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Industrial electricity, the business cycle and state level risk premiums

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Table of Contents

Abstract

Industrial electricity usage measured at the state level can predict stock returns of companies with headquarters in the state. Although predictive powers vary from state to state, we show that in general there is a state local relationship between industrial electricity usage and stock returns. We also find that the state level industrial electricity usage has stronger predictive powers on the risk premiums on the state level stock indexes than national industrial electricity usage has on risk premiums on the broad U.S stock index.

1. Introduction

This thesis examines the relationship between the state business cycle and state risk premiums in the U.S. and whether this relationship can be used to predict future stock returns. Da, Huang and Yun (2015) show that industrial electricity usage is an indicator for the business cycle and that it can be used to predict future risk premiums at the national level in the U.S., while Cowal and Moskowitz (1999) show that investors have a strong bias towards companies with headquarters located in their home state. We combine the findings of Da, Huang and Yun (2015) with the findings of Coval and Moskowitz (1999) in order to examine whether there is a predictive relationship between risk premiums and business cycle at the state level within the U.S. We do this by creating value weighted stock indexes for each of the 50 states and running predictive regressions on the log of the risk premiums of these indexes using the log of the year over year growth of state level industrial electricity usage as an independent variable.

Looking at each state individually, we find that in most, but not all states, the year-over-year growth rate in industrial electricity usage predicts future risk premiums on companies with headquarters located within the state. When the states are combined to form a panel dataset, the panel regression shows that industrial electricity usage predicts falling future premiums over the next 12 months with an adjusted R-squared of 2.4 percent with fixed state effects. We also find that for the same sample period as our state level data, the national industrial electricity usage does not have any predictive power on risk premiums. This shows that there is a local, predictive relationship between the state business cycle and state stock returns.

1.1 Return predictability

Whether stock returns can be forecasted or not is an open-ended question. Research on return predictability is plagued by mixed empirical results, weak out of sample performance, and statistical biases. Still, there is a lot of research going into stock return predictability and a number of predictable relationships are presented in the financial literature.

One major source of skepticism towards return predictability is the efficient market hypothesis. The efficient market hypothesis is central to financial theory, and states that financial markets do not allow investors to make an above average return without taking an above average risk (Malkiel 2003). The hypothesis is thoroughly tested on historical data from all major stock exchanges and, with few exceptions, the data is consistent with the efficient markets hypothesis (Jensen 1978). One could therefore be led to believe that changes in asset returns are inherently unpredictable. To explain stock return predictability in the context of efficient markets one either needs to include an element of irrationality such as fads, speculative bubbles or noise trading or there needs to be market equilibrium with time varying real rates of return (Balvers, Cosimano and McDonald 1990). Campbell (1999) also argues that to make sense of asset markets, one needs to model it with a high and time-varying risk premium. The Risk premium is the difference in returns on risky assets such as equity and corporate bonds and risk-free assets such as government bonds. Furthermore, Campbell argues that the variations in the risk premium are correlated with the state of the economy (Campbell 1999). For these reasons researchers have considered the relationship between consumption, the business cycle and asset returns (Campbell and Thompson 2008). They find that variations in the risk premium on common stocks and bonds have a clear business cycle pattern with higher premiums in economic downturns and lower premiums during peaks in the business cycle (Fama and French 1989). One of the reasons for this cyclicality is the individual investor's investment decision with respect to personal consumption. In economic downturns consumption tends to fall relative to the investors habit of consumption. This leads to a higher rate of substitution between current and future consumption and higher risk aversion. This causes the market risk premium to rise during recessions (Campbell and Cochrane 1999).

Although theory points to a strong relationship between stock return predictability and the business cycle, the general empirical findings do not always support the existence of such a relationship. The regular CAPM model outperforms the consumption based CAPM model (Mankiw and Shapiro 1984) and financial variables based on prices typically outperform macroeconomic variables based on quantity (Cochrane 2007). However, this does not mean that such a predictive relationship does not exist. Several research papers show significant predictive relationships between stock returns and macroeconomic variables. According to

Lettau and Ludvigson (2001), the real and the excess returns on stocks can be predicted by deviations in detrended wealth, consumption and labor income (Lettau and Ludvigson 2001). Other researchers, such as Cooper and Priestley (2009) and Da, Huang and Yun (2015), show that changes in risk premiums can be predicted using other proxies for the business cycle such as the output gap or industrial electricity usage.

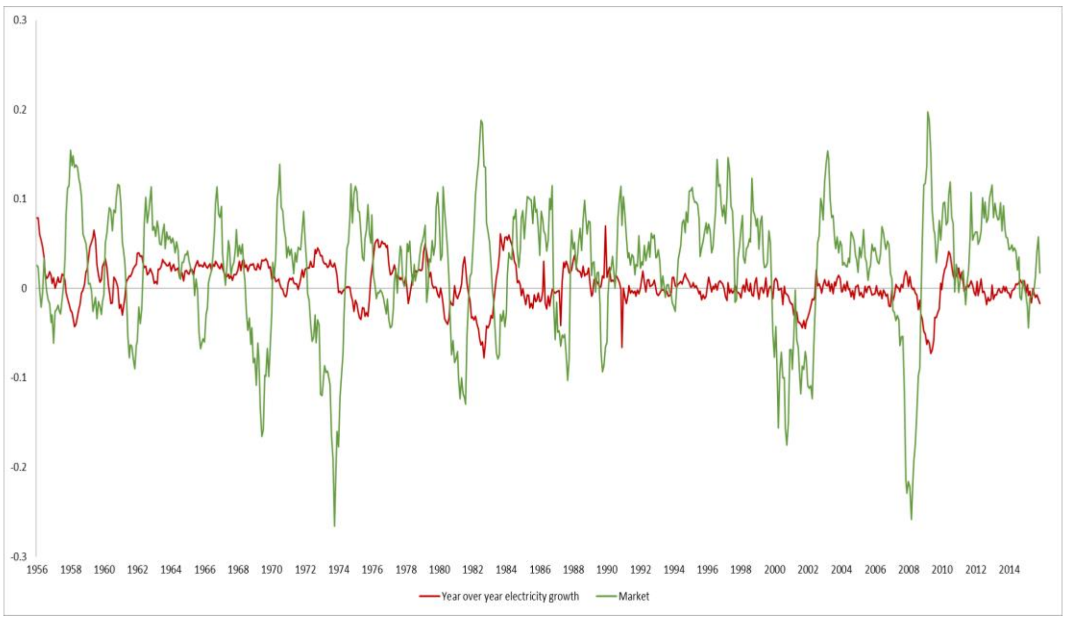
1.2 Proxies for the Business Cycle

Some of the main criticisms against stock return predictability are aimed at the statistical soundness of the research. Predictability studies suffer from statistical biases, unstable in-sample results and weak out-of-sample performance. For studies looking into the relationship between stock returns and the business cycle there are other problems. The most obvious business cycle variables such as GDP growth do not perform well when predicting stock returns. There are also some challenges with regards to causality. For example, in the case of financial proxies for the business cycle that contain asset prices, one cannot know if any predictability is due to price fads being washed away or countercyclical movement with the business cycle (Cooper and Priestley 2009).

To make sure that the observed predictability is not caused by mispriced stocks moving back to the correct pricing, one needs an indicator for the business cycle that does not contain any price information. Several such proxy-variables for the business cycle have been suggested. Cooper and Priestley (2009) argue that the output gap, or the difference between actual and potential production, is a prime business cycle indicator. They show that the output gap can predict stock and bond returns with both economically and statistically significant predictive powers. For the one-year horizon the R-squared for stock returns is 11 percent, which is high compared to other predictive macroeconomic variables.

One of the challenges faced when trying to find good indicators for the business cycle is the availability and quality of data. One area where quality data is abundant is the energy sector of the United States (U.S). The energy sector in the U.S. is highly regulated and the Energy Information Agency (EIA) in the U.S collects and publishes high quality data from the energy sector. The business cycle literature links electricity usage, and especially the industrial electricity usage, with the business cycle. Electricity is an important input factor in most industrial activity and due to the fact that it is very expensive to store electricity, it can be used to track industrial activity in real time. Furthermore, the industrial sectors with the highest electricity usage are typically capital-intensive industries such as metal, machinery, fabricated products and construction. These industries are also highly cyclical for two reasons. First of all, capital intensive producers are usually more leveraged and therefore, more exposed to fluctuations in the business cycle than less capital-intensive sectors. More importantly, they are often producers of capital goods for other firms, and therefore face a more business cycle sensitive demand curve than other industries (Da, Huang and Yun 2015).

Figure 1: U.S. energy consumption growth and market risk premium



Despite an established link between industrial electricity consumption and the business cycle and the availability of high quality data, researchers do not thoroughly examine this area. Da, Huang and Yun (2015) tests this relationship by running predictability regressions on stock returns using the year over year growth rate in industrial electricity consumption. They show that, for a one-year horizon, a 1 percent increase in the industrial electricity growth rate in year t, indicates 0,92 percent lower excess returns in year t+1. The R-squared is 8,64 percent for the same time horizon. These results indicate that industrial electricity consumption has strong predictive powers on stock returns. They also find that the output growth in the steel, machinery, fabricated goods and the construction industry has a much higher predictive power on stock returns than output growth in industries with moderate to low sensitivity to electricity usage (Da, Huang and Yun 2015).

1.3 Geographical bias

Da, Huang and Yun (2015) looks at predictability of stock returns at a national level in the U.S. However, there is available industrial electricity data on the state level. This allows for further analysis into the state local relationship between the business cycle on stock returns. Capital markets in the U.S. are centralized and have a high degree of international investors. One could therefore be led to believe that any countercyclical effects of the state local business cycle would disappear as investors from all over the U.S. and the world participate in the U.S. stock market. However, it is well documented that investors have a strong bias towards domestic stocks. This is the reason why an indicator for the state of the U.S. economy can predict U.S. stock returns despite international trading on U.S. Stocks. Coval and Moskowitz (1999) find that this geographical bias also applies within the borders of a country. According to their research, U.S. investment managers exhibit a strong preference for firms with headquarters located in the state. The effect is strongest for smaller and highly leveraged firms producing non-traded goods. Pirinsky and Wang (2006) find that the stocks of companies with headquarters in the same geographical area display strong co-movement. They also find that this co-movement disappears when headquarters are relocated. Coval and Moskowitz explains this geographical effect as a result of information asymmetry between local and non-local investors (Coval and Moskowitz 1999). Using this investor bias, it is possible to take the geographical aspect of previous business cycle research one step further and study whether there is a local relationship between the business cycle and stock returns within the states of the U.S.

2. Data

2.1 Return data

Stock returns are obtained from the Center for Research in Security Prices (CRSP) for all listed companies in the U.S. The state level stock returns are computed by sorting all listed companies by their home state. The criterion is the state in which the company's headquarters are located at the beginning of the sample period, which is 1990. The locations of the company headquarters are obtained from Compustat. We then create an index for each state by calculating the value-weighted returns of all the companies headquartered within the different states.

For the regression, we use the log of excess returns on each of the state indexes. Excess returns are the stock returns in excess of the T-bill rate or the realized risk premium. The T-bill is obtained from the website of Kenneth French. We calculate the cumulative log of excess returns for the following periods: one month, six months and one year to see the effect of different time horizons.

2.2 Electricity data

We collect the monthly industrial electricity usage data at the state level in the U.S. from the Energy Information Administration's (EIA) Electric Power Statistics from 1990–2016. The industrial sector is defined by the EIA as an energy-consuming sector that consists of all facilities and equipment used for producing, processing, or assembling goods and encompasses the following types of activity: manufacturing, agriculture, forestry, fishing and hunting, mining, including oil and gas extraction, natural gas distribution and construction. The units are millions of kilowatt-hours used by the industry. The data is arranged by state and date over a period of 26 years. In the predictive regressions, we adjust the industrial electricity for growth in state population. The population data is obtained from Federal Reserve Economic Data at yearly intervals. After adjusting for population, we divide the population adjusted electricity usage by the same month the previous year to get a year over year growth rate. We then take the log of the year over year growth rate of the industrial electricity usage. For the full industrial electricity correlation table and correlation matrix, see Table 13 and Table 8.

The national industrial electricity data is also obtained from EIA for the period January 1978 to November 2016. For the period 1956 to 1978 we use vintage data collected from hard copies by Da, Hung and Yun (2015). The latter data is lagged by two months to more accurately reflect the information available to investors at the time of the investment decision. This is because the data in EIA's database for the years prior to 1978 has been revised before publishing and it is therefore different than the data investors would have had access to at the time of investment.

Two key concerns regarding the electricity data are seasonality and weather effects. By taking the year-over-year growth rate, we can remove any within year seasonal effects. This approach does not account for any effects on electricity usage caused by different weather from year to year. However, heating or air-conditioning account for a relatively small part of the industrial electricity usage. Da, Huang and Yun (2015) test the importance of weather effects and find that it has little effect on the results. For this reason, we do not adjust the electricity data for weather.

3. Methodology

3.1 Predictive regression

To test whether industrial electricity consumption can predict state level stock returns we obtain electricity data for each of the 50 states. The electricity series are controlled for population growth by dividing the electricity usage by the number of residents in the state at the time. The population data is obtained from the Federal Reserve Bank of St. Louis for each state at a yearly frequency. As suggested by Da, Huang and Yun (2015), we use a year over year growth rate in industrial electricity consumption in order to mitigate the effects of seasonality. In other words, we use the electricity growth rate from November of year $t - 1$ to November of year t to predict excess stock returns over different time horizons following November of year t. The model is as follows:

$$log(1 + Rs_t - Rf_t) = \alpha + \beta * log\left(\frac{EL_{t-1}}{EL_{t-13}}\right) + \varepsilon_t$$

where Rs is the holding period return on the security, Rf is the risk-free rate and EL is the one-month industrial electricity consumption.

Since each year-over-year observation contains electricity growth from 12 months and the regressions are conducted at monthly frequencies, the predictive regressions are overlapping.

3.2 Tests

To assess potential issues with our data, we ran a series of tests for stationarity, autocorrelation and structural breaks. We tested the national level time series using Augmented Dickey-Fuller (See Appendix Table 9) and found no evidence of unit root. Similarly, we looked at the correlograms and determined that autocorrelation in the residuals is not going to affect the results (See Appendix Figure 3).

For the regressions on the broad U.S index we ran Multiple Structural Breaks tests and found 3 structural breaks in our data (See Appendix Table 10).

3.3 Potential weaknesses

When computing the state level stock market indexes, we use company headquarters as a geographical indicator. However, this might be problematic as some companies might have a stronger presence in one state while still maintaining their official headquarters in another. This could be an issue if the other types of local presence strongly influence investor preference, such as factories rather than headquarters. In addition, it is likely that investors have a similar geographic bias towards companies who are close, but located across the state border and vice versa for companies located in other parts of a state.

Another challenge with running the State level regressions is state specific characteristics. The fifty states in the U.S are very different in terms of size and industrial composition. This is likely to affect the relationship between the industrial electricity usage and stock returns of local companies. For this reason, it might be difficult to interpret results at the state level. In order to mitigate some of these issues, we run a panel regression with fixed effects.

The sample period might also be a problem. Predictability studies often look at sample periods stretching from the 1940's and 1950's. The monthly state level electricity data is only available from 1990. This makes it hard to study how the relationship between stock returns and industrial electricity usage has changed over time. The fact that there is little room for dividing the data into several sub sample periods makes it harder to study the robustness of the relationship. A longer sample period would also allow for more natural experiments on changes in state level variables. Such natural experiments could help to identify what role different state characteristics have on the industrial electricity, the business cycle and stock returns.

Lastly, we can expect the electricity data to contain a lot of noise. Changes in growth rates might be due to other factors than the business cycle. For example, could new production technology or economic transitioning from the manufacturing sector to the services sector affect the industrial electricity usage?

4. Main Findings

4.1 Results State level

We run predictive regressions on state local stock returns using the state level industrial electricity data for all the states in the US. The results are somewhat mixed. According to theory, there is a negative relationship between the business cycle and future stock returns. For this reason, we expect to find significant negative coefficients. We find this negative relationship in many states. However, we also find many states with insignificant coefficients of both signs and some states with significant positive regression betas. We find the strongest results for the 12-month cumulative returns. For the 12 month returns there are 17 states with significant negative coefficients, 17 states with negative but insignificant coefficients, nine states with insignificant positive coefficients and seven with significant positive coefficients (see appendix Table 12).

The significant positive coefficients are disconcerting and need some commenting. Since it is difficult enough to find significant predictive relationships that are in line with theory, significant predictive relationships that go against theory raise some concerns about problems in data series or mistakes in the models. However, the mixed results are to be expected. The correlations matrix (See table 13 and 14 in the appendix) shows that all the stock indexes have strong positive correlations with both the other states and the broad U.S. market index. However, the correlation matrix for industrial electricity usage show a much wider range of correlations, from strong positive to strong negative. There seem to be important state specific characteristics that lead some states industrial electricity demand to be either uncorrelated or negatively correlated with the U.S. business cycle. Exactly what causes these differences is difficult to determine. Da, Huang and Yun (2015) find that the electricity usage of power intensive industries such as steel, machinery, fabricated gods and construction has higher predictive power than the electricity usage in sectors with low to medium power intensity. While Coval and Moskowitz (1999) find that the geographical bias is strongest towards small and highly leveraged companies producing non-traded goods. To go into the composition of all 50 states with respect to these and other variables is beyond the scope of this thesis. But our data shows that there are substantial variations in the industrial electricity growth over time between the different states that we do not find in the risk premium data. This leads to some states with positive coefficients. The apparent differences between the states point to the presence of noise in the industrial electricity data. For this reason, industrial electricity usage does not perform as a predictor of the risk premiums in all the 50 states.

Although the results are mixed, overall, they seem to be leaning towards a negative relationship between industrial electricity usage and stock returns. However, interpreting the aggregate results of 50 separate regression outputs is a messy operation. We therefore run time series panel regressions for all the states.

Table 1: Output for state level panel regressions with fixed effects

This table shows the regression output from regressing the future monthly market risk premium of all U.S. states as a dependent on the monthly industrial electricity usage year-over-year growth from each state. The model is a fixed effects panel regression. This means that a dummy variable that captures the state specific variation is included in the regression to account for unobservable variables that might affect the dependent. The 1 month, 6 months and 12 months cumulative risk premiums were used as dependent variables

State level	Fixed effects		
	1 month	6 months	12 months
R squared	0.002442	0.014185	0.027392
Adj. R squared	-0.000766	0.010963	0.02415
Beta	-0.008526	-0.057808	-0.064306
p-value	0.0554	0	0.0001

For the simple pooled regression, it becomes clear that overall there is a negative relationship between the business cycle and stock returns at the state level (See Appendix Table 5). However, the explanatory power is low. When running the regressions with fixed state effects, the adjusted R-Squared increases. This shows that the within state predictability power of industrial energy consumption is higher than the predictability of the variable at a national level. By running the regression with fixed effects, we remove the across state variation, as we assume that the differences from state to state are large and unobservable. In a simple model we could, for example, look at the variation in risk premium and electricity consumption around their means for each state and then regress them to get the beta. By subtracting the mean we would remove state specific variations if they are constant. Because of the size and scope of the dataset, this method becomes too messy so we instead use the fixed effects model. This model includes a dummy variable for each state that captures the effects of all state specific variables that can affect risk premium. When looking at the state level predictability with fixed effects we observe that on average the beta is negative and statistically significant.

A significant predictive relationship at the state level data is not sufficient to conclude that there is a local state level relationship between energy consumption and returns. There is a possibility that, due to state specific economic conditions, electricity data from some states works better as proxies for the general U.S. business cycle than the national energy consumption and therefore can be used to predict stock returns, in other states as well and for the whole of the U.S. This could mean that the predictability we observe locally is due to high correlation we see between the local and national market index (See Appendix Table 8). To determine whether there is an actual state local effect, we run the state level electricity data on the returns on the broad market index in the U.S.

Table 2: USA risk premium regressed on state level energy growth panel output with fixed effects

This table shows the regression output from regressing the future monthly market risk premium of the entire U.S. as a dependent variable on the year over year growth rate of the state level monthly industrial electricity usage in all U.S states. The model is a fixed effects panel regression. This means that a dummy variable that captures the state specific variation is included in the regression to account for unobservable variables that might affect the dependent. The 1 month, 6 months and 12 months cumulative risk premiums were used as dependent variables.

State energy/USA Risk premium	Fixed effects		
	1 month	6 months	12 months
R-squared	0.000213	0.000113	0.000688
Adj. R squared	-0.003003	-0.003155	-0.002644
Betas	0.005734	0.011192	0.040259
P-values	0.069	0.1885	0.0013

This result is much weaker in terms of R-squared and significance of coefficients than what we found for the local return series. This shows that there is a local predictive relationship between industrial electricity usage in one state and stock returns on companies in the same state. It also supports the theory of geographical bias in capital markets.

4.2 Results National Level

The results of the panel regressions are in line with theory, but they are much weaker than the results of other predictability studies that tests proxies for the business cycle. Most importantly, it is much weaker than what Da Huang and Yun (2015) find for the industrial electricity in the whole of the U.S. Their model has an explanatory power of 8,64 percent. There are several possible explanations to why there is a large difference between our results. Intuitively, it seems likely that the geographical biasedness of equity investors is not strong enough to drive stock prices and carry the predictive relationship locally the same way it drives stock prices at the national level. However, there are other possible explanations that deserve examination. Da, Huang and Yun (2015) have a sample period from 1956 to 2010, while the state level electricity data is only available from 1990. To check if the sample period is of any importance and to get comparisons for our results, we replicated the results for the U.S. as a whole presented by Da, Huang and Yun using national level industrial electricity data.

Running the national level industrial electricity usage and national level risk premiums for the whole available sample period (1956-2016) we got results very similar to what Da, Huang and Yun found (2015). Keep in mind we have added six more years to the sample period, for this reason differences between the results are to be expected. When we divide the data into two sub sample periods (1956-1989) and (1990-2016) we find a much stronger predictive relationship in the first sample period than what Da, Hung and Yun (2015) find, with an R-squared of 18,3 percent, a beta of –1,2 with a p-value of zero. For the sample period after 1990 the predictive relationship is non-existent.

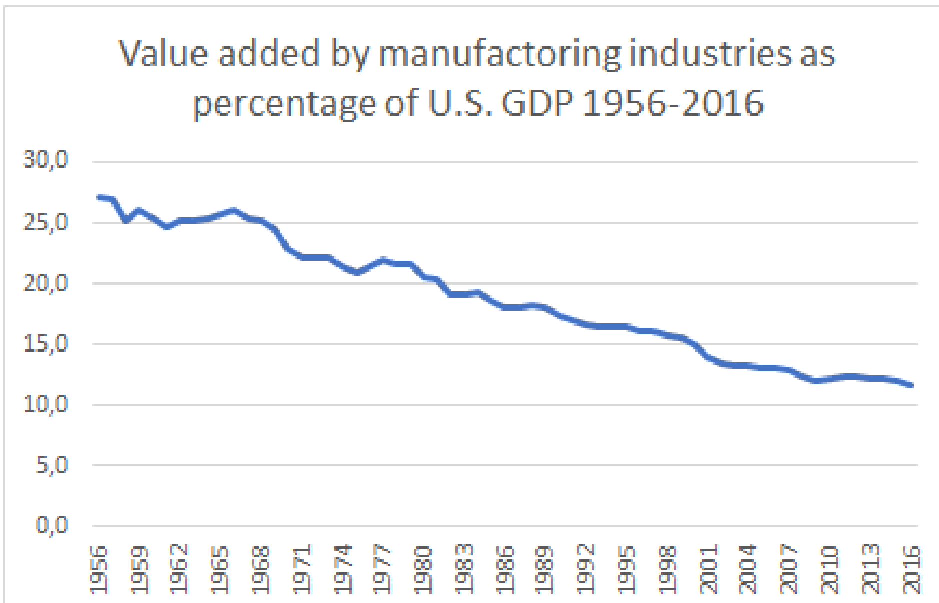
Table 3: Simple linear regression output for three different periods at a national level

This table shows the regression output from regressing future 12 months cumulative U.S. market risk premium as a dependent variable on the year over year growth rate in industrial electricity consumption. The table shows the results from three different sample periods.

Regression output: USA 12 months (year-over-year energy growth)				
Period	Beta	P	R^2	N
1956-2016	-0.89186	0	0.076872	719
1956-1989	-1.2322	0	0.183499	408
1990-2016	0.076412	0.77152	0.000273	311

The differences between the sample periods are substantial, and deserve some examination. There are two possible explanations to why the strong relationship between industrial electricity usage and stock returns disappears before 1990. The first one is that the industrial composition of the U.S. economy changed from power intensive heavy industries like metal, manufacturing and electrochemical processing to less power intensive tertiary sector activities like software development, entertainment and other services. Another explanation is that investors became aware of the predictive powers of industrial electricity and eventually traded it away. Since we still find a predictive relationship at the state level after 1990, the latter is unlikely. The more plausible explanation is that the role of industry has changed. The size of the manufacturing sector in the U.S relative to other sectors has fallen substantially. From the beginning of Da, Huang and Yun's sample period the value added by manufacturing as a percentage of GDP in the U.S steadily declines from 27.2 percent in 1956 to 11.7 percent in 2016. As the manufacturing industry's contribution to the GDP, relative to other sectors, falls, the information in industrial electricity series will have a weaker relationship with the actual business cycle in the U.S.

Figure 2: Industrial composition in the U.S



4.3 State level predictability

The fact that the predictive relationship Da Huang and Yun (2015) find seems to be nonexistent from 1990-2016 is very interesting, considering the significant results we find at the state level for the same sample period. Since the national industrial electricity usage is the sum of all state level electricity usage and the national level market return is the aggregate of state level stock returns, one would expect to find somewhat similar results at both the state level and the national level. However, the fact that we find a significant effect at the state level that does not exist at the national level is surprising. This supports both the theory about geographical bias among investors and the existence of a local countercyclical risk premium. But also raises a few concerns regarding problems with the data and validity of our results.

There are two possible reasons to why there is a significant difference between the national level results and the aggregate state level results. The first one is that local predictive relationships are diversified away at the national level. If the dependent variable of the regression, Yt, is the log of the national level stock index risk premium at time t, then it is also equal to the log of the aggregated value weighted returns of all U.S companies or the log of the aggregated value weighted returns of the fifty state indexes at time t. Similarly, the independent variable Xt is equal to the log of the growth rate of the sum of industrial electricity usage in all of 50 states. If the different states are in different stages of the business cycle then the effect on the national level industrial electricity usage and stock returns of one state in a slump could cancel out the effect of another state in a boom. When we run the panel data, each state level observation is used to compute coefficients at each point in time. This allows the model to pick up the effect of industrial electricity usage on stock returns in each state without the noise of all the 49 other states. The correlations between the state stock indexes are very high. But the correlations between the different industrial electricity series vary a lot between the different states. There will be a lot of noise in the data when the industrial electricity usage of all the states is summed up, because some states tend to increase their industrial electricity usage in periods when other states are decreasing it. Dividing the U.S. up to form a panel of states adds power to the regression.

Another explanation to why the panel data results differ from the national level results might be that the panel results are driven by stronger effects in smaller states. The company returns in each state index are value weighted, but there are very large differences in the market value of the different state indexes. In our panel regression, all the state indexes have the same weight. This means that a coefficient estimated from the few companies in the Alaska index is given the same weight as coefficients estimated with the hundreds of companies in the New York index. To check if small states drive the panel results, we divide the panel in to two, sorted by size of state GDP (BEA 2017). We then run separate panel regressions on the 25 states with the lowest GDP and the 25 states with the highest GDP.

Table 4: High GDP vs. Low GDP panel regression results with fixed effects

This table shows the regression output from regressing future 12 months cumulative state level risk premiums as a dependent variable on the year over year growth rate in industrial electricity consumption. The states were divided into two panels, one containing the 25 with the lowest GDP and one containing the 25 states with the highest GDP.

Fixed effects panel regression		
	High GDP	Low GDP
R-squared	0.022727	0.029884
Adjusted R-Squared	0.019469	0.026649
Beta	-0.029048	-0.114863
P-value	0.0799	0.0001

As we can see, the size of the GDP of the states affects the predictable relationship. This could account for some of the differences we find between the aggregated state level regressions and national level regressions. However, we find significant results for both groups. This means that the predictive relationship at the state level is not caused by anomalies in the smaller states.

5. Conclusion

The aim of this thesis is to examine the state local predictive relationship between the business cycle and equity risk premiums in the states of the U.S. We do this by running predictive regressions on the equity risk premiums of local companies with local industrial electricity usage as an independent variable. Results vary across states, but we find that in most cases industrial electricity usage in one state has significant predictive powers on stock returns of companies with headquarters in that state. Our findings show a negative relationship between the variables, i.e. high electricity usage in one month predicts lower risk premiums over the next 12 months.

This is in line with mainstream asset pricing theory which predicts a countercyclical risk premium. We also show that the state local business cycle affects state local stock specifically. Predictive regressions on the broad market index for the U.S. using state level electricity data produces much weaker results than regressions on state local companies.

The predictive relationship we find at the state level after 1990 is significantly weaker than the relationship Da, Huang and Yun (2015) find at the national level for the sample period 1956-2010. However, when we replicate their model for the sample period 1990-2016 at the national level, we find no significant predictive powers. We therefore conclude that the predictive relationship described by Da, Huang and Yun is no longer present and that state level industrial electricity data outperforms national level data as a predictor of risk premiums after 1990. The fact that the state level data outperforms the national data is also evidence for a local predictive relationship between the business cycle and stock returns.

In addition to supporting the earlier findings regarding the business cycle and countercyclical risk premiums, our finding also bridges some of the gap between business cycle research and research on investor biasedness towards local stocks. We find that the local electricity data outperforms the national data. This indicates that local investors are affected by the local business cycle and that this in turn influences their investment decision in a way that drives risk premiums at the state level. This result is in line with previous findings, such as Coval and Moskowitz (1999) and Pirinsky and Wang (2006). It also shows that the state level business cycle is of importance when it comes to understanding risk premiums in the U.S. capital market.

The results of the state level model vary a lot between the different states. To identify all the factors that lead to these differences is beyond this thesis. The existence of a local relationship between the business cycle and stock returns opens up the possibility of further research into the relationship between business cycle indicators and stock returns. One area that could be of interest is how different factors affect this relationship.

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7. Appendix

Table 5: Output for state level panel regressions without any effects

This table shows the regression output from regressing the monthly market risk premium of 50 U.S. states as a dependent variable on the monthly year over year growth rate in industrial electricity usage in each state. The model used was a simple panel regression without any effects. The 1 month, 6 months and 12 months cumulative risk premiums are dependent variables.

State level	No effects		
	1 month	6 months	12 months
R squared	0.000269	0.001904	0.001345
Adj. R squared	0.000205	0.001839	0.001278
Beta	-0.00896	-0.06029	-0.071307
p-value	0.0405	0	0

Table 6: USA risk premium regressed on state level energy growth panel output with no effects

This table shows the regression output from regressing the monthly risk premium of the entire U.S. as a dependent variable on the year over year state level monthly industrial electricity usage in each state. The model is a simple panel regression without any effects. The 1 month, 6 months and 12 months cumulative risk premiums are dependent variables.

State energy/USA Risk premium		No effects	
	1 month	6 months	12 months
R-squared	0.000206	0.000109	0.000665
Adj. R squared	0.000141	0.000044	0.000599
Betas	0.005543	0.01082	0.038928
P-values	0.0733	0.1953	0.0016

Table 7: Descriptive statistics for national and state level risk premium and industrial energy consumption year-over-year growth

This table presents mean, standard deviation, variance, kurtosis and skewness of the monthly risk premium and year over year growth rate in industrial electricity consumption for the 50 states and the entire USA from 1990 to 2016

	Risk premium					Energy growth				
State	Mean	SD	Sample Var	Kurtosis	Skewness	Mean	SD	Sample Var	Kurtosis	Skewness
USA	0.0069	0.0424	0.0018	1.3791	-0.6768	0.9904	0.0350	0.0012	3.0403	-1.0802
AK	0.0130	0.0805	0.0065	4.2120	0.1065	1.0589	0.1132	0.0128	1.5825	0.7577
AL	0.0139	0.0541	0.0029	1.5843	-0.4732	1.0023	0.0764	0.0058	3.4051	-0.1386
AR	0.0091	0.0559	0.0031	1.5199	0.1267	1.0108	0.0691	0.0048	2.2269	-0.3558
AZ	0.0178	0.0590	0.0035	1.6365	-0.2245	0.9932	0.0740	0.0055	0.8140	0.0107
CA	0.0185	0.0608	0.0037	2.6333	0.2382	0.9888	0.0837	0.0070	2.2013	-0.2947
CO	0.0187	0.0591	0.0035	2.8170	-0.1190	1.0195	0.1277	0.0163	26.8061	3.6942
CT	0.0148	0.0491	0.0024	1.1926	-0.2587	0.9770	0.0910	0.0083	1.4443	-0.1603
DE	0.0121	0.0481	0.0023	2.0810	0.1489	0.9763	0.1184	0.0140	7.5022	0.6146
FL	0.0167	0.0466	0.0022	1.4910	-0.1364	0.9833	0.0512	0.0026	1.7191	0.1043
GA	0.0120	0.0397	0.0016	1.2273	-0.3005	0.9900	0.0485	0.0024	1.4492	-0.5150
HI	0.0110	0.0471	0.0022	1.5869	-0.3926	0.9909	0.0371	0.0014	2.4031	0.2425
IA	0.0145	0.0585	0.0034	4.9587	0.1817	1.0224	0.0668	0.0045	7.7556	1.2881
ID	0.0165	0.0918	0.0084	1.1485	0.1709	0.9935	0.1314	0.0173	2.0422	0.6456
IL	0.0118	0.0394	0.0016	2.2823	-0.6443	1.0016	0.0799	0.0064	6.0672	0.3897
IN	0.0133	0.0502	0.0025	2.3136	-0.1241	1.0013	0.0684	0.0047	2.3208	-0.3180
KS	0.0123	0.0635	0.0040	1.0215	-0.1914	1.0059	0.0525	0.0028	-0.2190	-0.2784
KY	0.0162	0.0547	0.0030	2.6769	0.2375	0.9919	0.1029	0.0106	1.3221	-0.3466
LA	0.0125	0.0477	0.0023	1.9896	-0.1350	1.0083	0.0736	0.0054	1.7596	0.0876
MA	0.0138	0.0504	0.0025	1.6351	-0.1270	0.9981	0.1960	0.0384	10.5014	1.9422
MD	0.0107	0.0384	0.0015	0.6079	-0.1954	0.9809	0.3288	0.1081	14.1604	2.5399
ME	0.0217	0.0872	0.0076	23.7278	2.1020	0.9844	0.1165	0.0136	1.9136	0.0919
MI	0.0121	0.0604	0.0036	13.1567	1.3530	0.9966	0.1026	0.0105	6.0217	1.0044
MN	0.0138	0.0391	0.0015	2.1251	-0.2765	0.9896	0.0913	0.0083	5.0031	-0.8861
MO	0.0140	0.0441	0.0019	1.1926	-0.1449	0.9975	0.1178	0.0139	2.7557	0.0967
MS	0.0151	0.0550	0.0030	0.5215	0.0575	1.0075	0.0707	0.0050	8.9694	1.1025
MT	0.0191	0.0909	0.0083	3.8384	0.8825	1.0013	0.2342	0.0548	3.4051	0.8027
NC	0.0139	0.0539	0.0029	2.6941	-0.2943	0.9801	0.0611	0.0037	0.2284	-0.0960
ND	0.0135	0.0600	0.0036	6.2572	-0.3087	1.0555	0.1249	0.0156	2.1193	1.2932
NE	0.0151	0.0637	0.0041	3.9470	0.7251	1.0270	0.0754	0.0057	3.5786	1.0294
NH	0.0214	0.0847	0.0072	7.6646	1.1265	0.9788	0.1069	0.0114	5.8531	-0.4550
NJ	0.0133	0.0417	0.0017	0.6452	-0.2093	0.9695	0.0889	0.0079	2.3423	0.0277
NM	0.0143	0.0701	0.0049	3.7236	-0.6367	1.0101	0.0635	0.0040	1.3403	-0.3816
NV	0.0216	0.0907	0.0082	20.7829	2.4705	0.9974	0.0600	0.0036	0.5336	-0.2416
NY	0.0118	0.0435	0.0019	1.4561	-0.3727	0.9823	0.1411	0.0199	2.5547	0.9793
OH	0.0123	0.0367	0.0013	1.0572	-0.2159	0.9850	0.0668	0.0045	0.9076	-0.5970
OK	0.0115	0.0543	0.0030	0.5953	-0.0736	1.0081	0.0680	0.0046	2.7442	-0.3357
OR	0.0200	0.0724	0.0052	4.5245	0.4419	0.9792	0.0883	0.0078	4.6279	0.0543

	Risk premium					Energy growth				
State	Mean	SD	Sample Var	Kurtosis	Skewness	Mean	SD	Sample Var	Kurtosis	Skewness
PA	0.0118	0.0485	0.0024	1.6471	-0.3143	0.9995	0.0576	0.0033	2.9791	0.3231
RI	0.0121	0.0531	0.0028	1.0828	-0.2392	0.9825	0.1077	0.0116	2.4077	0.1294
SC	0.0142	0.0538	0.0029	1.6121	-0.0694	0.9912	0.0580	0.0034	1.4119	-0.7214
SD	0.0149	0.0625	0.0039	2.0113	-0.1589	1.0129	0.0719	0.0052	0.9098	-0.3821
TN	0.0131	0.0515	0.0027	3.4652	0.1009	0.9764	0.1176	0.0138	2.7564	-1.1930
TX	0.0123	0.0420	0.0018	1.1813	-0.4372	0.9914	0.0594	0.0035	0.4146	-0.2718
UT	0.0143	0.0751	0.0056	4.8069	0.1254	0.9994	0.0851	0.0072	1.4207	0.4481
VA	0.0151	0.0461	0.0021	0.9990	-0.1712	0.9925	0.0691	0.0048	0.7984	0.1887
VT	0.0264	0.1079	0.0116	7.8143	1.2531	0.9991	0.0637	0.0041	5.9969	0.5733
WA	0.0179	0.0702	0.0049	2.3274	0.3168	0.9797	0.1513	0.0229	3.6072	-1.0596
WI	0.0141	0.0498	0.0025	2.5214	-0.1164	1.0027	0.0459	0.0021	0.8522	-0.6756
WV	0.0160	0.0569	0.0032	1.2862	0.0470	1.0114	0.0898	0.0081	4.1193	-0.4703
WY	0.0106	0.1166	0.0136	17.1378	2.4994	1.0043	0.0876	0.0077	2.1421	0.3969

Table 8: Correlation of state level variables with national level variables

Table shows the correlations between U.S. state level risk premiums and national risk premium as well as the year over year growth rate in industrial electricity consumption at a state level and at a national level. The sample period is January 1990 to December 2016 from 1990 to 2016. All the variables are monthly.

Risk premium		Electricity growth	
State/US	Correlation	State/US	Correlation
AK	0.338	AK	0.029
AL	0.690	AL	0.682
AR	0.443	AR	0.617
AZ	0.785	AZ	0.358
CA	0.872	CA	0.300
CO	0.817	CO	0.203
CT	0.896	CT	0.367
DE	0.776	DE	0.111
FL	0.882	FL	0.412
GA	0.837	GA	0.688
HI	0.601	HI	0.201
IA	0.699	IA	0.421
ID	0.570	ID	0.435
IL	0.904	IL	0.402
IN	0.689	IN	0.717
KS	0.613	KS	0.381
KY	0.681	KY	0.239

Risk premium		Electricity growth	
State/US	Correlation	State/US	Correlation
LA	0.666	LA	0.478
MA	0.919	MA	-0.327
MD	0.762	MD	0.094
ME	0.460	ME	0.148
MI	0.746	MI	0.549
MN	0.862	MN	0.683
MO	0.853	MO	0.471
MS	0.558	MS	0.380
MT	0.483	MT	0.269
NC	0.799	NC	0.500
ND	0.458	ND	0.280
NE	0.673	NE	0.307
NH	0.678	NH	0.165
NJ	0.819	NJ	0.292
NM	0.416	NM	0.329
NV	0.639	NV	0.174
NY	0.941	NY	0.213
OH	0.813	OH	0.777
OK	0.609	OK	0.360
OR	0.737	OR	0.472
PA	0.905	PA	0.393
RI	0.650	RI	0.057
SC	0.740	SC	0.720
SD	0.451	SD	0.400
TN	0.763	TN	0.431
TX	0.863	TX	0.492
UT	0.647	UT	0.321
VA	0.812	VA	0.469
VT	0.302	VT	0.352
WA	0.722	WA	0.403
WI	0.843	WI	0.619
WV	0.531	WV	0.480
WY	0.234	WY	0.008

Table 9: Unit root tests for national level industrial energy growth and risk premium

Augmented Dickey Fuller test for detecting non-stationarity performed on monthly US risk premium and the year over year growth rate in industrial electricity consumption. Sample period from January 1990 to December 2016. Results show that there is no unit root in either of series.

Augmented Dickey Fuller test for USA risk premium			
Null Hypothesis: PREMIUM has a unit root			
Exogenous: Constant			
Lag Length: 0			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-24.5523	0
Test critical values:	1% level	-3.43908	
	5% level	-2.86528	
	10% level	-2.56882	

Augmented Dickey Fuller test for USA energy growth			
Null Hypothesis: GROWTH has a unit root			
Exogenous: Constant			
Lag Length: 12			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.17062	0
Test critical values:	1% level	-3.43923	
	5% level	-2.86535	
	10% level	-2.56886	

Table 10: Structural break test for USA risk premium

Results of a Bai-Perron Multiple Breakpoint test for US 12-month cumulative risk premium executed in Eviews with monthly data from 1955 to 2016.

Break Test	Break	F-statistic	Scaled F-statistic
0 vs. 1 *	1999M11	1,837,355	3,674,709
1 vs. 2 *	1984M02	8,435,856	1,687,171
1 vs. 2	---	---	---
2 vs. 3 *	1968M07	2,019,947	4,039,893
2 vs. 3	---	---	---
3 vs. 4	---	---	---
3 vs. 4	---	---	---

Table 11: Size of GDP in US states

Table that presents a summary of US state level GDP statistics.

Rank	State	GDP	% US GDP
1	CA	2,602,672	14.10%
2	TX	1,616,801	8.76%
3	NY	1,487,998	8.06%
4	FL	926,817	5.02%
5	IL	791,608	4.29%
6	PA	724,936	3.93%
7	OH	625,715	3.39%
8	NJ	581,122	3.15%
9	GA	525,360	2.85%
10	NC	517,904	2.81%
11	MA	507,913	2.75%
12	VA	494,349	2.68%
13	MI	487,239	2.64%
14	WA	469,739	2.55%
15	MD	378,280	2.05%
16	IN	341,909	1.85%
17	MN	335,147	1.82%
18	TN	328,770	1.78%

Rank	State	GDP	% US GDP
19	CO	323,692	1.75%
20	WI	309,536	1.68%
21	AZ	302,952	1.64%
22	MO	300,891	1.63%
23	CT	263,379	1.43%
24	LA	235,109	1.27%
25	OR	226,821	1.23%
26	SC	209,716	1.14%
27	AL	204,861	1.11%
28	KY	197,043	1.07%
29	OK	182,937	0.99%
30	IA	178,766	0.97%
31	UT	156,352	0.85%
32	KS	153,258	0.83%
33	NV	147,475	0.80%
34	AR	120,689	0.65%
35	NE	115,345	0.62%
36	MS	107,680	0.58%
37	NM	93,297	0.51%
38	HI	83,917	0.45%
39	NH	77,855	0.42%
40	WV	73,374	0.40%
41	DE	70,387	0.38%
42	ID	67,275	0.36%
43	ME	59,275	0.32%
44	RI	57,433	0.31%
45	ND	52,089	0.28%
46	AK	50,713	0.27%
47	SD	48,139	0.26%
48	MT	45,994	0.25%
49	WY	37,858	0.21%
50	VT	31,092	0.17%

Table 12: Output for state level simple linear regressions

This table shows the regression output from regressing the monthly market risk premium of 50 U.S. states as a dependent variable on the monthly year over year growth rate in industrial electricity usage in each state.

	1 month			6 months			12 months		
State	R square	Beta	p-value	R square	Beta	p-value	R square	Beta	p-value
AK	0.0009	0.0224	0.6084	0.0016	-0.0760	0.4867	0.0000	-0.0187	0.9034
AL	0.0001	-0.0061	0.8770	0.0241	-0.2691	0.0065	0.0047	-0.1666	0.2375
AR	0.0000	-0.0052	0.9083	0.0019	-0.0753	0.4421	0.0077	-0.2073	0.1294
AZ	0.0052	-0.0566	0.2043	0.0433	-0.4019	0.0002	0.0524	-0.5496	0.0001
CA	0.0249	0.1079	0.0053	0.0236	0.2775	0.0071	0.0086	0.2507	0.1088
CO	0.0044	-0.0350	0.2425	0.0145	-0.1628	0.0350	0.0096	-0.1773	0.0908
CT	0.0042	-0.0333	0.2522	0.0020	0.0552	0.4401	0.0055	-0.1205	0.2019
DE	0.0150	-0.0478	0.0308	0.0049	-0.0624	0.2208	0.0018	-0.0521	0.4660
FL	0.0009	-0.0258	0.6080	0.0007	0.0581	0.6434	0.0001	0.0297	0.8532
GA	0.0043	0.0521	0.2483	0.0045	0.1224	0.2394	0.0301	0.4526	0.0026
HI	0.0006	0.0303	0.6728	0.0025	0.1465	0.3827	0.0042	0.2521	0.2610
IA	0.0000	-0.0008	0.9877	0.0143	-0.2692	0.0364	0.0307	-0.5150	0.0023
ID	0.0002	0.0094	0.8104	0.0059	0.1474	0.1818	0.0190	0.3824	0.0170
IL	0.0001	0.0169	0.8958	0.0001	-0.0137	0.8462	0.0001	0.0169	0.8958
IN	0.0035	-0.0430	0.2954	0.0002	-0.0271	0.8020	0.0141	0.3386	0.0396
KS	0.0025	-0.0604	0.3768	0.0034	-0.1981	0.3074	0.0014	-0.1796	0.5224
KY	0.0030	-0.0272	0.3381	0.0378	-0.2170	0.0006	0.0423	-0.3058	0.0003
LA	0.0005	-0.0147	0.6930	0.0007	-0.0449	0.6430	0.0003	-0.0361	0.7836
MA	0.0032	0.0146	0.3218	0.0127	0.0798	0.0485	0.0131	0.1190	0.0474
MD	0.0018	-0.0049	0.4499	0.0333	-0.0475	0.0013	0.0209	-0.0542	0.0122
ME	0.0207	-0.0984	0.0111	0.0005	0.0343	0.7027	0.0113	0.2180	0.0661
MI	0.0009	-0.0176	0.5938	0.0040	-0.0953	0.2727	0.0035	-0.1171	0.3078
MN	0.0010	-0.0126	0.5735	0.0212	-0.1381	0.0108	0.0149	-0.1514	0.0344
MO	0.0000	-0.0002	0.9928	0.0003	0.0175	0.7513	0.0003	0.0237	0.7689
MS	0.0054	-0.0577	0.1945	0.0496	-0.4279	0.0001	0.0316	-0.4953	0.0020
MT	0.0267	-0.0584	0.0039	0.0875	-0.2399	0.0000	0.0328	-0.1769	0.0016
NC	0.0036	-0.0514	0.2923	0.0141	-0.2489	0.0379	0.0072	-0.2288	0.1432
ND	0.0150	-0.0667	0.0305	0.0592	-0.3323	0.0000	0.1101	-0.6153	0.0000
NE	0.0038	-0.0531	0.2809	0.0111	-0.2251	0.0660	0.0031	0.1422	0.3362
NH	0.0005	0.0150	0.7006	0.0039	0.1015	0.2784	0.0010	-0.0797	0.5777
NJ	0.0092	-0.0425	0.0920	0.0021	-0.0476	0.4261	0.0087	-0.1436	0.1078
NM	0.0002	-0.0153	0.8108	0.0043	-0.1804	0.2550	0.0072	-0.3646	0.1417
NV	0.0061	-0.1074	0.1705	0.0023	-0.1919	0.4037	0.0012	-0.2057	0.5508
NY	0.0018	0.0133	0.4523	0.0015	0.0303	0.4987	0.0035	-0.0680	0.3063
OH	0.0036	-0.0316	0.2888	0.0173	-0.1725	0.0214	0.0180	-0.2432	0.0202
OK	0.0001	0.0072	0.8722	0.0000	0.0069	0.9501	0.0000	-0.0171	0.9112
OR	0.0141	0.0908	0.0365	0.0292	0.3185	0.0027	0.0118	0.2921	0.0603
PA	0.0168	-0.1093	0.0223	0.0129	-0.2437	0.0473	0.0211	-0.4237	0.0118

	1 month			6 months			1 month		
State	R square	Beta	p-value	R square	Beta	p-value	R square	Beta	p-value
RI	0.0280	0.0792	0.0031	0.0301	0.2119	0.0023	0.0098	0.1618	0.0870
SC	0.0002	-0.0129	0.7982	0.0103	-0.2165	0.0764	0.0138	-0.3495	0.0423
SD	0.0027	-0.0447	0.3607	0.0169	-0.2550	0.0228	0.0351	-0.4927	0.0011
TN	0.0012	-0.0133	0.5352	0.0294	-0.1607	0.0026	0.0185	-0.1649	0.0185
TX	0.0001	0.0054	0.8905	0.0078	-0.1574	0.1224	0.0166	-0.3193	0.0257
UT	0.0003	-0.0154	0.7590	0.0114	0.2645	0.0618	0.0121	0.4348	0.0571
VA	0.0031	-0.0362	0.3314	0.0105	-0.1657	0.0739	0.0058	-0.1697	0.1898
VT	0.0039	-0.1021	0.2694	0.0001	0.0349	0.8892	0.0013	0.2239	0.5272
WA	0.0025	0.0188	0.3768	0.0117	0.0861	0.0590	0.0289	0.1976	0.0031
WI	0.0002	0.0144	0.8120	0.0133	-0.3076	0.0439	0.0276	-0.5768	0.0039
WV	0.0090	-0.0572	0.0958	0.0370	-0.2843	0.0007	0.0719	-0.5549	0.0000
WY	0.0014	0.0453	0.5152	0.0036	0.2000	0.2927	0.0053	0.3362	0.2081

Figure 3: Residual autocorrelation

Test for serial autocorrelation and partial autocorrelation of the residuals of a regression using monthly US risk premium as a dependent variable and monthly industrial electricity consumption year-over-year growth as an independent variable. The sample period is from 1955 to 2016.

Sample: 1/01/1956 10/02/2016
Included observations: 731

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.087	0.087	5.6001	0.018
		2	-0.046	-0.054	7.1651	0.028
		3	0.022	0.031	7.5228	0.057
		4	0.035	0.028	8.4466	0.077
		5	0.053	0.051	10.554	0.061
		6	-0.054	-0.062	12.685	0.048
		7	-0.024	-0.010	13.128	0.069
		8	-0.018	-0.025	13.371	0.100
		9	-0.009	-0.007	13.430	0.144
		10	0.012	0.012	13.530	0.196
		11	0.010	0.016	13.605	0.256
		12	0.034	0.033	14.447	0.273
		13	-0.008	-0.013	14.494	0.340
		14	-0.072	-0.071	18.324	0.192
		15	0.022	0.029	18.680	0.229
		16	-0.001	-0.016	18.682	0.286
		17	0.019	0.026	18.952	0.331
		18	-0.036	-0.033	19.910	0.338
		19	-0.023	-0.006	20.296	0.377
		20	-0.032	-0.044	21.049	0.394
		21	-0.050	-0.044	22.935	0.347
		22	-0.034	-0.034	23.790	0.358
		23	-0.026	-0.017	24.320	0.386
		24	-0.016	-0.011	24.503	0.433
		25	-0.028	-0.020	25.087	0.458
		26	-0.013	-0.004	25.225	0.506
		27	0.022	0.016	25.588	0.542
		28	-0.011	-0.023	25.673	0.591
		29	0.003	0.008	25.678	0.643
		30	-0.004	-0.008	25.689	0.691
		31	0.016	0.021	25.880	0.727
		32	-0.045	-0.057	27.407	0.698
		33	-0.027	-0.010	27.962	0.716
		34	0.035	0.027	28.922	0.715
		35	0.031	0.026	29.682	0.722
		36	-0.027	-0.032	30.261	0.738

Figure 4: State vs. US risk premium

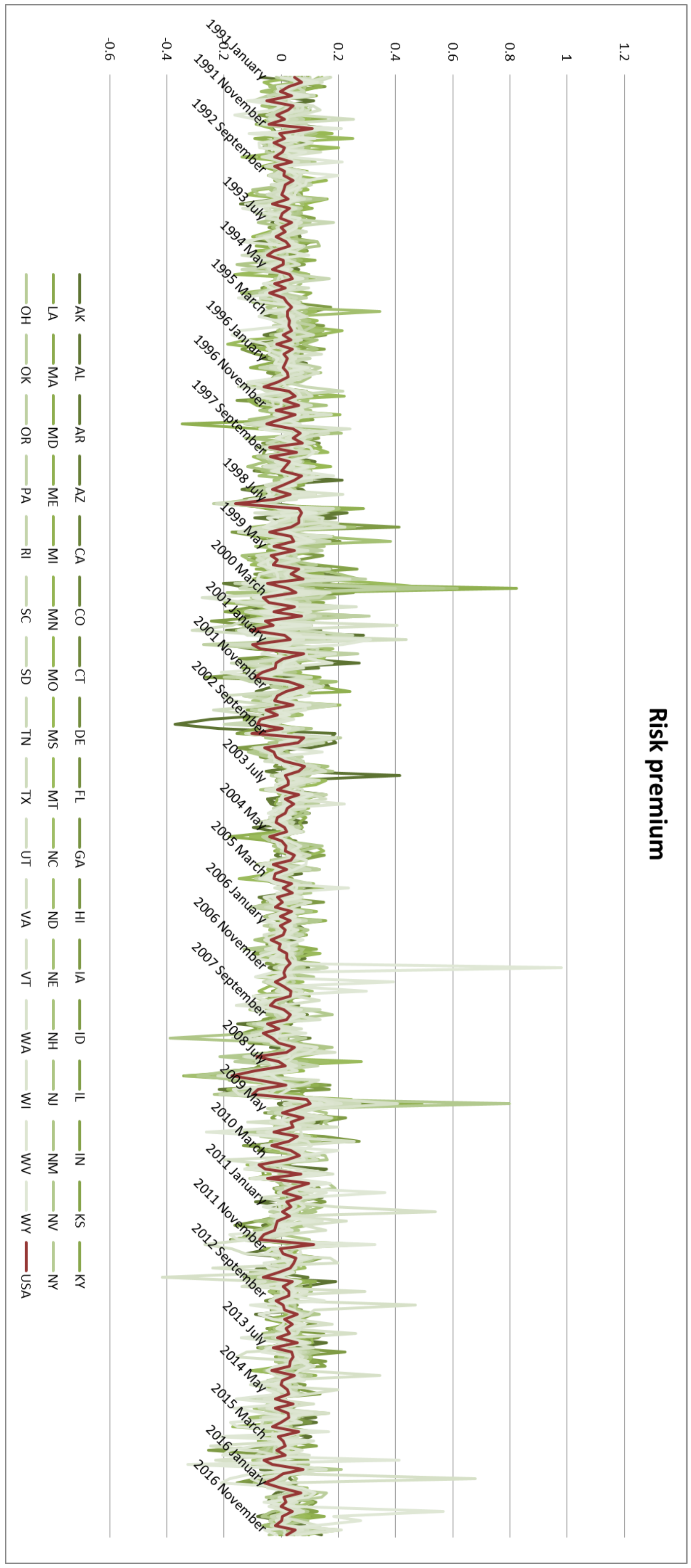

Table 13: Industrial electricity usage growth correlation matrix

State level industrial electricity consumption growth correlation matrix

	AK	AL	AR	AZ	CA	CO	CT	DE	FL	GA	HI	IA	ID	IL	IN	KS	KY	LA	MA	MD	ME	MI	MN	MO	MS	MT	NC	ND	NE	NH	NJ	NM	NV	NY	OH	OK	OR	PA	RI	SC	SD	TN	TX	UT	VA	VT	WA	WI	WV	WY
AK	1.0																																																	
AL	0.0	1.0																																																
AR	0.1	0.6	1.0																																															
AZ	-0.1	0.3	0.2	1.0																																														
CA	0.0	0.1	0.1	0.1	1.0																																													
CO	0.0	0.1	0.2	0.0	0.0	1.0																																												
CT	0.1	0.2	0.3	0.2	0.0	0.1	1.0																																											
DE	0.1	0.0	0.1	-0.1	0.0	0.0	0.1	1.0																																										
FL	0.1	0.3	0.3	0.2	0.3	0.1	0.2	0.1	1.0																																									
GA	0.0	0.6	0.5	0.4	0.1	0.1	0.3	0.0	0.4	1.0																																								
HI	0.1	0.1	0.1	0.3	0.0	0.0	0.1	0.0	0.1	0.4	1.0																																							
IA	0.1	0.3	0.2	0.1	0.1	0.1	0.1	0.0	0.2	0.3	0.1	1.0																																						
ID	0.0	0.3	0.2	0.2	0.3	0.1	0.1	0.1	0.2	0.2	0.2	0.1	1.0																																					
IL	0.0	0.2	0.2	0.1	0.1	0.2	0.2	0.0	0.3	0.3	0.1	0.1	0.3	1.0																																				
IN	0.0	0.6	0.5	0.2	-0.1	0.1	0.2	0.1	0.2	0.6	0.1	0.3	0.2	0.2	1.0																																			
KS	0.0	0.4	0.5	0.2	0.2	0.2	0.1	0.0	0.3	0.3	0.1	0.1	0.1	0.2	0.3	1.0																																		
KY	-0.1	0.2	0.2	0.0	-0.2	0.2	0.0	0.2	0.1	0.1	0.0	0.2	0.1	0.1	0.3	0.0	1.0																																	
LA	-0.1	0.3	0.3	0.4	0.0	0.1	0.1	-0.1	0.1	0.5	0.1	0.2	0.0	0.1	0.5	0.1	0.1	1.0																																
MA	-0.1	-0.3	-0.3	-0.5	-0.1	0.0	-0.2	0.0	-0.3	-0.3	-0.2	-0.2	-0.1	-0.2	-0.2	-0.3	0.0	-0.2	1.0																															
MD	-0.1	0.1	-0.1	-0.2	-0.3	-0.1	0.0	0.2	0.0	0.1	0.0	0.0	0.0	0.0	0.2	-0.2	0.1	-0.1	0.0	1.0																														
ME	0.1	0.1	0.2	0.2	0.2	0.0	0.1	0.0	0.1	0.1	0.1	0.0	0.1	0.1	0.0	0.2	-0.1	0.1	-0.2	-0.2	1.0																													
MI	0.1	0.3	0.3	0.1	0.1	0.4	0.2	0.2	0.2	0.3	0.1	0.2	0.4	0.3	0.3	0.2	0.1	0.1	-0.2	0.1	0.1	1.0																												
MN	0.1	0.5	0.5	0.3	0.1	0.1	0.3	0.0	0.1	0.5	0.0	0.3	0.2	0.2	0.6	0.2	0.2	0.4	-0.2	0.0	0.1	0.4	1.0																											
MO	0.0	0.2	0.3	0.1	0.2	0.1	0.1	0.1	0.3	0.2	0.0	0.1	0.2	0.1	0.4	0.3	0.1	0.1	-0.1	-0.1	0.1	0.2	0.3	1.0																										
MS	-0.1	0.4	0.4	0.2	0.0	0.1	0.0	-0.1	0.0	0.3	0.1	0.3	0.1	0.1	0.2	0.3	0.2	0.3	-0.2	-0.1	0.0	0.2	0.3	0.0	1.0																									
MT	0.1	0.2	0.1	0.0	-0.1	-0.1	0.1	-0.1	-0.1	0.2	0.1	0.2	0.0	0.0	0.3	0.0	0.0	0.1	-0.1	0.2	-0.3	0.1	0.3	0.1	0.1	1.0																								
NC	0.0	0.3	0.4	0.2	0.1	0.1	0.2	0.0	0.3	0.5	0.1	0.2	0.2	0.2	0.3	0.3	0.0	0.3	-0.2	0.0	0.2	0.2	0.2	0.3	0.2	0.0	1.0																							
ND	0.0	0.2	0.1	0.3	0.1	0.0	0.2	0.0	0.1	0.1	0.1	0.1	0.2	0.1	0.2	0.2	0.0	0.3	-0.4	0.0	0.1	0.2	0.2	0.1	0.2	0.0	0.1	1.0																						
NE	0.1	0.2	0.2	0.0	0.0	0.2	0.1	0.2	0.1	0.2	0.1	0.1	0.4	0.3	0.3	0.2	0.1	0.0	0.1	0.1	0.0	0.2	0.2	0.2	0.1	0.0	0.2	0.0	1.0																					
NH	0.1	0.1	0.1	0.1	0.1	-0.3	0.1	0.0	0.1	0.2	0.1	0.0	0.2	0.2	0.0	0.1	-0.3	0.0	-0.1	0.0	0.2	0.1	0.1	0.1	0.0	0.0	0.1	0.1	0.0	1.0																				
NJ	0.0	0.2	0.3	0.1	0.2	0.1	0.2	0.2	0.3	0.2	0.0	0.1	0.2	0.2	0.1	0.3	0.0	-0.1	-0.4	0.0	0.1	0.3	0.1	0.3	0.1	-0.1	0.1	0.1	0.1	0.1	1.0																			
NM	-0.1	0.2	0.2	0.3	0.1	0.1	0.2	0.1	0.2	0.3	0.2	0.1	0.3	0.3	0.2	0.2	0.1	0.3	-0.2	0.0	0.2	0.2	0.2	0.1	0.1	0.0	0.2	0.1	0.2	0.0	0.2	1.0																		
NV	0.0	0.1	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.2	0.1	0.1	0.2	0.0	0.2	0.2	0.1	0.1	0.0	-0.1	0.1	0.0	0.1	0.1	0.1	0.0	0.1	0.0	0.0	0.0	0.1	0.2	1.0																	
NY	0.0	0.1	0.0	0.0	0.1	-0.1	0.4	0.1	0.0	0.1	0.0	0.1	0.0	0.0	0.1	-0.1	-0.1	0.1	-0.1	0.2	-0.1	0.0	0.0	0.0	0.0	0.2	0.1	0.1	-0.2	0.1	0.0	-0.1	0.0	1.0																
OH	0.0	0.5	0.4	0.3	0.3	0.3	0.3	0.0	0.3	0.5	0.1	0.4	0.4	0.4	0.5	0.3	0.3	0.3	-0.3	-0.1	0.1	0.4	0.5	0.3	0.3	0.2	0.4	0.3	0.2	0.0	0.2	0.3	0.1	0.2	1.0															
OK	0.1	0.3	0.4	0.2	0.1	0.1	0.1	0.0	0.1	0.2	0.0	0.2	0.2	0.1	0.3	0.4	0.0	0.1	-0.2	-0.1	0.1	0.3	0.4	0.2	0.3	0.0	0.2	0.2	0.0	0.1	0.2	0.1	0.2	0.0	0.3	1.0														
OR	0.0	0.2	0.1	0.2	0.3	0.0	0.1	0.0	0.1	0.3	0.1	0.2	0.2	0.1	0.4	0.0	-0.1	0.4	-0.1	0.0	0.0	0.2	0.4	0.3	0.0	0.1	0.2	0.0	0.1	0.1	-0.1	0.2	0.0	0.1	0.3	0.1	1.0													
PA	0.1	0.3	0.3	0.3	0.1	0.1	0.2	0.0	0.3	0.3	0.0	0.1	0.1	0.2	0.2	0.3	0.0	0.1	-0.2	0.0	0.0	0.2	0.2	0.2	0.1	0.0	0.2	-0.1	0.1	0.1	0.3	0.2	0.1	0.1	0.3	0.2	0.1	1.0												
RI	0.2	0.0	0.1	-0.1	0.0	0.1	0.1	0.0	0.0	0.1	0.0	0.0	0.0	0.1	0.0	0.0	-0.2	0.0	0.0	0.0	0.0	-0.1	0.0	0.0	-0.1	0.1	0.1	-0.2	0.1	0.1	0.1	0.0	0.1	0.0	0.0	0.1	0.1	0.1	1.0											
SC	0.1	0.5	0.6	0.2	0.2	0.1	0.3	0.2	0.4	0.7	0.2	0.3	0.2	0.2	0.6	0.4	0.2	0.4	-0.3	0.1	0.2	0.3	0.5	0.4	0.2	0.1	0.7	0.1	0.2	0.0	0.2	0.3	0.2	0.2	0.5	0.3	0.4	0.3	0.1	1.0										
SD	0.0	0.3	0.2	0.4	0.1	-0.1	0.1	-0.2	0.0	0.2	0.0	0.2	0.3	0.2	0.4	0.2	0.0	0.4	-0.2	-0.2	0.1	0.1	0.6	0.1	0.3	0.2	0.1	0.4	0.1	0.2	0.0	0.1	0.1	0.0	0.4	0.3	0.3	0.0	0.0	0.2	1.0									
TN	-0.3	0.4	0.4	0.2	-0.1	0.1	0.1	0.0	0.1	0.3	0.1	0.2	0.2	0.2	0.4	0.3	0.3	0.2	-0.3	0.0	0.0	0.2	0.2	0.3	0.5	0.3	0.1	0.1	0.1	0.1	0.2	0.1	0.0	-0.1	0.3	0.1	0.1	0.2	0.0	0.2	0.1	1.0								
TX	0.1	0.2	0.4	0.3	0.2	0.1	0.3	0.1	0.2	0.3	0.1	0.2	0.1	0.0	0.3	0.2	0.0	0.3	-0.3	0.0	0.2	0.2	0.3	0.2	0.2	0.1	0.2	0.1	-0.1	0.1	0.1	0.2	0.1	0.2	0.2	0.2	0.2	0.2	0.0	0.3	0.2	0.0	1.0							
UT	0.0	0.2	0.1	0.2	0.2	0.0	0.1	0.0	0.1	0.2	0.1	0.2	0.3	0.1	0.1	0.1	0.0	0.1	-0.1	-0.1	0.1	0.2	0.2	0.1	0.2	0.1	0.1	0.1	0.1	0.2	0.1	0.2	0.2	0.0	0.2	0.1	0.3	0.1	0.1	0.2	0.3	0.2	0.1	1.0						
VA	0.0	0.3	0.4	0.2	0.1	0.0	0.2	0.0	0.3	0.4	0.1	0.3	0.1	0.2	0.3	0.3	0.1	0.2	-0.2	-0.1	0.1	0.2	0.3	0.2	0.2	0.1	0.5	0.2	0.2	0.0	0.1	0.1	0.1	0.0	0.4	0.2	0.1	0.3	0.1	0.4	0.1	0.2	0.2	0.1	1.0					
VT	0.1	0.3	0.4	0.2	0.0	0.1	0.2	-0.2	0.2	0.3	0.1	0.2	0.1	0.2	0.3	0.2	0.0	0.2	-0.2	-0.1	0.1	0.1	0.2	0.3	0.2	0.1	0.3	0.0	0.0	0.2	0.1	0.0	0.1	0.2	0.3	0.2	0.2	0.2	0.0	0.4	0.1	0.2	0.1	0.1	0.2	1.0				
WA	0.0	0.2	0.1	0.1	0.2	-0.1	0.0	-0.1	0.0	0.2	0.1	0.1	0.3	0.2	0.3	0.1	-0.2	0.1	0.1	0.0	0.1	0.2	0.4	0.2	0.0	0.2	0.1	0.3	0.2	0.2	0.0	0.2	0.0	0.0	0.3	0.1	0.4	0.0	-0.1	0.2	0.4	0.0	0.1	0.2	0.1	0.0	1.0			
WI	0.1	0.4	0.5	0.3	0.1	0.2	0.3	0.1	0.3	0.6	0.2	0.3	0.3	0.4	0.5	0.3	0.1	0.4	-0.3	0.0	0.1	0.3	0.5	0.2	0.3	0.1	0.5	0.2	0.3	0.1	0.2	0.2	0.2	0.1	0.5	0.2	0.1	0.3	0.3	0.5	0.3	0.2	0.3	0.2	0.4	0.3	0.1	1.0		
WV	0.1	0.3	0.3	0.4	0.2	0.1	0.2	0.0	0.3	0.3	0.1	0.2	0.1	0.2	0.3	0.3	0.1	0.3	-0.5	-0.3	0.1	0.3	0.4	0.4	0.2	0.1	0.3	0.2	0.1	0.1	0.3	0.3	0.1	0.0	0.4	0.2	0.3	0.3	0.0	0.4	0.2	0.2	0.3	0.2	0.3	0.3	0.0	0.3	1.0	
WY	0.0	0.1	-0.1	0.2	0.1	0.1	0.0	0.0	0.0	0.0	0.1	0.0	0.1	-0.1	0.0	0.0	-0.1	-0.1	-0.1	0.0	0.1	0.1	0.0	0.0	-0.1	-0.2	-0.1	0.1	0.1	0.1	0.1	-0.1	0.0	0.0	0.0	0.0	0.0	0.1	-0.1	0.0	0.0	-0.1	0.0	-0.1	0.0	-0.1	0.0	0.0	0.1	1.0

Table 14: Risk premium correlation matrix

State level risk premium correlation matrix

	AK	AL	AR	AZ	CA	CO	CT	DE	FL	GA	HI	IA	ID	IL	IN	KS	KY	LA	MA	MD	ME	MI	MN	MO	MS
AK	1.0																								
AL	0.3	1.0																							
AR	0.0	0.3	1.0																						
AZ	0.3	0.6	0.3	1.0																					
CA	0.2	0.5	0.3	0.7	1.0																				
CO	0.3	0.5	0.2	0.8	0.9	1.0																			
CT	0.3	0.7	0.4	0.8	0.8	0.8	1.0																		
DE	0.3	0.7	0.4	0.6	0.6	0.6	0.8	1.0																	
FL	0.4	0.7	0.3	0.8	0.8	0.8	0.9	0.7	1.0																
GA	0.3	0.7	0.5	0.6	0.6	0.6	0.8	0.7	0.8	1.0															
HI	0.3	0.6	0.3	0.6	0.4	0.5	0.6	0.6	0.6	0.6	1.0														
IA	0.3	0.6	0.2	0.7	0.6	0.7	0.7	0.7	0.7	0.6	0.6	1.0													
ID	0.1	0.4	0.2	0.5	0.6	0.6	0.5	0.5	0.5	0.4	0.3	0.4	1.0												
IL	0.4	0.7	0.4	0.7	0.7	0.7	0.9	0.8	0.8	0.8	0.7	0.7	0.5	1.0											
IN	0.2	0.6	0.3	0.5	0.5	0.5	0.7	0.6	0.6	0.6	0.5	0.5	0.4	0.7	1.0										
KS	0.3	0.5	0.3	0.6	0.5	0.5	0.6	0.5	0.6	0.6	0.5	0.4	0.3	0.6	0.4	1.0									
KY	0.3	0.5	0.2	0.6	0.6	0.7	0.7	0.5	0.7	0.5	0.5	0.6	0.4	0.6	0.5	0.5	1.0								
LA	0.3	0.6	0.3	0.6	0.5	0.5	0.7	0.6	0.6	0.6	0.5	0.5	0.3	0.7	0.4	0.5	0.5	1.0							
MA	0.3	0.6	0.4	0.7	0.9	0.8	0.8	0.7	0.8	0.7	0.5	0.6	0.5	0.8	0.6	0.5	0.6	0.6	1.0						
MD	0.2	0.6	0.2	0.7	0.6	0.6	0.7	0.6	0.7	0.7	0.5	0.6	0.4	0.7	0.5	0.4	0.5	0.6	0.7	1.0					
ME	0.2	0.3	0.0	0.4	0.5	0.5	0.4	0.3	0.5	0.3	0.4	0.4	0.3	0.4	0.4	0.3	0.5	0.2	0.4	0.4	1.0				
MI	0.3	0.6	0.3	0.7	0.6	0.6	0.7	0.7	0.7	0.7	0.6	0.7	0.5	0.8	0.6	0.5	0.6	0.5	0.7	0.5	0.3	1.0			
MN	0.3	0.7	0.5	0.7	0.7	0.7	0.9	0.8	0.8	0.8	0.7	0.7	0.5	0.9	0.7	0.6	0.6	0.7	0.8	0.7	0.4	0.8	1.0		
MO	0.3	0.7	0.4	0.8	0.7	0.7	0.9	0.8	0.8	0.7	0.6	0.7	0.5	0.8	0.7	0.5	0.6	0.7	0.8	0.7	0.4	0.7	0.8	1.0	
MS	0.2	0.6	0.2	0.4	0.4	0.4	0.5	0.5	0.5	0.5	0.5	0.5	0.4	0.6	0.5	0.3	0.4	0.4	0.5	0.4	0.4	0.5	0.6	0.6	1.0
MT	0.2	0.4	0.1	0.4	0.6	0.6	0.4	0.4	0.5	0.3	0.4	0.4	0.4	0.4	0.3	0.3	0.4	0.2	0.5	0.3	0.5	0.4	0.4	0.4	0.4
NC	0.4	0.7	0.4	0.6	0.6	0.6	0.8	0.7	0.7	0.7	0.6	0.6	0.4	0.9	0.6	0.5	0.6	0.6	0.7	0.6	0.4	0.7	0.8	0.7	0.6
ND	0.2	0.4	0.2	0.5	0.3	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.3	0.5	0.4	0.4	0.4	0.5	0.4	0.5	0.2	0.4	0.5	0.5	0.4
NE	0.2	0.5	0.3	0.6	0.6	0.6	0.7	0.6	0.7	0.6	0.5	0.6	0.4	0.7	0.4	0.4	0.5	0.5	0.6	0.5	0.3	0.6	0.7	0.7	0.5
NH	0.3	0.4	0.2	0.6	0.8	0.7	0.6	0.5	0.7	0.5	0.5	0.5	0.4	0.6	0.4	0.4	0.6	0.4	0.7	0.5	0.5	0.5	0.5	0.6	0.4
NJ	0.3	0.6	0.4	0.6	0.7	0.6	0.7	0.6	0.6	0.7	0.5	0.5	0.5	0.8	0.7	0.5	0.6	0.6	0.8	0.6	0.4	0.6	0.7	0.7	0.4
NM	0.2	0.3	0.1	0.4	0.4	0.3	0.4	0.3	0.4	0.4	0.4	0.4	0.3	0.4	0.3	0.2	0.4	0.4	0.4	0.4	0.3	0.3	0.4	0.4	0.3
NV	0.2	0.4	0.1	0.6	0.6	0.7	0.6	0.6	0.7	0.5	0.5	0.6	0.4	0.6	0.5	0.4	0.6	0.4	0.6	0.5	0.5	0.7	0.6	0.6	0.4
NY	0.3	0.7	0.5	0.7	0.8	0.7	0.8	0.8	0.8	0.8	0.6	0.6	0.5	0.9	0.7	0.6	0.6	0.7	0.9	0.7	0.4	0.7	0.8	0.8	0.5
OH	0.3	0.7	0.5	0.7	0.6	0.6	0.8	0.7	0.7	0.8	0.7	0.7	0.5	0.8	0.6	0.5	0.6	0.7	0.7	0.6	0.3	0.7	0.8	0.8	0.5
OK	0.2	0.5	0.1	0.6	0.5	0.5	0.6	0.5	0.6	0.5	0.4	0.5	0.4	0.6	0.4	0.4	0.4	0.6	0.5	0.7	0.3	0.4	0.5	0.6	0.3
OR	0.3	0.4	0.3	0.7	0.8	0.7	0.7	0.5	0.7	0.6	0.5	0.5	0.5	0.6	0.4	0.4	0.6	0.4	0.8	0.5	0.5	0.5	0.6	0.6	0.4
PA	0.4	0.7	0.4	0.8	0.7	0.7	0.8	0.8	0.8	0.8	0.6	0.7	0.5	0.9	0.6	0.6	0.6	0.7	0.8	0.7	0.4	0.8	0.8	0.8	0.5
RI	0.2	0.6	0.4	0.6	0.5	0.4	0.7	0.6	0.6	0.7	0.5	0.5	0.3	0.7	0.6	0.5	0.5	0.5	0.5	0.5	0.3	0.6	0.7	0.7	0.4
SC	0.4	0.6	0.3	0.7	0.7	0.7	0.7	0.6	0.8	0.6	0.6	0.6	0.5	0.7	0.5	0.5	0.6	0.5	0.7	0.6	0.4	0.7	0.7	0.7	0.5
SD	0.3	0.4	0.1	0.5	0.3	0.4	0.5	0.4	0.5	0.4	0.4	0.5	0.2	0.5	0.4	0.3	0.4	0.5	0.4	0.4	0.2	0.4	0.5	0.5	0.3
TN	0.3	0.8	0.4	0.7	0.5	0.6	0.8	0.7	0.7	0.7	0.6	0.8	0.4	0.8	0.6	0.5	0.6	0.6	0.7	0.6	0.3	0.8	0.8	0.8	0.6
TX	0.3	0.6	0.3	0.8	0.7	0.7	0.8	0.7	0.8	0.7	0.6	0.7	0.5	0.8	0.6	0.6	0.6	0.7	0.8	0.9	0.4	0.7	0.8	0.8	0.5
UT	0.2	0.4	0.3	0.5	0.6	0.6	0.5	0.4	0.5	0.5	0.3	0.4	0.4	0.5	0.4	0.4	0.4	0.3	0.6	0.4	0.3	0.4	0.5	0.5	0.4
VA	0.3	0.6	0.3	0.7	0.7	0.7	0.8	0.7	0.8	0.7	0.6	0.7	0.5	0.8	0.6	0.5	0.6	0.6	0.8	0.7	0.4	0.6	0.8	0.8	0.4
VT	0.2	0.3	0.0	0.3	0.2	0.3	0.3	0.3	0.3	0.3	0.1	0.3	0.2	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3	0.3	0.3	0.2
WA	0.2	0.4	0.4	0.5	0.7	0.6	0.6	0.5	0.6	0.6	0.3	0.4	0.4	0.6	0.4	0.4	0.4	0.3	0.7	0.5	0.3	0.5	0.5	0.5	0.4
WI	0.3	0.7	0.4	0.8	0.7	0.7	0.8	0.7	0.8	0.8	0.6	0.7	0.5	0.8	0.6	0.6	0.6	0.7	0.7	0.7	0.4	0.8	0.9	0.8	0.5
WV	0.3	0.6	0.2	0.5	0.4	0.4	0.5	0.5	0.6	0.5	0.6	0.5	0.3	0.5	0.4	0.3	0.5	0.4	0.4	0.5	0.3	0.6	0.6	0.6	0.6
WY	0.1	0.2	0.1	0.3	0.2	0.2	0.2	0.2	0.3	0.2	0.1	0.2	0.2	0.2	0.1	0.3	0.2	0.2	0.2	0.2	0.1	0.2	0.2	0.3	0.2

	MT	NC	ND	NE	NH	NJ	NM	NV	NY	OH	OK	OR	PA	RI	SC	SD	TN	TX	UT	VA	VT	WA	WI	WV	WY
MT	1.0																								
NC	0.4	1.0																							
ND	0.2	0.3	1.0																						
NE	0.4	0.6	0.3	1.0																					
NH	0.5	0.5	0.3	0.5	1.0																				
NJ	0.3	0.7	0.4	0.5	0.4	1.0																			
NM	0.2	0.3	0.4	0.3	0.3	0.4	1.0																		
NV	0.5	0.5	0.4	0.5	0.7	0.5	0.3	1.0																	
NY	0.4	0.8	0.4	0.6	0.6	0.8	0.4	0.5	1.0																
OH	0.3	0.7	0.5	0.6	0.5	0.7	0.4	0.5	0.8	1.0															
OK	0.2	0.4	0.5	0.5	0.4	0.4	0.3	0.4	0.6	0.5	1.0														
OR	0.5	0.6	0.3	0.5	0.7	0.5	0.4	0.6	0.6	0.5	0.4	1.0													
PA	0.4	0.8	0.4	0.7	0.6	0.7	0.4	0.6	0.9	0.8	0.6	0.7	1.0												
RI	0.3	0.6	0.4	0.5	0.4	0.6	0.4	0.5	0.6	0.7	0.4	0.4	0.6	1.0											
SC	0.5	0.6	0.4	0.6	0.6	0.6	0.4	0.6	0.7	0.7	0.4	0.6	0.7	0.5	1.0										
SD	0.3	0.4	0.4	0.3	0.3	0.4	0.4	0.4	0.4	0.4	0.4	0.3	0.4	0.4	0.4	1.0									
TN	0.3	0.7	0.4	0.6	0.4	0.6	0.3	0.6	0.7	0.8	0.4	0.5	0.8	0.7	0.7	0.4	1.0								
TX	0.4	0.6	0.5	0.6	0.6	0.7	0.4	0.6	0.9	0.7	0.8	0.6	0.8	0.6	0.7	0.5	0.7	1.0							
UT	0.4	0.5	0.3	0.4	0.4	0.5	0.3	0.4	0.6	0.5	0.3	0.5	0.5	0.4	0.5	0.2	0.4	0.5	1.0						
VA	0.4	0.7	0.4	0.6	0.6	0.7	0.5	0.6	0.7	0.7	0.5	0.6	0.7	0.6	0.7	0.5	0.7	0.7	0.5	1.0					
VT	0.2	0.3	0.2	0.2	0.2	0.2	0.2	0.3	0.3	0.3	0.2	0.2	0.3	0.2	0.3	0.3	0.3	0.3	0.1	0.3	1.0				
WA	0.3	0.5	0.2	0.5	0.5	0.6	0.2	0.4	0.7	0.5	0.3	0.5	0.6	0.4	0.5	0.2	0.5	0.5	0.6	0.5	0.2	1.0			
WI	0.4	0.7	0.5	0.7	0.6	0.7	0.4	0.6	0.8	0.8	0.5	0.6	0.9	0.6	0.8	0.5	0.8	0.8	0.5	0.7	0.3	0.5	1.0		
WV	0.3	0.5	0.3	0.5	0.4	0.3	0.3	0.4	0.5	0.5	0.4	0.4	0.5	0.4	0.5	0.4	0.6	0.5	0.3	0.5	0.2	0.3	0.6	1.0	
WY	0.2	0.2	0.1	0.2	0.2	0.2	0.1	0.2	0.2	0.2	0.2	0.1	0.2	0.2	0.2	0.1	0.2	0.3	0.2	0.2	0.1	0.2	0.3	0.2	1.0