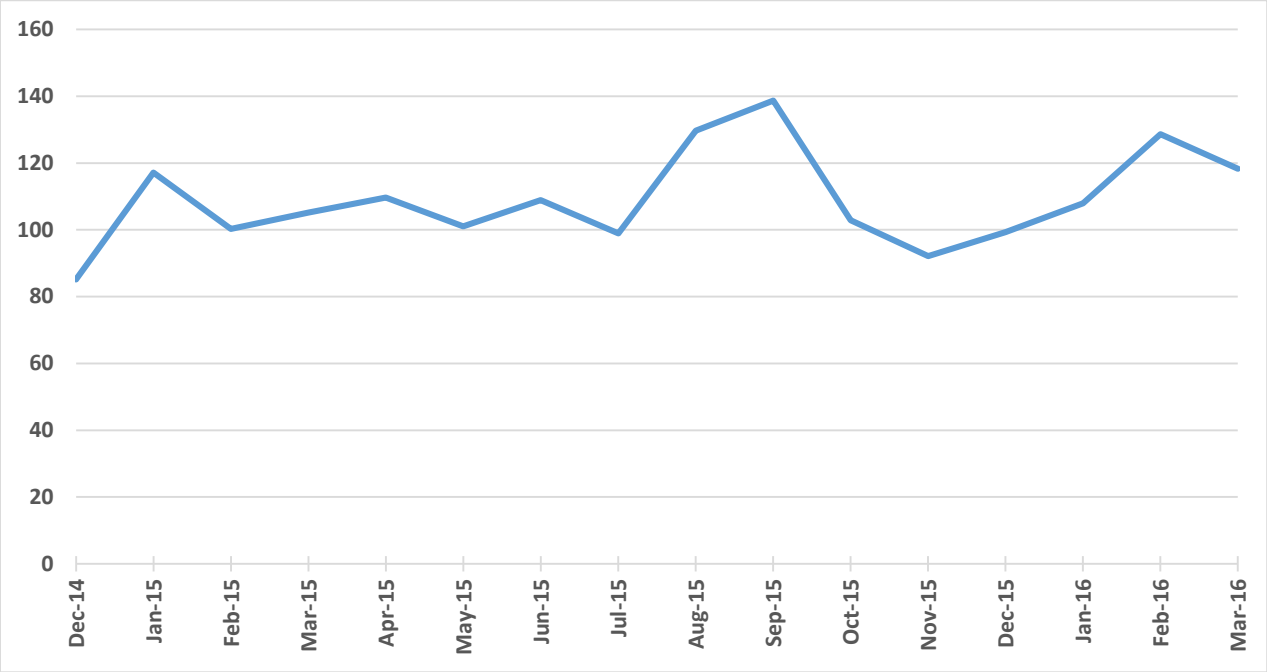
The monthly results of the EPU between 1990 and 2014 suggest that events explicitly involving economic and financial matters have the strongest effects on economic political uncertainty. While elections and serious national security events consistently spike the index, only explicit economic events appear to keep uncertainty high for extended periods. This may be because economic events tend to both last a long time and foster severe partisanship. In contrast, elections, while partisan by nature, have a set end date and tend to only last a few months. National security events may have long lasting implications, but are more likely to motivate consensus and common goals that help mitigate uncertainty relatively quickly. Regardless, the EPU appears to suggest that overtly economic and financial events will have a stronger impact on firms' financial decisions than other events.

After a relatively calm 2014, the EPU began to track upwards again. Figure 3 shows that the EPU has remained above 100 for nearly all of the 15 months following December, 2014,

spiking the highest during the Chinese stock crash in September, 2015. Although still far below the uncertainty seen during the financial crisis, the most recent EPU measurements may indicate that 2014 was an aberration and that uncertainty has yet to return to its pre-crisis levels.

There is reason to believe that uncertainty will continue to remain high as well. Internationally, China remains mired in economic downturn, much of Europe faces a mass migration crisis that threatens to severely strain its economic, social and political systems, and the United Kingdom will hold a referendum on European Union membership on June 23rd, 2016. Domestically, the U.S. will hold elections in the fall that will likely feature the most expensive presidential campaign in history. All four of the leading presidential candidates – Hillary Clinton, Bernie Sanders, Donald Trump, and Ted Cruz – have proposed sweeping economic and regulatory policy changes, including large tax increases on upper income brackets and corporations (Sanders), some version of universal free college tuition (Clinton, Sanders), severe restrictions on free trade (Sanders, Trump), massive tax cuts (Trump), and the abolition of the Internal Revenue Service (Cruz). Merely the possibility of the implementation of any of the above policies would likely cause major increases in uncertainty. In addition, the next President will likely appoint the replacement for late Supreme Court Justice Antonin Scalia; a move that would probably shift the court from its former ideologically balanced composition to a decisively liberal majority should Clinton, Sanders, or any other Democrat win. The potential drastic alteration to the nation's high court would also likely create high levels of uncertainty.

**Figure 7: Monthly Economic Policy Uncertainty Index since December 1st, 2014**




### C. Hypothesized Relationship between the EPU and WCR

Firms increase cash in times of uncertainty (Julio & Yook, 2012; Opler, et al. 1999). As noted above, a positive WCR requires financing while a negative WCR provides financing. Therefore, I expect WCR to decline when the EPU increases. This negative correlation would represent rational decisions by firms to reduce their WCR's in order to provide more cash, and therefore flexibility to deal with unknowns. Additionally, there can be more value in waiting to invest until uncertainty subsides than investing immediately, even when an investment has a large NPV (Bernanke, 1983; McDonald & Siegel, 1986). I expect this dynamic to further entice firms to reduce WCR in times of increasing uncertainty. Because the EPU somewhat correlates with economic downturns, a negative correlation between WCR and the EPU may also represent some firms' involuntary decisions to reduce WCR. For these firms, the reduction of WCR may

provide liquidity necessary for survival. However, the number of firms involuntarily reducing WCR likely pales in comparison to the number of firms employing WCR reduction as an optimal strategy. Therefore, this paper focuses on voluntary WCR reduction.

Of course, not all firms will respond to policy uncertainty in the same way. Just as Hill, Kelly, and Highfield (2010) concluded that several firm and industry factors correlated with the proportion of WCR that a firm holds, I expect that certain firm characteristics will help explain WCR and EPU correlation. I discuss two of these characteristics below: product market and asset profile.

**1. Product Market**

A product market is where a firm sells its end product, whether it is a good or a service. The more products of similar utility and quality on the market, the more competitive the market is. In highly competitive product markets, firms often do not have much leeway when making various business decisions because customers can buy the product from any number of producers. This is most obvious in pricing decisions – a sugar manufacturer has to price its sugar at the market price for sugar. But it is also relevant in other business decisions. For instance, the sugar manufacturer will likely be unable to negotiate better terms with its sugar cane suppliers because those suppliers could easily defect to other sugar manufacturers. In less competitive markets, the opposite is true. The providers of telecommunication services can partially set market prices because few competitors can enter an industry with such high barriers to entry. Similarly, telecommunications companies do not need to provide stellar customer service because customers have few other choices if they want telecommunication services.

I expect that firms operating in relatively uncompetitive industries will adjust their WCR's in times of high uncertainty more than firms operating in less competitive industries. In part, this is because firms with few competitors possess a greater ability to impose stricter credit terms on customers (reducing accounts receivable) and demand more lenient credit terms from suppliers (increasing accounts payable). It is also because firms with a small number of competitors will experience few costs but may reap future benefits by waiting for clarity in uncertain situations. For instance, stocking out because it declined to purchase enough inventory will not likely harm a firm with few competitors in the same way that it would hurt a firm with many competitors. However, the decision to wait to invest in that inventory may provide a future benefit if a political event renders the inventory obsolete or makes it cheaper.

While it is most obvious to think of a product market in terms of how competitive an industry is, it is also important to look at the type of competition within an industry. Product markets can be either heterogeneous or homogeneous. In a heterogeneous industry, there may be monopolistic competition – a number of firms operate within the same nominal industry, but they offer enough variation in their products or services that in reality there is not much competition between them. For example, although laptop manufacturers produce the same product, different types of laptops come with very different features and branding that generally render them imperfect substitutes. Firms operating in homogeneous industries offer almost no variation in their products and therefore see fierce competition. These industries include commodity producers, such as sugar manufacturers. So, just as with firms with sparse industry competition, firms operating in heterogeneous product markets have a greater ability to adjust their WCR's. Therefore, I expect firms operating in heterogeneous product markets to adjust

their WCR's more in response to political uncertainty than firms in homogenous product markets.

**2. Asset Profile**

Assets are resources of economic value that a firm possesses. These resources range from large tangible assets, such as machines, to semi-tangible assets, such as mineral reserves, to intangible assets, such as goodwill or patents. While tangible assets can be unique firm differentiators, intangible assets are almost always inimitable. That is to say, a firm with large amounts of intangible assets possesses significant resources that other firms cannot replicate. Intangibility acts as a proxy measurement of the "uniqueness" of a firm. For that reason, I expect that less tangible firms face fewer direct competitors and will adjust WCR more in response to policy uncertainty than tangible firms.

As noted above, while intangible assets are virtually always unique and specific, tangible assets can be as well. For instance, a firm may possess proprietary machines that allow it to produce higher quality products than competitors. These machines are tangible, but provide the firm with a distinctive competitive advantage. So, whether tangible or intangible, the more specific a firm's assets are to that firm, the more likely it is that the firm produces products or services with few substitutes. Therefore, I expect that firms with greater asset specificity will adjust WCR more in response to political uncertainty than firms with more generic assets.

# Chapter 4

# Empirical Design

## A. Empirical Design

I study a broad panel of U.S. public firms within the Compustat database from 1990-2014. I exclude financial firms (SIC codes 6000 - 6799) and utility firms (SIC 4900 - 4949), which is common in the empirical finance and accounting literature. Working capital requirements such as accounts receivable, accounts payable and inventory for financial institutions are fundamentally different than other manufacturing or service related companies. Further, both financial and utility companies face heavier regulations, which might affect firm-level behavior. I require that all observations have non-missing variables for both dependent and control variables in the regression analyses (see the Table 8 for variable descriptions).

The resulting baseline sample consists of an unbalanced panel of 11,230 unique firms over 25 years for a total of 100,556 firm-year observations. I examine firm-year observations rather than firm-quarter observations due to the data requirements. Often, Compustat quarterly data does not disclose certain components of net operating working capital or other variables that help explain working capital behavior. Additionally, seasonal effects and accounting timing recognition might confound the results when examining quarterly data. I winsorize the dependent and several independent variables at the 1% level to mitigate the influence of extreme outliers in the data that might influence statistical and economic inferences (see Table 8). Summary statistics are provided in Table 1.

## B. Variable Descriptions

### 1. Economic Policy Uncertainty

I employ the EPU to proxy for policy-related uncertainty. A primary benefit of examining policy-related uncertainty is that the measure is largely exogenous – firms likely have difficulty controlling or manipulating it. Other uncertainty proxies such as firm-level sales volatility and stock price volatility likely suffer from stronger endogeneity issues as managers and directors have more control over firm decisions that generate those volatilities.

For this study, I primarily focus on the average EPU index over the lagged three-month period before the annual filing month. For example, roughly 61% of my sample's fiscal year end is December. For those firm-year observations, I average the EPU index over the September – November time frame (from that year), and use that as a proxy for the firm's policy-related uncertainty. I follow a similar procedure with firms with different fiscal year-ends. A three month lag is reasonable in that the cash conversion cycles (DSO plus DIO minus DPO) for most firms are within three months. My results are statistically and economically similar when using a lagged twelve-month proxy rather than the lagged three-month proxy.

### 2. Control Variables

I utilize the control variables from Hill, Kelly and Highfield (2010) described in the previous chapter. They hypothesize and find that firms' working capital behaviors are related to operating conditions such as sales growth, contribution margins (gross margins), and sales volatility. They also find that firms' abilities to finance operating working capital is important.

They find that operating cash flows, the market-to-book ratios, firm size (as measured by the natural logarithm of the market value of equity in constant dollars) and market share are important determinants of firms' net working capital behavior. The authors do not investigate uncertainty or the heterogeneity of firms' responses in different industries.

## C. Industry Classifications

The fundamental premise behind the empirical predictions is that industries differ in their working capital investment behavior relative to economic policy uncertainty. I focus on three primary observable industry characteristics that likely relate to product market heterogeneity that might shed some additional light on how firms behave. Since theory is not clear on specific predictions, I rely on the empirical data. Sample splits are outlined in the Table 1. Table 2 displays the correlations between industry groups.

### 1. Industry-Level Tangibility

First, I examine industry-level heterogeneity in firms' net operating working capital behavior and economic policy uncertainty based on balance sheet characteristics. Firms in industries with predominantly more property, plant and equipment (PP&E) relative to total assets may behave differently than other firms, as they likely have better opportunities to obtain external financing at more advantageous terms. However, firms within industries with higher proportions of PP&E (higher tangibility) might have less flexibility to change production inputs due to asymmetric adjustment costs of capital during times of uncertainty.

I calculate the within-year, within-industry median value of net PP&E (4-digit SIC level, including firms not included in the baseline sample) scaled by total assets. Firm-years contained in the top half of annual industries are classified as being "High Tangibility" firms. Firm-years in the lower half of annual industries are classified as "Low Tangibility."

**2. Homogeneity of Growth Opportunities**

The second industry classification scheme attempts to examine the essence of competition for growth opportunities. I calculate the yearly, within-industry coefficient of variation of market-to-book ratios (4-digit SIC level, including firms not contained in the baseline sample). Market-to book ratios (MTB) are common proxies in the finance literature for growth opportunities. I order industries annually and classify the bottom half as Low-CV industries. Firm-years contained in these industries with low coefficients of variation are classified as Low-CV observations.

There are several advantages of examining firms in industries with low coefficients of variation of MTB. First, this metric more directly measures the homogeneity of the market's valuations of industry participants' growth opportunities. Inherently, this is a market-based measure and provides additional information to the industry structure and the within-industry firm behavior classifications described above. Second, the Low-CV classification should account for industries with potentially threatening entrants and industries with prominent private rivals.

**3. Gross Margins**

Prior studies in industrial organization literature use the price-cost margin (also known as the Lerner Index) to proxy for product substitutability (eg. Demsetz (1997); Nevo (2001)). To the extent that the price-cost margin reflects the price elasticity of demand, low (high) margins are correlated with high (low) levels of substitutability in the product markets. Alternatively, the closer (further) a firm is from perfect competition, the more (less) that prices tend toward marginal costs. Recent finance literature defines the price-cost margin (gross margin) as sales minus cost of goods sold, divided by sales[1]. For each industry-year (4-digit SIC level, including firms not contained in the baseline sample), I use the median firm's gross margin as a proxy for product substitutability. I classify the industries in the bottom half of the yearly ranking as Low-Margin industries. Firm-years contained in these industry-years comprise the Low-Margin group.

A primary advantage of examining industry gross margins is that they reflect observable firm behaviors. Product substitutability can occur from both public and private rivals, and gross margins reflect industry equilibria. All else equal, firms with high substitutability likely share more opportunities and product market competition as their peers.

**4. Industry Concentration**

The corporate finance literature typically employs the Herfindahl-Hirschman index (HHI) as a proxy for within-industry competition. The underlying concept behind the HHI assumes that

[1] Sometimes, the price-cost margin is computed as sales divided by operating costs (cost of goods sold plus SG&A). Recent finance literature typically defines price-cost margin as (sales-cogs)/sales

industry structure is exogenous, that unit prices reduce as concentration declines and that lower concentration reflects higher competition. There are two primary complications when using Compustat-based HHI. First, certain industries might contain more prominent private firms, which are not reflected in the public data. Ali, Klasa and Yueng (2009) find that some empirical results are unsubstantiated (or reversed) when using the HHI with Census data, which includes private firms. However, Census data only contains infrequently updated HHI information for manufacturing firms, which complicates comparisons with other, service-oriented industries. Second, the exogenous nature of the classification neglects the strategic threats of potential entrants that might cause concentrated industries to behave in a highly competitive manner. Further, the HHI does not reflect that certain product markets might accommodate several niche sub-markets. Therefore, some unconcentrated industries might be the byproduct of entrants' abilities to differentiate. In this study, I find that the Compustat-based HHI negatively correlates with other proxies of industry-level competition, and I do not find significant statistical results over my sample period.

## D. Empirical Tests

Empirical analyses are Ordinary Least Squared (OLS) regressions that include fixed industry effects to control for unobserved factors shared by an industry. Such factors might include the regulatory and legal regimes, labor costs, overall market perceptions of industry growth, and the financing environment unrelated to the control variables. I cannot include fixed year effects because the EPU index is time-based. Including fixed year effects would create

collinearity in the regressions. Further, standard errors are clustered at the firm level to account for serial correlation in the error terms, as suggested by Petersen (2009).

# Chapter 5

# Results

## A. Summary Statistics

Table 1 shows the summary statistics for the sample of the 100,556 observed firm years. I used nine independent variables to investigate the measurement of WCR to lagged sales, accounts receivable to lagged sales, accounts payable to lagged sales, and inventory to lagged sales. Eight of the independent variables functioned as controls while policy uncertainty acted as the driver-of-interest of WCR and its components. In Table 2, I provide a correlation matrix containing tangibility, heterogeneity, and the Lerner Index. The three measurements show only modest correlations, demonstrating the value of quantifying policy uncertainty's effects on WCR with each measurement. The remainder of this section discusses my results for the overall sample, industry-level tangibility, industry-level heterogeneity, industry-level Lerner Index, and a sample comparing firms with low industry-level tangibility, high industry-level heterogeneity, and high industry-level Lerner Index to firms not possessing all three of those characteristics.

## Table 1: Sample Summary Statistics

| | Overall Sample | | | Industry-Level Tangibility | | | | Industry-Level Heterogeneity | | | | Industry-Level Lerner Index | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Low | | High | | Low | | High | | Low | | High | |
| | Mean | Median | SD | Mean | Median | Mean | Median | Mean | Median | Mean | Median | Mean | Median | Mean | Median |
| **Dependent Variables** | | | | | | | | | | | | | | | |
| $WCR_{t+1}$ / $Sales_t$ | **0.155** | **0.175** | **0.551** | 0.175 | 0.209 | 0.125 | 0.127 | 0.168 | 0.173 | 0.148 | 0.177 | 0.144 | 0.158 | 0.162 | 0.186 |
| $AR_{t+1}$ / $Sales_t$ | **0.198** | **0.152** | **0.534** | 0.224 | 0.169 | 0.159 | 0.125 | 0.177 | 0.142 | 0.208 | 0.157 | 0.179 | 0.133 | 0.210 | 0.164 |
| $AP_{t+1}$ / $Sales_t$ | **0.206** | **0.070** | **1.113** | 0.243 | 0.069 | 0.152 | 0.070 | 0.171 | 0.068 | 0.223 | 0.071 | 0.211 | 0.070 | 0.203 | 0.070 |
| $Inventory_{t+1}$ / $Sales_t$ | **0.125** | **0.094** | **0.162** | 0.142 | 0.109 | 0.101 | 0.075 | 0.128 | 0.102 | 0.124 | 0.090 | 0.131 | 0.098 | 0.122 | 0.092 |
| **Independent Variables** | | | | | | | | | | | | | | | |
| Policy $Uncertainty_t$ | **1.089** | **0.975** | **0.341** | 1.085 | 0.975 | 1.096 | 0.975 | 1.111 | 0.980 | 1.078 | 0.972 | 1.080 | 0.968 | 1.095 | 0.975 |
| Sales $growth_t$ | **0.082** | **0.074** | **0.362** | 0.082 | 0.079 | 0.083 | 0.068 | 0.070 | 0.064 | 0.088 | 0.080 | 0.075 | 0.069 | 0.087 | 0.077 |
| Gross $margin_t$ | **0.236** | **0.344** | **0.939** | 0.203 | 0.383 | 0.284 | 0.299 | 0.233 | 0.299 | 0.237 | 0.370 | 0.063 | 0.227 | 0.339 | 0.431 |
| Operating cash $flow_t$ | **-0.066** | **0.103** | **0.707** | -0.157 | 0.089 | 0.069 | 0.118 | -0.003 | 0.107 | -0.096 | 0.101 | -0.063 | 0.099 | -0.067 | 0.107 |
| Market-to-$book_t$ | **3.456** | **1.596** | **6.252** | 4.413 | 1.928 | 2.041 | 1.336 | 2.638 | 1.384 | 3.847 | 1.750 | 2.951 | 1.309 | 3.756 | 1.832 |
| Log size (2014 $dollars)_t$ | **5.351** | **5.309** | **2.479** | 5.072 | 4.989 | 5.763 | 5.844 | 5.695 | 5.754 | 5.190 | 5.099 | 5.393 | 5.385 | 5.326 | 5.258 |
| Sales Growth $Volatility_t$ | **0.301** | **0.176** | **0.374** | 0.334 | 0.195 | 0.253 | 0.150 | 0.256 | 0.153 | 0.323 | 0.190 | 0.284 | 0.162 | 0.311 | 0.186 |
| Distress $Indicator_t$ | **0.043** | **0.000** | **0.203** | 0.054 | 0.000 | 0.027 | 0.000 | 0.030 | 0.000 | 0.049 | 0.000 | 0.034 | 0.000 | 0.048 | 0.000 |
| Market $share_t$ | **0.074** | **0.009** | **0.162** | 0.063 | 0.005 | 0.090 | 0.018 | 0.109 | 0.026 | 0.051 | 0.005 | 0.098 | 0.020 | 0.060 | 0.005 |

## Table 2: Industry Classification Correlation Matrix

| Correlation Matrix by Industry Classifications | | | |
|---|---|---|---|
| | Tangibility | Heterogeneity | Lerner Index |
| Tangibility | ● | | |
| Heterogeneity | -0.1973 | ● | |
| Lerner Index | -0.2331 | 0.2006 | ● |

## B. Overall Sample

As hypothesized, the results of the overall sample strongly suggest that increases in policy uncertainty drive decreases in WCR. Table 3 shows that policy uncertainty's effect on WCR to lagged sales is statistically significant at the 1% level, both when controlling for industry fixed effects and for firm fixed effects. Industry fixed effects control for ongoing differences between industries such as competitive interactions and the regulatory environment. Firm fixed effects control for ongoing differences between firms, such as one firm always having a higher WCR than another firm. Because I controlled for both factors and still observed very strong correlations, my results show within-industry variation of WCR relative to the EPU and within-firm variation of WCR relative to the EPU.

Economically, a one standard deviation increase in the EPU yields a 5.85% decrease in the WCR to lagged sales ratio when controlling for industry fixed effects. A one standard deviation increase in the EPU yields a 3.39% decrease in the WCR to lagged sales ratio when controlling for firm fixed effects. Considering the average sampled firm holds hundreds of millions in WCR, these declines represent massive decreases in absolute terms.

Intuitively, my results also show negative correlations between both accounts receivable and inventory with policy uncertainty and a positive correlation between accounts payable and policy uncertainty. When controlling for industry fixed effects, all three components are statistically significant at the 5% level. When controlling for firm fixed effects, accounts receivable and accounts payable are statistically significant at the 10% level and inventory shows no statistical relationship.

## Table 3: Overall Sample Results

OLS panel regressions for $WCR_{t+1}$ / $Sales_t$, $AR_{t+1}$ / $Sales_t$, $AP_{t+1}$ / $Sales_t$, and $Inventory_{t+1}$ / $Sales_t$. The sample includes all Compustat firm-years from 1990-2014 as summarized in Chapter 4. Variable descriptions are located in the Table 8, Appendix A. Regressions (1), (3), (5) and (7) include industry fixed effects to account for unobserved factors common to an industry. Regressions (2), (4), (6) and (8) include firm fixed effects. Standard errors are clustered at the firm level, and robust t-statistics are in parentheses *** p < 0.01, ** p < 0.05, and * p<0.10.

| | $WCR_{t+1}$ / $Sales_t$ | | $AR_{t+1}$ / $Sales_t$ | | $AP_{t+1}$ / $Sales_t$ | | $Inventory_{t+1}$ / $Sales_t$ | |
|---|---|---|---|---|---|---|---|---|
| Policy Uncertainty$_t$ | -0.0266*** | -0.0154*** | -0.0129** | -0.0109* | 0.0301** | 0.0242* | -0.0041** | -0.0003 |
| | (-3.9493) | (-2.6191) | (-2.0774) | (-1.7290) | (2.1147) | (1.8389) | (-2.2860) | (-0.2329) |
| Sales growth$_t$ | 0.0412*** | 0.0327*** | -0.0913*** | -0.0797*** | -0.2183*** | -0.1862*** | -0.0146*** | -0.0146*** |
| | (3.5271) | (2.7074) | (-6.7634) | (-5.9597) | (-8.4580) | (-6.7903) | (-6.3344) | (-6.7084) |
| Gross margin$_t$ | 0.0987*** | 0.0509*** | -0.0760*** | -0.0463*** | -0.2756*** | -0.1449*** | -0.0023 | -0.0045** |
| | (7.8089) | (4.0307) | (-6.3462) | (-3.2838) | (-8.5095) | (-5.4784) | (-0.9830) | (-2.0643) |
| Operating cash flow$_t$ | 0.1424*** | 0.0829*** | 0.0286** | 0.0215 | -0.2100*** | -0.1304*** | -0.0074*** | -0.0007 |
| | (10.3680) | (5.5952) | (2.3958) | (1.3986) | (-6.2940) | (-3.8565) | (-2.8568) | (-0.2340) |
| Market-to-book$_t$ | -0.0105*** | -0.0059*** | 0.0011 | 0.0030** | 0.0206*** | 0.0157*** | -0.0009*** | 0.0000 |
| | (-8.3188) | (-4.4343) | (1.1629) | (2.4807) | (7.5328) | (5.1389) | (-3.2546) | (0.0305) |
| Log size (2014 dollars)$_t$ | 0.0072*** | 0.0120*** | 0.0010 | 0.0013 | -0.0170*** | -0.0184*** | -0.0044*** | 0.0019** |
| | (4.5110) | (3.5429) | (0.7763) | (0.4857) | (-5.2003) | (-2.5921) | (-8.8147) | (2.5106) |
| Sales growth volatility$_t$ | -0.0517*** | -0.0383* | 0.1173*** | 0.0127 | 0.2412*** | 0.0474 | 0.0202*** | 0.0067 |
| | (-3.0619) | (-1.8187) | (6.8733) | (0.5328) | (6.5394) | (0.9526) | (5.7697) | (1.5724) |
| Distress indicator$_t$ | -0.0184 | 0.0032 | 0.0038 | -0.0130 | -0.0002 | -0.0460 | 0.0104** | 0.0029 |
| | (-0.9797) | (0.1695) | (0.1864) | (-0.6735) | (-0.0053) | (-1.0495) | (2.2518) | (0.6892) |
| Market share$_t$ | -0.1399*** | -0.0175 | -0.0101 | 0.0274 | 0.1639*** | 0.0401** | -0.0236*** | -0.0092* |
| | (-8.5013) | (-1.2290) | (-0.5843) | (1.0308) | (5.8854) | (2.0311) | (-3.9594) | (-1.6520) |
| Industry fixed effects | Yes | No | Yes | No | Yes | No | Yes | No |
| Firm fixed effects | No | Yes | No | Yes | No | Yes | No | Yes |
| Observations | 100,556 | 100,556 | 100,556 | 100,556 | 100,556 | 100,556 | 100,556 | 100,556 |
| Adjusted R-squared | 0.2047 | 0.5015 | 0.0556 | 0.2880 | 0.2025 | 0.4813 | 0.3483 | 0.6771 |

### C. Industry-Level Tangibility

Table 4 demonstrates a strong inverse between policy uncertainty and the WCR to lagged sales ratio among firms in low tangibility industries. The relationship is statistically significant at the 1% level. The sample shows no relationship between the EPU and WCR to lagged sales ratio among firms in high tangibility industries. This data aligns with my hypothesis that in times of high policy uncertainty, low tangibility firms possess a greater ability to reduce WCR and stand to gain more and risk less from reductions. Economically, a one standard deviation decrease in the EPU yields an 8.87% reduction in the WCR to lagged sales ratio among firms operating in low tangibility industries.

The sample suggests that accounts payable and inventory drive the inverse relationship between WCR and the EPU. Both WCR components show statistical significance at the 1% level. Accounts receivable does not show any statistical relationship with policy uncertainty.

## Table 4: Industry-Level Tangibility Results

OLS panel regressions for $WCR_{t+1}$ / $Sales_t$, $AR_{t+1}$ / $Sales_t$, $AP_{t+1}$ / $Sales_t$, and $Inventory_{t+1}$ / $Sales_t$. The sample includes all Compustat firm-years from 1990-2014 as summarized in Chapter 4. Variable descriptions are located in the Table 8, Appendix A. All regressions include industry fixed effects to account for unobserved factors common to an industry. Standard errors are clustered at the firm level, and robust t-statistics are in parentheses *** p < 0.01, ** p < 0.05, and * p<0.10.

| | **$WCR_{t+1}$ / $Sales_t$** | | **$AR_{t+1}$ / $Sales_t$** | | **$AP_{t+1}$ / $Sales_t$** | | **$Inventory_{t+1}$ / $Sales_t$** | |
|---|---|---|---|---|---|---|---|---|
| | Low | High | Low | High | Low | High | Low | High |
| Policy Uncertainty$_t$ | -0.0458*** | 0.0021 | -0.0128 | -0.0098 | 0.0583*** | -0.0039 | -0.0076*** | 0.0015 |
| | (-4.4808) | (0.2872) | (-1.4707) | (-1.1036) | (2.6279) | (-0.2742) | (-2.8098) | (0.8723) |
| Sales growth$_t$ | 0.0530*** | 0.0093 | -0.0873*** | -0.0953*** | -0.2461*** | -0.1350*** | -0.0147*** | -0.0143*** |
| | (3.5639) | (0.5172) | (-5.6050) | (-3.7636) | (-7.5574) | (-3.3072) | (-4.9447) | (-4.2961) |
| Gross margin$_t$ | 0.0924*** | 0.1309*** | -0.0657*** | -0.1319*** | -0.2455*** | -0.4370*** | -0.0032 | 0.0025 |
| | (7.0072) | (3.5624) | (-5.8105) | (-3.1081) | (-7.9318) | (-3.9209) | (-1.2088) | (0.6236) |
| Operating cash flow$_t$ | 0.1317*** | 0.1824*** | 0.0205* | 0.0499 | -0.1907*** | -0.2946*** | -0.0036 | -0.0208*** |
| | (8.7622) | (4.9728) | (1.8278) | (1.0898) | (-5.3195) | (-3.1481) | (-1.2305) | (-3.7158) |
| Market-to-book$_t$ | -0.0107*** | -0.0114*** | 0.0003 | 0.0059 | 0.0193*** | 0.0328*** | -0.0006** | -0.0019*** |
| | (-7.6019) | (-3.5889) | (0.2974) | (1.6056) | (6.6023) | (4.1214) | (-2.0137) | (-4.5575) |
| Log size (2014 dollars)$_t$ | 0.0096*** | 0.0044** | 0.0036** | -0.0008 | -0.0212*** | -0.0082** | -0.0063*** | -0.0015*** |
| | (4.1068) | (2.4684) | (2.4638) | (-0.3442) | (-4.6910) | (-2.1500) | (-8.5603) | (-2.8543) |
| Sales growth volatility$_t$ | -0.0782*** | 0.0047 | 0.1110*** | 0.1211*** | 0.3014*** | 0.0926 | 0.0215*** | 0.0167*** |
| | (-3.5652) | (0.2031) | (5.7041) | (3.7680) | (6.4861) | (1.6308) | (4.5873) | (3.8616) |
| Distress indicator$_t$ | -0.0331 | 0.0334 | -0.0095 | 0.0406 | 0.0161 | -0.0754 | 0.0143** | -0.0020 |
| | (-1.3903) | (1.3935) | (-0.4999) | (0.7462) | (0.3256) | (-1.2342) | (2.4312) | (-0.3606) |
| Market share$_t$ | -0.1961*** | -0.0898*** | -0.0275 | -0.0079 | 0.2394*** | 0.0671** | -0.0218*** | -0.0282*** |
| | (-7.9285) | (-5.3257) | (-1.2267) | (-0.6068) | (5.3618) | (2.3808) | (-2.6938) | (-3.7370) |
| Industry fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 59,955 | 40,601 | 59,955 | 40,601 | 59,955 | 40,601 | 59,955 | 40,601 |
| Adjusted R-squared | 0.2102 | 0.1902 | 0.0517 | 0.0713 | 0.1983 | 0.2362 | 0.3262 | 0.3882 |

### D. Industry-Level Heterogeneity

Firms operating in industries with high heterogeneity appear to reduce WCR substantially in response to increases in policy uncertainty. Table 5 shows that the inverse relationship between the EPU and WCR is statistically significant at the 1% level for firms in industries with high heterogeneity. Economically, a one standard deviation increase in the EPU yields a 7.65% decrease in the WCR to lagged sales ratio for these firms. Firms in industries with low heterogeneity (more homogeneity) do not show a statistical relationship between the EPU and WCR. These results substantiate my hypothesis that firms with high heterogeneity will adjust more to policy uncertainty because they face fewer competitive restraints due to their product differentiation.

The sample produces less obvious results concerning the components of WCR. Logically, firms in industries with high heterogeneity show increases in accounts payable and decreases in inventory as uncertainty rises. These relationships are statistically significant at the 5% and 1% levels, respectively. Perplexingly, however, the accounts receivables of firms in industries with low heterogeneity show a negative correlation with WCR that is significant at the 1% level while high industry-level heterogeneity firms do not show a statistically significant relationship. This indicates that firms in industries with low heterogeneity get customers to pay them back more quickly, a confusing result that I did not expect. This result may merely be a statistical anomaly, but may warrant future research.

## Table 5: Industry-Level Heterogeneity Results

OLS panel regressions for $WCR_{t+1}$ / $Sales_t$, $AR_{t+1}$ / $Sales_t$, $AP_{t+1}$ / $Sales_t$, and $Inventory_{t+1}$ / $Sales_t$. The sample includes all Compustat firm-years from 1990-2014 as summarized in Chapter 4. Variable descriptions are located in the Table 8, Appendix A. All regressions include industry fixed effects to account for unobserved factors common to an industry. Standard errors are clustered at the firm level, and robust t-statistics are in parentheses *** p < 0.01, ** p < 0.05, and * p<0.10.

| | **$WCR_{t+1}$ / $Sales_t$** | | **$AR_{t+1}$ / $Sales_t$** | | **$AP_{t+1}$ / $Sales_t$** | | **$Inventory_{t+1}$ / $Sales_t$** | |
|---|---|---|---|---|---|---|---|---|
| | Low | High | Low | High | Low | High | Low | High |
| Policy Uncertainty$_t$ | -0.0105 | -0.0337*** | -0.0231*** | -0.0061 | 0.0126 | 0.0398** | 0.0022 | -0.0076*** |
| | (-1.1003) | (-4.1085) | (-2.9182) | (-0.7234) | (0.5758) | (2.3912) | (0.8727) | (-3.4292) |
| Sales growth$_t$ | 0.0540** | 0.0365*** | -0.0664*** | -0.0979*** | -0.2168*** | -0.2142*** | -0.0036 | -0.0178*** |
| | (2.4939) | (2.6359) | (-3.2091) | (-5.7649) | (-4.0737) | (-7.1934) | (-0.8790) | (-6.4199) |
| Gross margin$_t$ | 0.1216*** | 0.0909*** | -0.0527*** | -0.0825*** | -0.3231*** | -0.2585*** | 0.0013 | -0.0035 |
| | (6.0897) | (6.5369) | (-3.1781) | (-6.0632) | (-6.5628) | (-7.3094) | (0.3172) | (-1.4193) |
| Operating cash flow$_t$ | 0.1274*** | 0.1453*** | -0.0061 | 0.0380*** | -0.2369*** | -0.2025*** | -0.0083** | -0.0072** |
| | (5.4048) | (10.0228) | (-0.2749) | (2.7968) | (-4.1246) | (-5.8641) | (-2.0152) | (-2.5652) |
| Market-to-book$_t$ | -0.0184*** | -0.0088*** | -0.0007 | 0.0015 | 0.0334*** | 0.0175*** | -0.0016*** | -0.0007*** |
| | (-6.7073) | (-6.8234) | (-0.3591) | (1.4189) | (4.9661) | (6.3936) | (-3.4070) | (-2.5950) |
| Log size (2014 dollars)$_t$ | 0.0071*** | 0.0092*** | 0.0044*** | 0.0007 | -0.0134*** | -0.0195*** | -0.0036*** | -0.0043*** |
| | (3.1621) | (4.7242) | (2.8993) | (0.4386) | (-2.8067) | (-4.7942) | (-5.3402) | (-7.5115) |
| Sales growth volatility$_t$ | -0.0533** | -0.0546*** | 0.0750*** | 0.1295*** | 0.1878*** | 0.2640*** | 0.0160*** | 0.0212*** |
| | (-2.1871) | (-2.9115) | (3.5416) | (6.2518) | (3.3537) | (6.5297) | (3.1853) | (5.3281) |
| Distress indicator$_t$ | 0.0084 | -0.0238 | -0.0154 | 0.0096 | -0.0880 | 0.0225 | 0.0134* | 0.0094* |
| | (0.2498) | (-1.2017) | (-0.5240) | (0.3920) | (-1.2886) | (0.5303) | (1.7466) | (1.8610) |
| Market share$_t$ | -0.1119*** | -0.2237*** | -0.0346*** | -0.0390** | 0.1010*** | 0.2328*** | -0.0192*** | -0.0416*** |
| | (-6.2225) | (-9.2058) | (-2.6563) | (-2.0454) | (3.0427) | (5.2290) | (-2.6577) | (-5.1812) |
| Industry fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 31,668 | 68,308 | 31,668 | 68,308 | 31,668 | 68,308 | 31,668 | 68,308 |
| Adjusted R-squared | 0.2865 | 0.1808 | 0.0648 | 0.0508 | 0.2576 | 0.1863 | 0.4733 | 0.2981 |

## E. Industry-Level Lerner Index

I find that WCR negatively correlates with policy uncertainty among firms in industries with high gross margins, as measured by the Lerner Index. As seen in Table 6, the inverse relationship is statistically significant at the 1% level. Economically, a one standard deviation increase in the EPU yields a 7.02% decrease in the WCR to lagged sales ratio of firms with high Lerner Indexes. I find no meaningful relationship between the EPU and WCR among firms with low Lerner Indexes. These findings support my hypothesis and suggest that firms with high gross margins enjoy a greater ability to adjust WCR in times of high political uncertainty because they generally face less competition.

My results suggest that firms in high margin industries mostly adjust WCR through inventory reductions; the EPU and inventory share an inverse relationship that is significant at the 1% level. These firms also may convert their receivables to cash more quickly as the data shows a negative correlation between the EPU and accounts receivable that is significant at the 10% level. I find that the EPU and accounts payable do not share a meaningful relationship among firms in high margin industries.

## Table 6: Industry-Level Lerner Index Results

OLS panel regressions for $WCR_{t+1}$ / $Sales_t$, $AR_{t+1}$ / $Sales_t$, $AP_{t+1}$ / $Sales_t$, and $Inventory_{t+1}$ / $Sales_t$. The sample includes all Compustat firm-years from 1990-2014 as summarized in Chapter 4. Variable descriptions are located in the Table 8, Appendix A. All regressions include industry fixed effects to account for unobserved factors common to an industry. Standard errors are clustered at the firm level, and robust t-statistics are in parentheses *** p < 0.01, ** p < 0.05, and * p<0.10.

| | **$WCR_{t+1}$ / $Sales_t$** | | **$AR_{t+1}$ / $Sales_t$** | | **$AP_{t+1}$ / $Sales_t$** | | **$Inventory_{t+1}$ / $Sales_t$** | |
|---|---|---|---|---|---|---|---|---|
| | Low | High | Low | High | Low | High | Low | High |
| Policy Uncertainty$_t$ | -0.0118 | -0.0332*** | -0.0104 | -0.0164* | 0.0222 | 0.0277 | 0.0023 | -0.0082*** |
| | (-1.1211) | (-3.8440) | (-1.1242) | (-1.9579) | (0.9467) | (1.5069) | (0.7562) | (-3.9158) |
| Sales growth$_t$ | 0.0396** | 0.0417*** | -0.0773*** | -0.0975*** | -0.2430*** | -0.2033*** | -0.0158*** | -0.0141*** |
| | (2.0011) | (2.9105) | (-3.6166) | (-5.5855) | (-5.3064) | (-6.6396) | (-3.9083) | (-5.1991) |
| Gross margin$_t$ | 0.1179*** | 0.0853*** | -0.0788*** | -0.0778*** | -0.3155*** | -0.2512*** | 0.0024 | -0.0065** |
| | (6.8796) | (4.9057) | (-4.5776) | (-4.9453) | (-7.4969) | (-5.6976) | (0.5898) | (-2.2818) |
| Operating cash flow$_t$ | 0.1344*** | 0.1466*** | 0.0580** | 0.0169 | -0.1532** | -0.2374*** | -0.0071 | -0.0078*** |
| | (5.2999) | (9.1049) | (2.3460) | (1.2891) | (-2.5546) | (-6.1017) | (-1.1913) | (-2.9827) |
| Market-to-book$_t$ | -0.0080*** | -0.0117*** | 0.0014 | 0.0012 | 0.0179*** | 0.0218*** | -0.0014** | -0.0007** |
| | (-3.5685) | (-7.6743) | (0.5732) | (1.2858) | (3.2509) | (7.0773) | (-2.2354) | (-2.4669) |
| Log size (2014 dollars)$_t$ | 0.0042 | 0.0095*** | -0.0014 | 0.0021 | -0.0219*** | -0.0155*** | -0.0041*** | -0.0043*** |
| | (1.5681) | (4.7701) | (-0.6681) | (1.3413) | (-3.6646) | (-4.0303) | (-4.6488) | (-7.5962) |
| Sales growth volatility$_t$ | -0.0940*** | -0.0290 | 0.1113*** | 0.1173*** | 0.3039*** | 0.2050*** | 0.0193*** | 0.0202*** |
| | (-3.5650) | (-1.4153) | (5.4017) | (5.0476) | (5.1231) | (4.6204) | (3.1123) | (5.0927) |
| Distress indicator$_t$ | 0.0267 | -0.0399* | 0.0765* | -0.0282 | 0.0177 | -0.0051 | 0.0230** | 0.0036 |
| | (0.7597) | (-1.8624) | (1.8408) | (-1.2254) | (0.2255) | (-0.1127) | (2.1534) | (0.8129) |
| Market share$_t$ | -0.1062*** | -0.1814*** | -0.0088 | -0.0112 | 0.1851*** | 0.1710*** | -0.0184** | -0.0329*** |
| | (-4.2679) | (-8.0037) | (-0.4072) | (-0.3867) | (3.7226) | (4.9592) | (-2.0827) | (-4.5065) |
| Industry fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 37,511 | 63,045 | 37,511 | 63,045 | 37,511 | 63,045 | 37,511 | 63,045 |
| Adjusted R-squared | 0.2380 | 0.1864 | 0.0630 | 0.0512 | 0.2266 | 0.1881 | 0.3865 | 0.3224 |

### F. All Three Industry-Level Classifications

Table 7 compares how firms operating in industries with low tangibility, high gross margins, and high heterogeneity adjust WCR in response to rising policy uncertainty with firms in industries where at least one of those classifications is not true (high industry-level tangibility, low industry-level gross margins, and/or low industry-level heterogeneity). A total of 34,287 firm years meet these standards while 66,269 firm years do not. Because the results above reveal strong inverse relationships between WCR and policy uncertainty when classifying firms by just one of the characteristics, it should follow that firms in industries with all three characteristics should also show a robust inverse relationship. As expected, I find this to be the case. Firms in industries with all three characteristics show a correlation that is statistically significant at the 1% level and have the strongest correlation out of all of my samples. Economically, I find that a one standard deviation increase in policy uncertainty yields a 9.68% decrease in the WCR to lagged sales ratio. Firms in industries without all three characteristics show no meaningful relationship.

Inventory reduction appears to be the primary method firms possessing all three industry-level characteristics reduce WCR in response to policy uncertainty. The inverse relationship between the EPU and inventory is significant at the 1% level. A direct relationship between the EPU and accounts payable is also statistically significant, but only at the 10% level. Interestingly, similar to my heterogeneity sample, the accounts receivable of the group of firms not possessing all three industry-level characteristics shows a statistically significant relationship with policy uncertainty. However, because this unexpected relationship is only significant at the 10% level, it is likely a statistical anomaly.

## Table 7: Low Tangibility, High Lerner Index, and High Heterogeneity Firm Results

OLS panel regressions for $WCR_{t+1}$ / $Sales_t$, $AR_{t+1}$ / $Sales_t$, $AP_{t+1}$ / $Sales_t$, and $Inventory_{t+1}$ / $Sales_t$. The sample includes all Compustat firm-years from 1990-2014 as summarized in Chapter 4. Variable descriptions are located in the Table 8, Appendix A. All regressions include industry fixed effects to account for unobserved factors common to an industry. Standard errors are clustered at the firm level, and robust t-statistics are in parentheses *** p < 0.01, ** p < 0.05, and * p<0.10.

| | **$WCR_{t+1}$ / $Sales_t$** | | **$AR_{t+1}$ / $Sales_t$** | | **$AP_{t+1}$ / $Sales_t$** | | **$Inventory_{t+1}$ / $Sales_t$** | |
|---|---|---|---|---|---|---|---|---|
| | LT, HLI, HH | Other Firms | LT, HLI, HH | Other Firms | LT, HLI, HH | Other Firms | LT, HLI, HH | Other Firms |
| Policy Uncertainty$_t$ | -0.0550*** | -0.0099 | -0.0114 | -0.0125* | 0.0461* | 0.0202 | -0.0144*** | 0.0010 |
| | (-4.3679) | (-1.3217) | (-1.0235) | (-1.7263) | (1.7168) | (1.2513) | (-4.2033) | (0.5176) |
| Sales growth$_t$ | 0.0460** | 0.0361** | -0.0861*** | -0.0963*** | -0.2095*** | -0.2229*** | -0.0166*** | -0.0137*** |
| | (2.3160) | (2.4776) | (-4.3935) | (-5.4146) | (-5.0140) | (-6.7820) | (-4.3048) | (-4.8683) |
| Gross margin$_t$ | 0.0748*** | 0.1138*** | -0.0687*** | -0.0811*** | -0.2175*** | -0.3132*** | -0.0097*** | 0.0019 |
| | (4.0879) | (7.4781) | (-4.2624) | (-5.0299) | (-5.2095) | (-7.5308) | (-2.6856) | (0.6382) |
| Operating cash flow$_t$ | 0.1432*** | 0.1386*** | 0.0109 | 0.0417** | -0.2320*** | -0.1857*** | -0.0046 | -0.0083** |
| | (8.1749) | (7.5156) | (0.9533) | (2.0591) | (-5.6562) | (-4.1526) | (-1.3831) | (-2.2147) |
| Market-to-book$_t$ | -0.0100*** | -0.0113*** | 0.0006 | 0.0015 | 0.0188*** | 0.0224*** | -0.0004 | -0.0013*** |
| | (-5.8094) | (-6.7056) | (0.6170) | (0.8781) | (5.3026) | (5.6462) | (-1.0318) | (-3.5078) |
| Log size (2014 dollars)$_t$ | 0.0101*** | 0.0067*** | 0.0062*** | -0.0013 | -0.0159*** | -0.0185*** | -0.0063*** | -0.0033*** |
| | (3.6379) | (3.6222) | (3.6578) | (-0.7669) | (-3.1520) | (-4.5504) | (-7.1293) | (-6.0068) |
| Sales growth volatility$_t$ | -0.0580** | -0.0487** | 0.0966*** | 0.1285*** | 0.2758*** | 0.2206*** | 0.0261*** | 0.0162*** |
| | (-2.1631) | (-2.5584) | (3.9461) | (6.0693) | (4.9250) | (5.1007) | (4.5144) | (4.0464) |
| Distress indicator$_t$ | -0.0492* | 0.0073 | -0.0347** | 0.0399 | 0.0147 | -0.0095 | 0.0043 | 0.0137** |
| | (-1.9362) | (0.3082) | (-1.9887) | (1.1901) | (0.2814) | (-0.1792) | (0.7289) | (2.1143) |
| Market share$_t$ | -0.2843*** | -0.1137*** | -0.0865*** | 0.0115 | 0.2799*** | 0.1455*** | -0.0381*** | -0.0249*** |
| | (-7.1124) | (-6.7592) | (-3.1652) | (0.6451) | (3.8591) | (4.9437) | (-3.0984) | (-3.9136) |
| Industry fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 34,287 | 66,269 | 34,287 | 66,269 | 34,287 | 66,269 | 34,287 | 66,269 |
| Adjusted R-squared | 0.1744 | 0.2240 | 0.0427 | 0.0638 | 0.1804 | 0.2180 | 0.2602 | 0.3987 |

# Chapter 6

## Conclusion

Uncertainty plays a crucial role in investments and other important financial decisions. This paper seeks a better understanding of the effects policy uncertainty, measured by the EPU, has on firm-level operating working capital behavior, measured by WCR. In particular, I examine how the EPU affects firm-level WCR behavior as a whole and how it affects firm-level WCR behavior differently among firms operating in industries with varying product markets and asset profiles. I also assess how policy uncertainty affects the components of WCR as a secondary interest. To investigate these questions and arrive at conclusions, I conduct an empirical study that examines the relationship between the EPU and WCR among 100,556 firm years between January 1st, 1990 and December 31st, 2014. I control for various firm factors that Hill, Kelly, and Highfield (2010) show to influence WCR, as well as industry factors that affect WCR at the firm-level.

I find a strong inverse relationship between the EPU and WCR among all firms. The negative correlation is even stronger among firms operating in industries with low tangibility, high heterogeneity, or high Lerner Indexes. Intuitively, firms operating in industries where all three characterizations are met show the strongest inverse relationship. Firms operating in industries with high tangibility, low heterogeneity, or low Lerner Indexes show no statistical relationship between policy uncertainty and WCR.

The relationship between the EPU and the components of WCR is not as clear. For the most part, cuts in inventory appear to primarily drive WCR reduction in times of rising policy

uncertainty. Increases in accounts payable appear to somewhat contribute to WCR reduction while drops in accounts receivable do not seem relevant. However, I find some exceptions to these generalizations. Additionally, some of my findings surrounding accounts receivable run entirely contrary to my hypothesis.

The data strongly suggests that firms do explicitly alter WCR behavior in response to policy uncertainty. Additionally, I find that firms with greater ability and more incentive to alter WCR due to fewer competitive constraints do manipulate WCR in response to policy uncertainty at substantially greater rates than other firms. As mentioned above, changes in inventory appears to drive most of the WCR modification, though changes in accounts payable also explains some of the change. My data therefore strongly suggests that in times of rising uncertainty, firms operating in industries lacking fierce competition will reduce inventory levels and string out payments to suppliers.

While simply splitting firms into high and low halves for tangibility, heterogeneity, and the Lerner Index worked well to investigate the broad relationship between policy uncertainty and WCR, it may be beneficial for additional research to separate firms into more specific arrangements, such as quarters or quintiles. Further research could also investigate the correlation between policy uncertainty and the components of WCR more closely.

# Appendix A

## Variable Descriptions

### Table 8: Variable Descriptions

| | |
|---|---|
| **Dependent variables** | |
| $WCR_{t+1}$ / $sales_t$ | Measure for working capital requirement. Compustat ($ar_{t+1}$ + $inv_{t+1}$ - $ap_{t+1}$) / $revt_t$ |
| $AR_{t+1}$ / $sales_t$ | Accounts receivable. Compustat $ar_{t+1}$ / $revt_t$ |
| $AP_{t+1}$ / $sales_t$ | Accounts payable. Compustat $ap_{t+1}$ / $revt_t$ |
| $Inventory_{t+1}$ / $sales_t$ | Inventory. Compustat $inv_{t+1}$ / $revt_t$ |
| **Independent Variables** | |
| *Policy Uncertainty*$_t$ | The average of the previous three months' (lagged) EPU measure collected from www.policyuncertainty.com based on the Baker, Bloom and Davis (2015) methodology. For example, if a firm-year's fiscal year end is December, 2000, then *Policy Uncertainty*$_t$ equals the average of the EPU over the months of September – November, 2000. |
| *Sales growth*$_t$ | The logarithmic sales growth. Compustat ln($revt_t$ / $revt_{t-1}$). |
| *Gross margin*$_t$ | Compustat (*revt* – *cogs*)/*revt*, taken at time *t*. |
| *Operating cash flow*$_t$ | Proxy for operating cash flow (operating profits before depreciation less taxes) scaled by net assets (total assets minus cash and cash equivalents). Compustat (*oibdp* – *txt*) / (*at* – *che*), taken at time *t*. |
| *Market-to-book*$_t$ | Compustat (*csho*prcc_f* + *lt* – *ap*) / (*at* – *che*), taken at time *t*. |
| *Log size (2014 dollars)*$_t$ | The natural logarithm of the market value of equity measured in 2014 dollars as reported by the U.S. Bureau of Economic Analysis (BEA). Compustat ln(*csho*prcc_f * 2014 dollar deflator*), taken at time *t*. |
| *Sales growth volatility*$_t$ | Standard deviation of *Sales Growth*$_t$ over the previous 5 years (minimum of 3 observations) |

| | |
|---|---|
| *Distress indicator*$_t$ | Dummy variable = 1 if the coverage ratio (Compustat *oibdp / xint*) is less than one for two consecutive years, and if the leverage ratio (Compustat *dltt / at*) is in the top two deciles of its 4-digit SIC industry leverage ratio in a given year. |
| *Market share*$_t$ | Ratio of a firm-year's total revenue (Compustat revt) divided by the total 4-digit SIC industry revenue, at time *t*. 4-digit SIC industry-year values include observations in the Compustat database that do not meet this study's sample requirements. |

**Competition Classifications**

| | |
|---|---|
| *Tangibility* | Firm-year observations in the bottom 50$^{th}$ percentile of industries ordered by the median firm-year's tangibility as calculated by (net property, plant and equipment) / assets. Compustat *ppent* / *at*. 4-digit SIC industry-year values include observations in the Compustat database that do not meet this study's sample requirements. For each year, *t-1*, the values are ordered at the industry level, and the lowest half of industries comprises the *Low* group. |
| *Lerner Index* | Firm-year observations in the bottom 50$^{th}$ percentile of industries ordered by the median firm-year's gross margin as calculated by (sales – cost of goods sold) / sales. Compustat (*revt – cogs*)/*revt*. 4-digit SIC industry-year values include observations in the Compustat database that do not meet this study's sample requirements. For each year, *t-1*, the values are ordered at the industry level, and the lowest half of industries comprises the *Low* group. |
| *CV of MTB* | Firm-year observations in the bottom 50$^{th}$ percentile of industries ordered by the industry-level coefficient of variation of *(Market-to-book)*$_{t-1}$ each year. The coefficient of variation is defined as the standard deviation divided by the mean. 4-digit SIC industry-year values include observations in the Compustat database that do not meet this study's sample requirements. For each year, *t-1*, the values are ordered at the industry level, and the lowest half of industries comprises the *Low* group. |

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# ACADEMIC VITA
# KYLE MCCORMICK

## EDUCATION

**The Pennsylvania State University,** *The Schreyer Honors College, Smeal College of Business* **University Park, PA**
Master of Accounting | Bachelors of Science: Accounting; Finance | Minor: History *Graduation Date: May, 2016*
Beta Gamma Sigma Honor Society | Recipient of the 2012 President's Freshman Award

## PROFESSIONAL EXPERIENCE

**MACOM Technology Solutions Inc.** **Lowell, MA**
*Corporate Strategy & Development intern* *June 2015 – August 2015*
- Prepared the 2016 corporate strategy presentation for the Director of Corporate Development (DCD) and CEO
- Examined potential cost synergies between MACOM and an M&A target firm, aiding the DCD and CEO's decision to acquire the firm
- Modeled future stock prices over a five year planning horizon using an enterprise value and operating margin regression to provide executive management with a predictive equity value tool
- Confirmed one business unit no longer fit within the company's strategic plan, supporting MACOM's divestment from the unit
- Measured the potential solid-state RF energy market size and delivered findings to the Director of Technical Marketing
- Created PowerPoint presentations of key strategic financial metrics and data supporting corporate strategy sessions

**Ernst & Young LLP** **Houston, TX**
*Assurance Services Intern* *January 2015 – March 2015*
- Collaborated with team members to complete the integrated audits of a Fortune 100 energy company and a small oil and gas company
- Discovered and facilitated correction of a material error in a business unit cash account within the Fortune 100 client
- Completed the 10-K tie out for a business segment of the Fortune 100 client so that the audit could be officially completed
- Evaluated internal controls and recommended to management changes to strengthen governance at the small oil and gas client

**The Pennsylvania State University** **State College, PA**
*Office of Internal Audit Intern* *May 2014 – August 2014*
- Corresponded with Penn State professionals to complete audits of both the university's library system and background check policies
- Conducted an array of tests on the library's finances and business operations to produce an official audit report
- Confirmed the compliance of numerous departments with background check policies for an official audit report referenced by Senator George Mitchell's integrity monitoring team
- Examined the university's P-card transaction records to identify potential fraudulent use for investigation by the financial audit manager

## CAMPUS ACTIVITIES & LEADERSHIP

**Lion Ambassadors** **University Park, PA**
*Penn State's Highly Selective Student Alumni Corps* *January 2013-Present*
- Represent the university while guiding prospective and accepted students and their families on campus tours

**Membership Committee**
- Elected by general membership to select the class of 2014 members – only non-senior elected to the committee of 14
- Conducted the entire application and interview process before eventually selecting 28 out of approximately 100 candidates

**Guard the Lion Shrine Subhead**
- Organized and enabled five activities that were enjoyed by over 1,000 visitors at the annual homecoming event

**Strategic Planning Committee**
- Formulated ideas to improve the org, leading to a formal extended-absentee policy and the reinstitution of a popular internal program

**Schuyler Family Fund Allocation Committee**
- Elected to committee responsible for allocating money from the $1 million Schuyler Family Program Endowment fund

**Delta Sigma Pi** **University Park, PA**
*One of America's Foremost Professional Fraternities* *September 2011-Present*

**Pledge Committee**
- Conveyed fraternal expectations to and served in mentor role for incoming pledge class

**Global Business Brigades** **Piriati Embera, Panama**
*Service Organization Empowering Rural Communities in Developing Countries* *March 2011*

**Team Leader**
- Headed team of five that consulted with indigenous Panamanians about personal finance and small business strategies
- Oversaw the application of problem-solving skills to help two micro-businesses overcome unique challenges

## SKILLS

- Certified in Microsoft Word and Excel 2007 – expert proficiency in Microsoft Office 2013 application suite