

**THE RELATIONSHIP BETWEEN THE STOCK MARKETS AND THE REAL
ECONOMY: THE INFORMATIVE ROLE OF THE STOCK MARKET SECTORS'**

by

Diogo F. de Barros Rolo

MASTER OF SCIENCE - DISSERTATION IN FINANCE

Advised by

Prof. Dr. Álvaro Almeida

Faculdade de Economia

Universidade do Porto

2009

BIOGRAPHICAL NOTE

Diogo Filipe de Barros Rolo, born in 29th March, 1983 completed his BSc in Economics from Faculdade de Economia da Universidade do Porto in 2006. Later that year, he undertook an MSc program in Finance from the same University.

In 2007 he completed the study program of the degree and started working on his dissertation project. His research was on the relationship between the stock markets and the real economy, with a special focus on the informative role of the stock markets' sectors.

In 2006, simultaneously with the beginning of his MSc, he started working as a Project Manager for AdI – Agência de Inovação, the country's agency dedicated to the promotion of innovation within the Portuguese business sector. His responsibilities included managing projects submitted to attain government support.

One year later, in 2007, he moved to BPI's *Private Banking* unit. His main activities included a daily analysis of the financial markets, supporting customer relationships and also monitoring the performance of several investment portfolios.

In 2008 he moved within BPI from *Private Banking* to the Equities Department where he currently holds a position as International Equity Sales. His main responsibilities now include processing newsflow, interpreting financial analysis and advising a portfolio of institutional clients on investment decisions regarding listed Iberian companies.

I'd like to say thank you to my family for their incentive and never ending support throughout this period,

I'd also like to thank Carla Geraldles for her continuous support and also for the time spent teaching me the ways of Clementine and SPSS, and I would also like to mention Pedro Azevedo, who also shared with me a significant part of the time spent in research for this project,

I'm also recognized to Professor Maria Paula Brito for her early readings on my empirical work and finally also to my adviser, Professor Álvaro Almeida, for his insightful thoughts and guidance.

ABSTRACT

This dissertation analyzes the informative role that the stock market sectors' might have regarding the future evolution of the real economy. Using data for the US economy since 1992, we apply Discriminant Analysis to a group of stock market sectors comparing its discriminatory ability regarding the future evolution of the US GDP, with the one of a global market index, the S&P500. After a revision of the main literature on the relationship between the stock markets, the yield curve and leading indicators we estimate 247 models and conclude that indeed it is possible to have a model with high discriminatory power regarding the future evolution of GDP. With our results, we intend to highlight the informative role that the stock market sectors' have.

INDEX OF CONTENTS

1. INTRODUCTION	1
2. THE RELATIONSHIP BETWEEN THE STOCK MARKETS AND THE REAL ECONOMY	3
2.1. Stock returns and real activity	4
2.2. Other indicators with information on the real economy	8
3. DISCRIMINANT ANALYSIS: A METHODOLOGICAL OVERVIEW	13
3.1. Data	13
3.2. A number of possible methods: why did we use Discriminant Analysis?	15
3.3. What is Discriminant Analysis and how does it work?	20
3.4. Our work	22
3.4.1. Research Problem	22
3.4.2. Research Design Issues	23
3.4.3. Assumptions	25
3.4.4. Estimation of the Discriminant Functions	28
3.4.5. Interpretation of the Discriminant Functions	28
3.4.6. Validation of the Discrimination Results	30

4. EMPIRICAL RESULTS	31
4.1. Models estimated	
4.1.1. Models estimated in Section A: Finding the most interesting sectors	31
4.1.1.1. Estimations for the 18 sectors	31
4.1.1.2. Estimations for the S&P500	35
4.1.2. Models estimated in Section B: Finding the most interesting time frames	36
4.1.2.1. Estimation of 180 models	37
4.1.3. Model estimated in Section C: Achieving high quality information	40
4.1.3.1. Final Model Estimated	41
4.2. An out-of-sample test: data from 2008 and early 2009	46
4.3. Implications for portfolio managers	49
5. CONCLUSION	50
BIBLIOGRAPHY	
ANNEXES	

INDEX OF TABLES

Chapter 3: DISCRIMINANT ANALYSIS: A METHODOLOGICAL OVERVIEW	13
Table 3.1: DJ Stoxx Indices	13
Table 3.2: Linear Regressions' results with the original variable	15
Table 3.3. Linear Regressions' results with lag variables	16
Table 3.4. Intervals set for GDP evolution	19
Table 3.5. Lag variables created	24
 Chapter 4: EMPIRICAL RESULTS	
Table 4.1: Wilks' Lambda of the models estimated in Section A	33
Table 4.2: Wilks' Lambda of the models estimated for the S&P500	36
Table 4.3: Wilks' Lambda Test for models with at least one significant Discriminant Function out of the 180 models estimated	38
Table 4.4: Inclusion of additional variables in our final model	42
Table 4.5: Wilks' Lambda test performed on both Discriminant Functions of the best Model	42
Table 4.6: Coincidence Matrix for GDP of the best model	43
Table 4.7: Eigenvalues of the two discriminant functions of the best model	44

Table 4.8: Standardized Canonical Discriminant Function Coefficients of the best

Model 45

Table 4.9: Model Accuracy 48

INDEX OF IMAGES

Chapter 3: DISCRIMINANT ANALYSIS: A METHODOLOGICAL OVERVIEW

Image 3.1. Between and within-group variances 22

Chapter 4: EMPIRICAL RESULTS

Image 4.1. Canonical Discriminant Functions of the best model 44

ANNEX A

Table A.1: Core PCE evolution in the period under analysis	64
--	-----------

ANNEX B: ASSUMPTIONS OF DISCRIMINANT ANALYSIS

Table B.1: Normality of the variables: assumption check	65
Table B.2: Correlations between all “original” variables (lags excluded)	69
Table B.3: Correlations between all variables (lags included) (for the sector Auto)	70
Table B.4: Correlations between all variables (lags included) (for the sector Banks)	70
Table B.5: Correlations between all variables (lags included) (for the sector Basic Resources)	71
Table B.6: Correlations between all variables (lags included) (for the sector Chemicals)	71
Table B.7: Correlations between all variables (lags included) (for the sector Construction & Materials)	72
Table B.8: Correlations between all variables (lags included) (for the sector Financial Services)	72
Table B.9: Correlations between all variables (lags included) (for the sector Food)	73
Table B.10: Correlations between all variables (lags included) (for the sector Health Care)	73
Table B.11: Correlations between all variables (lags included) (for the sector Industrials)	74
Table B.12: Correlations between all variables (lags included) (for the sector Insurance)	74
Table B.13: Correlations between all variables (lags included) (for the sector Media)	75
Table B.14: Correlations between all variables (lags included) (for the sector Oil and	

Gas)	75
------	----

Table B.15: Correlations between all variables (lags included) (for the sector Producer and Household Goods)	76
--	----

Table B.16: Correlations between all variables (lags included) (for the sector Retail)	76
--	----

Table B.17: Correlations between all variables (lags included) (for the sector Technologies)	77
--	----

Table B.18: Correlations between all variables (lags included) (for the sector Telecoms)	77
--	----

Table B.19: Correlations between all variables (lags included) (for the sector Travel)	78
--	----

Table B.20: Correlations between all variables (lags included) (for the sector Utilities)	78
---	----

Table B.21: Correlations between all variables included in the final model	79
--	----

ANNEX C: RESULTS OF THE ESTIMATION OF THE 18 MODELS DESCRIBED IN SECTION “4.1.1. MODELS ESTIMATED IN SECTION A: FINDING THE MOST INTERESTING SECTORS”

Table C.1: Standardized Canonical Discriminant Function Coefficients	80
--	----

Table C.2: Structure Matrices	85
-------------------------------	----

Table C.3: Box’s M Test results for the 18 models estimated	89
---	----

Table C.4: Test of Equality of Group Means	90
--	----

ANNEX D: RESULTS OF THE ESTIMATION OF THE MODELS DESCRIBED IN SECTION “4.1.2. MODELS ESTIMATED IN SECTION B: FINDING THE MOST INTERESTING TIME FRAMES”

Table D.1: Test of Equality of Group Means	95
--	----

Table D.2: Wilk’s Lambda tests	111
--------------------------------	-----

ANNEX E: RESULTS OF THE ESTIMATION OF THE MODELS DESCRIBED IN SECTION “4.1.3. MODELS ESTIMATED IN SECTION C: ACHIEVING HIGH QUALITY INFORMATION”

Table E.1: Structure Matrix of the best model

123

1. INTRODUCTION

The goal of this dissertation is to gain a better insight into the relationship between the stock markets and the real economy. We will however pursue an approach that does not follow the regular standards of research in the area, since we will look not into the stock market as a whole, but rather at its different sectors. We will try to evaluate if there is relevant information in the sectors being ignored by most studies that use generic stock market indices.

In order to identify if this is true and, if it is, which sectors have more information, we applied a multivariate statistical technique called Discriminant Analysis (DA). We use DA to verify if there was a combination of different stock market sectors that allowed us to discriminate more properly the evolution of the real economy, while measured through GDP, than the market as a whole.

We will begin Chapter 2 by doing a theoretical overview on the relationship between the real economy and the stock market. We will go through the major empirical findings in this area and we will analyze the different theoretical frameworks that are used to understand the future evolution of the economy. We will look in detail not only at the stock market, but also at several other variables.

Chapter 3 consists in a methodological explanation of our work. We present our data and initial results alongside with the subsequent steps we took and corresponding explanations. The next step introduces Discriminatory Analysis and also the way it was applied in our work.

Chapter 4 will present our results. We start by identifying the models we estimated and the results obtained in three different stages of work, proceeding with the estimation of the best model we found to discriminate the evolution of GDP. We then do an application of the final model we obtained, on data that did not belong to our initial database. We end this Chapter analyzing the implications for portfolio managers of having sectors with a high discriminatory power over GDP, which leads us to classify them as cyclical sectors.

On Chapter 5 we present the major highlights of our work and how we reached them. We end this last chapter by proposing some directions in which other studies could go in order to find out more about the relationship between the stock markets and the real economy.

The Bibliography and our Annexes follow suit, ending our dissertation.

2. THE RELATIONSHIP BETWEEN THE STOCK MARKETS AND THE REAL ECONOMY

Both the economic and financial literature have dedicated considerable attention to several variables that contain information regarding the future evolution of the economy. This is however an extensive group which contemplates a number of variables that deem fit to be tested.

Our work will go through the importance of the stock markets helping us understand patterns of economic growth. However, to put our work in context, we will also mention variables other than the stock market that show informative power.

So in the next section we will do an overview on the work that has already been done regarding the relationship between economic variables and the real economy. This will include two subsections, a first one dedicated to literature that worked, as we do, with the stock market as the explanatory source of the real economy evolution, and a second one that will elaborate on several other variables and indicators that have also been studied.

2.1. Stock returns and real activity

The relationship between the stock market and the real economy has been a theme of discussion for a long time. Researchers have long been trying to understand if it is possible to look at the stock markets and better understand what will happen in advance in the real economy.

According to a fundamental model in Finance, the Discount Cash Flow model (DCF), stock prices should reflect investors expectations on the future real economic activity. The reason for this is that what the DCF model does is discount to the present date the cash flows that will be generated by the company in the future. This way, the value of a company equals the expected present value of the firm's future payouts (Damodaran, 1994)¹. The link to the real economy relies on the fact that future payouts should ultimately reflect the evolution of real economic activity. So in periods of strong economic growth, companies should generate more earnings and consequently pay back to his shareholders higher dividends, therefore increasing their present value. Times of milder economic activity should cause a retraction in the earnings generated, therefore lowering the current value of companies in the stock markets².

Consequently, as Binswager (2000) states, stock prices should lead measures of real activity like GDP given that stock prices are built on expectations of this activity.

Several authors have already studied this relationship and tried to find and document the way in which the stocks markets may lead the real economy³.

Different explanations have been suggested to the puzzling negative relationship observed between real stock returns and inflation that has been extensively analyzed in

¹ The DCF model is central to nearly all financial theory and therefore there are a number of references regarding its explanation. We used the more recent Damodaran approach in his book "Damodaran on Valuation: Security Analysis for Investment and Corporate Finance", 1994.

² However we highlight that it remains a prerogative of management to adopt an anti-cyclical posture and increase payout ratios during milder periods of economic activity with the intention of making the investment case on their companies more interesting.

³ Another stream of research that is generally find close together with the one we are studying in more detail, regards understanding the sources of return variations in the stock markets. In these studies, generally the dispute lies on whether the stock market prices follow a random walk or if they can be explained by variations in expected cash flows or in discount rates.

the literature. For the United States, Bodie (1976), Nelson (1976) and Fama and Schwert (1977) verified this relationship early on.

The first explanation we present is that of Fama (1981) who made an important contribution with his proxy theory, stating that there is a negative correlation between inflation and real economic activity, while on the other hand, there is a positive relation between real activity and stock returns. Therefore the conjunction of these two offers a justification to the above mentioned puzzling relationship between real stock returns and inflation.

Other authors later supported Fama, like Geske and Roll (1983) and Kaul (1987, 1990) albeit with a different approach, suggesting that a strong economic activity causes inflation and induces policy makers to implement a counter cyclical macroeconomic policy whose negative effect is greater than the initial positive effect of growth in the real economy.

Fama (1990) returned later to this field of research studying which factors could explain stocks movements. He demonstrated that monthly, quarterly and annually returns were highly correlated with future production growth rates. Moreover, he also demonstrated that this correlation had a tendency to increase with the length of the holding period. His argument was that the relationship between current stock returns and future production growth reflected all information about future cash flows.

Latter studies tried to validate Fama's influential work, namely Schwert (1990), that replicated Fama's work for the period of 1953-87 and used an additional 65 years of data testing for the period of 1889 to 1988. His findings were that Fama's results were robust for a much longer period than the one he used originally, with future production growth rates explaining a large fraction of the variation in stock returns. Also Choi et al (1999) extended the work of Fama (1990) and Schwert (1990), examining the relationship between industrial production growth and lagged real rates of return for the G7 countries while using different time series methodologies than the ones used originally by those two authors⁴. Their results indicate that industrial production and

⁴ The authors use two kinds of techniques to do their investigation. First they use in sample time series techniques to document the industrial production-stock return relation for both the US and the remaining G7 countries and then they use a out of the sample time series procedure, proposed by Ashley et al.

real stock prices are characterized by a stationary linear relation in all G-7 countries. In addition, real stock returns show significant evidence of short-run causality for the growth rate of industrial production in the US, UK, Japan, Canada, and Germany. As for the out of the sample results, tests show that in several sub-periods the US, UK, Japanese, and Canadian stock markets enhance predictions of future industrial production⁵.

Barro (1990) studied the relationship between lagged stock market returns and investment growth rates with his findings indicating that the lagged changes in stock market returns have a great deal of explanatory power over the growth rates of investment.

Estrella and Mishkin (1996) studied the subject with a different perspective, examining the performance of various financial variables as predictors of subsequent US recessions. In a departure from what most of the work at that time had studied, they tried not to predict a given value for future GDP but instead verify if they could predict a recession. Using interest rates, spreads, stock prices and macro and leading indicators they used a Probit model and tried to verify which variables and which time frames contained more relevant information regarding future recessions. Their major conclusion is that the best model to predict recessions is one that combines information from the stock market sector and from the debt market, with the difference being in the time frame in which both should be used. So the stock market contains more relevant information regarding the possibility of having a recession when we consider lags of 2 to 3 quarters, while the yield curve (although presenting interesting results in nearly all time frames) has the more relevant information precisely from 2 to 3 quarters of lag onwards. The authors' main conclusion is that the stock market and the yield curve can be used either separately or, given their fit to one another, they can be combined into one single model that would produce very reliable indications regarding future recessions.

(1980), in order to avoid the typical problems of OLS and Granger (1980) correlation in testing whether lagged stock returns predict industrial production growth.

⁵ We should however also mention that the authors put forward the possibility that industrial production growth may be easier to forecast on the basis of its own past, making stock market information redundant.

This information has obviously many useful applications. First of all, such a simple and easy to use model can give quick and helpful indications regarding the evolution of the real economy to economic policy makers. It can also help to verify if the conclusions of complex econometric models are in line with what economic theory postulates. Finally, these models can also easily provide a probability associated with the occurrence of a future recession.

We should at this stage mention that some authors have also studied this relationship in *the inverse* direction, capturing the influences of the stock market in the economy. These authors generally mention three mechanisms to explain this relationship.

The (i) first one is the q-channel and is based on an approach initially developed by Tobin (1961). Tobin's argument was that the ratio of the stock price to the replacement cost of capital (generally known as *Tobin's q*) should be considered as a good indicator of a company's incentive to invest. So if Tobin's q is greater than one, then capital is more valuable if employed inside the company and the increase in the company's market value is greater than what it costs to produce it. As rising stock prices directly result in an increase in Tobin's q, it would be profitable for the company to expand its capital stock, therefore leading to an increase in investment spending and consequently in aggregate output.

The (ii) second channel through which stock market prices can influence investment decisions is the balance sheet channel. Because of asymmetric information in credit markets, the ability of companies to borrow depends on their collateral. So as stock prices increase, the value that companies holding stocks can present as collateral increases, therefore enhancing their access to external funds for investment. However, in the case in which stock prices fall, the effect is twofold and important "second round effects" may happen. First of all, declines in stock prices decrease investment demand and therefore may lead to deterioration of aggregate demand. With profits and cash flows falling, a company's ability to finance its investment process may worsen as well, starting what Bernanke, Gertler and Gilchrist (1996) called the financial accelerator.

Finally the (iii) third channel is the consumption wealth channel. For individuals holding stocks, a general rise in stock prices implies an increase in financial wealth, therefore contributing to an increase in consumption and in the aggregated output.

2.2. Other indicators with information on the real economy

Another stream of research that is interesting to analyze is the one related with the ability of the yield curve to predict recessions⁶.

This relationship indicates that several spreads between long and short term rates tend to be lower at the beginning of recessions and then higher as expansions get under way. However, it wasn't until the late 80's that there was a boom in literature related with the predictive powers of the yield curve. Several studies began yielding statistical significance for the ability of the yield curve to predict with accuracy real GDP and GNP growth or recessions while comparing favorably with other leading indicators. A summary of the achievements of the yield curve regarding predictive ability for real growth in consumption, investment and aggregate GNP, as well as dated NBER recessions, can be find in Estrella and Hardouvelis (1991).

There are several theories that have been presented to understand this relationship between the yield curve and the economy. The first of them, the *expectations hypothesis*, sees long-term rates as a weighted average of expected future short-term rates and therefore in anticipation of a recession it is expectable to see a decline in future interest rates due to a more loose monetary policy intended to stimulate the economy, according to Haubrich and Dombrosky (1996). Also Bernanke (1990) contributes with a theory where the spread between the commercial paper rate and the

⁶ Unlike most work that uses the stocks markets or other indicator of financial activity to predict the evolution of real economic variables, the literature on the yield curve concentrated itself mostly in predicting recessions. This has to do with the choice of most authors to use Probit and Logit models in their statistical work, therefore ending with a probability of a recession, rather than a calculation of a specific GDP value. The good results that they have obtained are probably a justification of this choice being kept in most papers (for the US, since 1960, the yield curve inversions always preceded a recession, with just one exception, in 1967, that according to the NBER was not a recession, but that was characterized by a marked decline in industrial production, as Estrella (2005) states).

T-bill rate (which is viewed as a measure of perceived default risk) has its informative power in the fact that if investors have expectations that the economy will enter into a recession, this will increase the riskiness of privately issued debt, therefore rising the mentioned spread. Also Harvey (1988) as a theory based on the maximization of inter temporal consumer choices that has its foundations in the fact that consumers prefer a stable level of income and therefore if consumers anticipate a recession, they prefer to save and buy long term bonds in order to get a payoff during the recessionary period. By doing that they increase the demand for long term bonds, this way leading to a decrease of the corresponding yield.

But other than the yield curve, several other indicators have been studied regarding their predictive power over the real economy.

> Stock Watson Index

One of the most mentioned leading indicators in the literature is the Stock-Watson index, that contained on a wide variety of economic variables in an attempt to construct a index of leading indicators. The Stock and Watson (1989) Index has basically two distinguishing features.

First of all the model uses broad measures of economic activity to create a coincident index which was a weighted average of several indicators that gauged the entire performance of the economy from the industry, to income availability or the labor markets. Secondly, they also created a recession probability measure wich was produced by comparing the forecasts from the model with an elaborate up-and-down pattern that could be consistent with what the NBER might actually define as a recession. The index measured the probability that the economy would be in recession in six months (unfortunately, only in exactly six months, as we will see below).

The model experienced a growing appeal in the 1990s due to two interesting features. First of all, it put considerable weight on financial variables, reflecting the view that financial variables such as interest rates provide useful forward-looking macroeconomic

information, namely regarding the prediction of future economic activity⁷. Additionally, the model specification was developed on the basis of a state-of-the-art and exhaustive specification search. Finally, the model was updated on a monthly basis and therefore available to analysts periodically.

The key drawback of the index was its narrow focus, since it represented the probability that the economy would be in recession exactly in six months. Additionally the complexity we mentioned above has a hurdle for analysts who wanted to check its robustness.

So according to Filardo (1999) this indicator was quite successful while it was “in production” until June 2004, having been used either as a integrant part of the studies, either as a benchmark in several research papers and being at least a referral in all the relevant papers written on the subject (quite a few already mentioned in our work like Estrella and Mishkin (1996), Moneta (2005) among others).

However, in 2004, stating that their goal had been achieved⁸, the authors stopped producing their index and left the referrals for two substitutes: the CFNAI and the EuroCOIN.

> CFNAI (Chicago Fed National Activity Index)

This indicator is a monthly index constructed using 85 monthly indicators based on an extension of the methodology used to construct the original Stock-Watson. According to its website, “*The 85 economic indicators that are included in the CFNAI are drawn from four broad categories of data: production and income; employment, unemployment, and hours; personal consumption and housing; and sales, orders, and inventories. Each of these data series measures some aspect of overall macroeconomic*

⁷ And not turning points in the economic cycle.

⁸ In the website of the index, the authors explain their decision: “*One important purpose of the monthly XRI reports was to provide interested entities with forecasts about the current and future state of the business cycle. A second important purpose was to establish a real-time public forecasting record that could serve as the basis for further research and revision. We believe that we have achieved these two objectives. Over the past decade, there has been considerable progress on “next generation” methods for assessing the current state of the business cycle and for making near-term forecasts. Some of this research has produced new real-time indices.*”

activity. The derived index provides a single, summary measure of a factor common to these national economic data.”

> EuroCOIN

The other index that is Stock-Watson inspired is the EuroCOIN which is the current European equivalent of the CFNAI. The EuroCOIN, in the words of the CEPR (Center for Economic Policy Research), its creator, *“is the leading coincident indicator of the euro area business cycle available in real time. The indicator provides an estimate of the monthly growth of euro area GDP – after the removal of measurement errors, seasonal and other short-run fluctuations. The indicator is available very quickly, well before the GDP numbers are released.”*

However, the practical relevance of the EuroCOIN is yet to be verified, given that both the financial markets have not recognized its relevance and do not follow up closely on the indicator’s release and also the literature using this indicator is yet scarce (which however as to do with the short historical background of the indicator).

> Conference Board Leading Indicator

Other indicator mentioned by Filardo (1999) is The Conference Board⁹ Leading Indicator Index, which materializes the purpose of the Board's Business Cycle Indicators (BCI) to provide ways to analyze the expansions and contractions of the economic cycle. The Composite Index of Leading Indicators is one of three components of the BCI - the other two are the Composite Index of Coincident Indicators and the Composite Index of Lagging Indicators. Since the leading-indicators component attempts to judge the future state of the economy, this is also a widely followed index in the financial markets.

⁹ The Conference Board website identifies the entity: *“The Conference Board operates as a global independent membership organization working in the public interest. It publishes information and analysis, makes economics-based forecasts and assesses trends, and facilitates learning by creating dynamic communities of interest that bring together senior executives from around the world.”*

So these are the main indices used in this field of research. While the EuroCOIN has a small historic background making it less appealing for now to researchers, both the CFNAI and the Conference Board Leading Indicator are frequently cited in the literature in this area (its historical data goes back to the 1970s and 1950s respectively).

3. EMPIRICAL RESULTS: A METHODOLOGICAL OVERVIEW

3.1. Data

We will begin this section by presenting our data. We then move on to justify why Discriminant Analysis (DA) was the technique that we chose. Additionally, we will do an overview on DA explaining the technique and how it works. For now, we will present our dataset.

The indices that we used were the Dow Jones Stoxx indices as this was the source with a most comprehensive historic database for sectorial data, which we will then use to discriminate the future evolution of economic activity. We recall our initial purpose to find out if the stock market sectors' have a higher informative power over the evolution of the real economy than a global stock market index.

The information we used was available on the Internet¹⁰ and these were the sectors we worked with:

Table 3.1: DJ Stoxx Indices

Indices	Ticker
DJ STOXX Americas 600 Automobiles & Parts [3300]	USAuto
DJ STOXX Americas 600 Banks [8300]	USBanks
DJ STOXX Americas 600 Basic Resources [1700]	USBasRs
DJ STOXX Americas 600 Chemicals [1300]	USChem
DJ STOXX Americas 600 Construction & Materials [2300]	USConsMt
DJ STOXX Americas 600 Financial Services [8700]	USFinSer
DJ STOXX Americas 600 Food & Beverage [3500]	USFood
DJ STOXX Americas 600 Health Care [4500]	USHealth
DJ STOXX Americas 600 Industrial Goods & Services [2700]	USInd

¹⁰ Stoxx Ltd., the entity responsible for these indices, has these data available for download on its website at www.stoxx.com

DJ STOXX Americas 600 Insurance [8500]	USIns
DJ STOXX Americas 600 Media [5500]	USMed
DJ STOXX Americas 600 Oil & Gas [0500]	USOil
DJ STOXX Americas 600 Personal & Household Goods [3700]	USPHG
DJ STOXX Americas 600 Retail [5300]	USRet
DJ STOXX Americas 600 Technology [9500]	USTech
DJ STOXX Americas 600 Telecommunications [6500]	USTelco
DJ STOXX Americas 600 Travel & Leisure [5700]	USTravl
DJ STOXX Americas 600 Utilities [7500]	USUtil

The sectors here available and used by the Dow Jones Stoxx indices are based on the market standard Industry Classification Benchmark (ICB) division, with the companies categorized according to their primary source of revenue.

As for the information on the US GDP it was obtained through the OECD website¹¹. The quarterly information provided by the OECD is already seasonally adjusted. In this case, the only remaining choice we had to do was to choose if either we wanted a nominal or a real reading of GDP. So taking into consideration that our indices were nominal (in the sense that there were no adjustments made on the values to discount the effect of inflation over the years) we choose to work with nominal GDP for the sake of the coherence of our dataset. Although this has been our choice, we recognize an alternative solution of removing the effect of inflation from our sectorial data instead, but we also highlight that this would raise the issue of what deflator would be appropriate for each sectorial index.

Once we had the initial data to work with, given that the information contained only the daily values, we calculated quarterly growth rates for all indices¹². This had to be done due to the fact that there is only quarterly data available for the GDP and we had to have our stock market-related data compatible with the GDP data.

¹¹ The information used is available in the OECD website at <http://stats.oecd.org/>, the portal to retrieve statistical information. The specific series used (B1_GE) was obtained by choosing the “Gross Domestic Product” series under the tab “Quarterly National Accounts”.

¹² Quarterly returns calculated as the simple growth rate between the first and last value of the index

3.2. A number of possible methods: why did we use Discriminant Analysis?

When trying to study the relationship between the stock markets and the real economy we started off using linear regression models to try to find a relationship between the returns of the stock market and GDP¹³. However, we found that the results of simple linear models were poor.

In our work we estimated several models of linear regression. The first models had as a dependent variable GDP and as independent variables each of our 18 sectors and also our global market index, the S&P500¹⁴. The results are presented below.

Table 3.2: Linear Regressions' results with the original variable

	Linear Regression between the sector alone and GDP			
	Adj. R ²	F	Sig	DW
SPX	7,60%	6,204	0,150	1,923
USAUTOVAR	0,20%	1,137	0,291	1,761
USBANKSVAR	3,70%	3,449	0,068	1,718
USBASRSVAR	0,30%	1,216	0,274	1,742
USCHEMVAR	-1,60%	0,021	0,885	1,748
USCONSMATVAR	0,40%	1,254	0,267	1,720
USFINSERVAR	2,50%	2,617	0,111	1,846
USFOODVAR	-1,40%	0,135	0,715	1,719
USHEALTHVAR	-1,60%	0,000	0,993	1,751
USINDVAR	-0,30%	0,839	0,363	1,834
USINSVAR	4,40%	3,896	0,053	1,845
USMEDVAR	3,20%	0,548	0,462	1,818
USOILVAR	13,80%	1,206	0,276	0,809
USPHGVAR	-1,40%	0,139	0,711	1,727
USRETVAR	1,10%	4,668	0,035	0,632
USTECHVAR	0,70%	1,446	0,234	1,888
USTELCOVAR	1,50%	1,98	0,164	1,840
USTRAVELVAR	-1,60%	0,032	0,858	1,747
USUTILVAR	1,90%	2,221	0,141	1,733

So we can conclude from the results presented above that only one model presents itself as statistically significant at 5%, which is the model regarding the Retail sector.

¹³ We recall that reference to the “GDP variable” that we will use throughout the text for reasons of convenience, is in fact a seasonally adjusted nominal GDP rate of growth, as we discuss in detail below.

¹⁴ We used the ticker SPX to describe the index S&P500.

However, in this case, the adjusted R^2 of the model is a low 1.10%. As for the remaining models, their adjusted average R^2 (including the SPX model) is 1.76% which is a low value indicating that the simple linear regression models do not capture significant information from the stock market regarding GDP¹⁵.

We also estimated models containing the 8 lag variables for each sector we created. And in this case, our R^2 results deteriorate significantly and we even achieve a average adjusted R^2 which is negative. So in absolute terms we have worst results and the models achieved suffer from the same problem as before on their statistical significance tests. We present below our results.

Table 3.3: Linear Regressions' results with lag variables

	Linear Regression between the sector and its lag variables with GDP			
	Adj R^2	F	Sig	DW
SPX	17,90%	1,312	0,253	1,983
USAutoVAR	10,70%	0,720	0,688	1,779
USBanksVAR	12,90%	0,892	0,538	1,730
USBasRsVAR	9,60%	0,639	0,759	1,760
USChemVAR	8,30%	0,543	0,837	1,759
USConsMatVAR	10,80%	0,723	0,686	1,715
USFinSerVAR	12,80%	0,878	0,550	1,890
USFoodVAR	8,50%	0,559	0,824	1,725
USHealthVAR	8,90%	0,589	0,800	1,847
USIndVAR	10,00%	0,666	0,735	1,870
USInsVAR	13,70%	0,951	0,490	1,877
USMedVAR	9,40%	0,621	0,774	1,852
USOilVAR	10,10%	0,674	0,729	1,821
USPHGVAR	8,40%	0,552	0,829	1,740
USRetVAR	18,60%	1,392	0,214	0,695
USTechVAR	19,80%	1,509	0,168	0,806
USTelcoVAR	11,40%	0,769	0,645	1,863
USTravelVAR	8,30%	0,541	0,838	1,759
USUtilVAR	12,40%	0,851	0,574	1,766

Having obtained these results, we decided to proceed with our analysis trying to apply a different technique that had the ability to extract further information from our dataset.

In order to do so, one of the statistical tools that can be used is the discretization of variables.

¹⁵ Additionally there are still some autocorrelation problems in some models as their Durbin Watson (DW) statistic becomes more distant from the value of 2, something that happens in the only statistical significant model, Retail.

The rationale for that relies in the fact that the expectations regarding the future evolution of the economy that are built into stock prices anticipate not specific future rates of growth but instead different scenarios of growth for these economies. So our hypothesis is that by discretizing the evolution of GDP it becomes possible to find new patterns in the information precisely because the expectations that are behind stock prices are also formed in a categorical way.

In order to transform the GDP into a discrete variable we had to decide (1) in **how many intervals** would the information be partitioned and additionally (2) what would be **the cutting points** that would define the intervals in which the information would be segmented.

Regarding (1) the definition of the number of intervals in which we would separate the data on GDP, we decided to look at the definition of recession as a base for describing the states in which an economy can present itself. But when we did so, we did not find a clear definition of recession. Additionally this definition is a responsibility varying from institution to institution in each country. In the United States for example, it is the National Bureau of Economic Research (or NBER) the entity responsible for calling recessions. Their definition of recession follows: “(a recession is a) *significant decline in economic activity spread across the economy, lasting more than a few months*”. A generally accepted rule of thumb to call a recession is the at least two quarters of negative real GDP growth and although this rule captures most of the NBER dated recessions, not all recessions had two consecutive negative real GDP readings. The reason for this is that the NBER follows not only GDP but also other metrics and additionally it also takes into consideration the depth as well as the duration of the decline in economic activity¹⁶.

It was taking into consideration the blurry definitions of recession that exist that, instead of studying the economy merely as being in recession or not, we decided to set up three states of the economy. The first one, at which we called “*Contraction*” is defined by below-zero periods of real GDP growth; we defined also a second state of the economy at which we called “*Recession*” and that is defined by real GDP growth below the

¹⁶ Information available at the NBER website at www.nber.org

economy long term trend value and finally a third state, called “*Expansion*” in which the economy is growing above its long term trend. So by doing this separation into three states we intend to gather more information regarding the grey area that exists over the definition of recession. This enabled our analysis to find more information than what would be possible if we considered only two states of the economy.

After having set the number of intervals to be used in the analysis, it is still necessary to (2) define the cutting points that will allow us to separate our GDP information.

To do so we tried to put into theoretical context the values of both GDP and inflation. We analyzed the economic literature looking for the long term growth potential reference values for these two macroeconomic variables. We found that, regarding the US economy real long term GDP potential growth rate, 2% was a consensual value in the literature, according namely with Elwell (2006), among others. In fact, the same author refers 2% as the real historical growth rate for the US economy in the sub period of 1980 to 2004, which comprehends most of our sample.

The other parameter we also would have to look at was the inflation rate. After having set our states of the economy considering real rates of growth we then needed to take into consideration the inflation in order to transpose those real cutting points into their equivalent nominal values in our also nominal dataset. Our choice was the Personal Consumption Expenditure (PCE) index ex-food and energy, which is also the preferred measure of inflation by the FED. There are several reasons for this preference, but the most important argument is the volatility associated with energy and food prices. So excluding the effect of both, this allows the policy maker to focus only on structural price shifts, avoiding monetary policy changes to respond to only short-term spikes in food or energy prices.

So assuming for our work the FED’s choice, we calculated the average yearly core CPE for our period of analysis (1992-2007) and found that value to be of 2%¹⁷, number that we then integrated in our analysis.

¹⁷ Information regarding the evolution of the core PCE for the period under analysis is presented in Table A.1 of the Annex A (page 64).

Taking into consideration that our initial real cutting points were 0% and 2% and the level of inflation mentioned above the nominal cutting points we will considerate in our models will be 2% and 4%.

Table 3.4. Intervals set for GDP evolution

Nominal GDP	Real GDP	Legend
< 2%	0%	<i>Contraction</i>
]2%, 4%[	]0%, 2%[	<i>Recession</i>
> 4%	>2%	<i>Expansion</i>

Finally we had to verify if these values initially set by looking at the economic literature, in a second phase of the analysis respected the methodological restraints imposed by DA. For this Hair, *et al.*, (2005) mentions two indications:

- i. The categories must be mutually exclusive and exhaustive. This was achieved by working with open intervals in the first and last category, namely with the nominal quarterly GDP growth being classified as < 0.5% and > 1%.
- ii. There should be a small number of categories. Given that the number of discriminant functions computed is $\min \{k-1, p\}$, increasing the "k" number of categories will increase the number of discriminant functions and therefore not only the complexity of the problem, but also the difficulty in profiling differences between the groups under analysis.

Having set the number of intervals in which we would divide our sample and the cutting points we would use, we had to choose a technique that would work with a non-metric dependent variable and several metric independent ones given that linear regression models require both dependent and independent metric variables.

Multiple regression is the most widely used multivariate dependence technique due to its ability to predict and explain metric variables. But in the case that the dependent variable is non-metric, multiple regression cannot be used. In those situations, according to Hair, *et al.*, (2005), we have to choose between either DA or Logistic Regression.

However in our case there was not a true decision to be made, given that Logistic Regression implies that the discriminated variable can only have two categories. As for

DA, although it presents more strict assumptions, it also gives us the possibility of studying a categorical discriminated variable with three or more categories and since this was one of our premises given our intention to study three economic states, DA was our choice.

The downside regarding DA has basically to do with its strict assumptions. Unlike Logistic Regression (where the violation of some of the underlying assumptions does not eliminate interpretative value from the results obtained) in DA such violations have to be taken into consideration at the time of the interpretation of the results. However, in our case the verification of the essential assumptions for our data was not a problem, as we will see later on.

So although some authors, like Wilson and Press (1978), indicate Logistic Regression as a preferable method, our initial premise of having 3 categories in our discriminated variable would rule out this option. Additionally the same authors also indicate that it is unlikely that both methods of estimation yield different results.

Other solution that is sometimes referred in the literature implies the use of a quadratic formulation, instead of linear discriminant models. However, we advance two reasons on why that would be inappropriate in our case, according with Tafler's view (1982). First of all, we do not have in our study a departure from the assumption of multivariate normality. Also, like Tafler, we have a small sample size which advises against quadratic formulations. Besides, using a linear formulation also has the advantage of providing us with a clear interpretation of each of the discriminator variables, as stated in Morrison (1969).

3.3. What is Discriminant Analysis and how does it work?

According to Brown and Wicker (2000) DA is a descriptive and classificatory technique developed by R. A. Fisher in 1936, with two main goals:

- (a) Describe characteristics that are specific to distinct groups (called descriptive discriminant analysis);

(b) Classify cases (i.e., individuals, subjects, participants) into pre-existing groups based on similarities between that case and the other cases belonging to the groups (also called predictive discriminant analysis).

And how is this achieved? In order to classify the observations accordingly to their characteristics, DA implies following an algorithm. The fundamentals behind DA imply estimating a relationship between a categorical (or non-metrical) variable and one or several¹⁸ metric variables¹⁹. DA is then used to explain a nonmetric discriminated variable with two or more *a priori* categories. This will tell us how well it is possible to separate two or more groups of observations given several metric variables.

This relationship is obtained by creating discriminant functions²⁰. These discriminant functions are linear combinations of the discriminator variables, which are expected to discriminate more accurately between the objects in analysis than each of the variables considered alone.

$$Z_{jk} = a + W_1X_{1k} + W_2X_{2k} + \dots + W_nX_{nk} \text{ (Eq. 3.1.)}$$

Where

- Z_{jk} is the discriminant Z score of discriminant function j for object k
- W_i is the discriminant weight for discriminator (independent) variable i
- X_{ik} is the discriminator (independent) variable i for object k

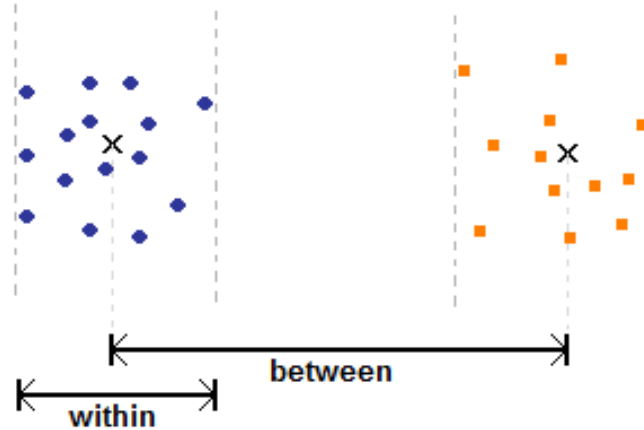
What happens next is the calculation of the weights for each discriminator variable (W_i) in the discriminant function in order to maximize the differences between the groups. To do so, there are two necessary steps: maximize the between-group variance and also minimize the within-group variance. The image below exemplifies.

¹⁸ Whenever we have more than one independent/discriminator variable, we have a multiple discriminant analysis.

¹⁹ It is possible to do an analogy on the denomination of the variables between DA and typical regression analysis. While in typical regression analysis we have a “dependent variable” and one or several “independent variables”, in DA we have a “discriminated” variable and one or several “discriminator” variables.

²⁰ The number of discriminant functions is determined by the expression $\min \{k-1, p\}$ with “ k ” representing the number of the categories of the dependent variable and “ p ” the number of variables.

Image 3.1. Between and within-group variances



Own source

So unlike linear regressions, where we use the Ordinary Least Square method (OLS) to minimize the Sum of Squared Residuals of a regression (SSR), in DA the total SSR is partitioned into (1) between-group squared residuals and also in (2) within-group squared residuals and it is the ratio of the $SSR_{\text{within groups}} / SSR_{\text{between groups}}$ that is minimized.

That is achieved through the OLS method that estimates the values of the parameter “ a ” and also the weights “ W_i ” that minimizes the above mentioned ratio.

3.4. Our work

In this section we will expose the methodology followed²¹ and also the decisions we had to make in order to ensure a correct application of DA.

3.4.1. Research Problem

Regarding the research problem, we already mentioned we wanted to understand what kind of state of the economy was associated with different patterns of behavior from the sectors in the stock market. This will allow us to later on conclude on differences in analysis done using a global market index and analysis using several sector indices.

²¹ Our work followed the structure presented by Hair, *et al.*, (2005)

3.4.2. Research Design Issues

A. Selection of discriminator variables

The first issue to be addressed has to do with our discriminator variables. However, given the theoretical background of our research, it was one of our initial premises to study the relationship between the stock market sectors and the GDP. So in this case, the selection of our discriminator variables was already completed.

B. Sample size considerations

In what concerns the data used, we had information for the stock market sectors from 31-12-1991 onwards, making available 64 quarters of data (we recall we needed the stock market sectors' information on a quarterly basis, given that GDP readings are also quarterly). This is not a very extensive dataset, but the robustness of our results is not jeopardized as Hair, *et al.*, (2005) confirms when stating that "*The minimum size recommended is five observations per discriminator variable*".

Either way, the analysis that we propose has the limitation that the sectorial data for the stock market is available only from the end of 1991 onwards. Therefore, although indeed it would be more comfortable to have a larger sample size, we believe our conclusions are not distorted by our analysis sample (given the proximity to the above mentioned ratio) and we find this analysis knowledge-accretive despite this limitation²². There's also another recommendation that Hair, *et al.*, (2005) put forward, this time regarding the sample size of each category. In order to decide on that, the rule given is that "*the smallest group size of a category must exceed the number of discriminator variables*". In our case, the smallest category has 15 observations, which although below the 18 recommended, we believe not to have a distortion effect over our conclusions given the proximity to that recommended level. In fact, there is no consensus on the literature regarding the existence of a threshold value for the validity of the analysis, with several authors also indicating several different minimum values. Therefore, and given that our sample is indeed close to the level referred by Hair, *et al.*, (2005) and that it respects the minimum value required to allow for the calculation of

²² This question has no closed answer, as several authors and sources propose different solutions. For example, SPSS (one of the most widely used statistical software namely to perform this kind of analysis) demands that: "*There must be at least two cases for each category of the dependent and the maximum number of independents is sample size minus 2.*", a criteria that we more than clearly verify.

linear discriminant functions (that is at least 2 observations per category) we decided to maintain our approach.

C. Variables used

Another research design issue has to do with the variables used. Given the relevance of the *time dimension* in our analysis, we believed we could further enhance the quality of the research done by adding lag variables.

The rationale for this choice is that information about a certain production period is spread over many previous periods given that not all information about future production becomes publically known over a very short period of time (Binswager, 2000) meaning that there is relevant information about what is happening in the market at a given time, in previous periods.

So besides the 18 discriminator variables that we used, we also created 8 lag variables for each discriminator variable, that were intended to gives us additional information regarding the information contained in previous periods.

Therefore taking one example, besides the variable “*Banks*” we also had a variable “*Banks_Lag_1Quarter*” that contained in period t , information regarding the evolution of the original variable “*Banks*” in period $(t-1)$. There is also a variable designated “*Banks_Lag_2Quarter*” that contains in period t information regarding the original “*Banks*” variable for period $t-2$ and the same methodology was applied to 6 other lag variables until “*Banks_Lag_8Quarter*” was created.

In the end, this resulted on the study of 162 variables.

Table 3.5. Lag variables created

	Banks	Banks_Lag_1Quarter	Banks_Lag_2Quarter	Banks_Lag_3Quarter	...
t_1	X_1	-	-	-	...
t_2	X_2	X_2	-	-	...
t_3	X_3	X_3	X_2	-	...
t_4	X_4	X_4	X_3	X_2	...
t_5	X_5	X_5	X_4	X_3	...
t_6	X_6	X_6	X_5	X_4	...
t_7	X_7	X_7	X_6	X_5	...
t_8	X_8	X_8	X_7	X_6	...

3.4.3. Assumptions

There are a number of assumptions that we need to verify in order to be able to apply DA according to Hair, *et al.*, (2005).

A. Multivariate normality of the independent / discriminator variables

The first one is that there has to be multivariate normality of the discriminator or independent variables. However it is accepted that if all variables independently follow a normal distribution, then we have multivariate normality. So in order to verify if our variables followed a normal distribution, we applied a Kolmogorov-Smirnov test that is basically used to compare the probability distribution of a sample of data with a reference probability distribution (one sample K-S test²³). In order to do that, we used the statistical software SPSS.

The results of this estimation are presented in Table B.1 of the Annex B²⁴ but our main conclusion is that all variables are normal, with a 95% statistical significance. These results confirm our intuition that the quarterly returns of a stock market (of its sectors, more precisely) indeed follow a normal distribution.

B. Lack of multicollinearity among independent / discriminator variables

According to Hair, *et al.*, (2005) although the effects of disregarding this assumption are not consensual in the literature, the consequences of disrespecting the mentioned assumption is “*specially critical when stepwise procedures are employed.*”. Also Tafler (1982) states that the presence of multicollinearity in the data is not a problem, unless it is so serious that the dispersion matrices cannot be inverted. This is not our case and therefore our data set does not present a problem regarding meeting this assumption.

All our results are presented in the Annex and for reasons of convenience for the reader we will not add this information on this section, but what we did in order to assess the

²³ It also possible to proceed on a two sample K-S test in which the comparison is made with two different samples.

²⁴ Tables in pages 65 to 68 of Annex B.

degree of multicollinearity in the data was to compute the correlation matrices of our variables. These results can be found in Tables B.2 to B.21 of Annex B²⁵.

Our conclusion is that when we analyze the correlation matrix that results from our 18 sectors, the degree of correlation is in fact high. However, when we do the same exercise with the lag variables, the degree of correlation becomes much lower what reduces the problem of multicollinearity.

Our output shows the correlation matrix for all the 18 sectors combined together, also the 18 correlation matrices for our typical 9 variables (the original variable and its 8 lags) in each sector and finally the matrix for our final model.

This means that given that our models always include lag and non lag variables, there will always be some degree of multicollinearity, however this will always be reduced by the presence of lag variables. This argument is also valid for our final model that presents a low degree of multicollinearity, as we can see in the correlation matrix that is presented in the annex.

C. Equal dispersion matrices

Another assumption of DA is that the dispersion and covariance structures (matrices, in the case of covariance) for the groups, defined by the different categories of the discriminated variable, must be equal.

In order to do this, we can perform a Box's M test. According to the null hypothesis of this test, all covariance matrices are equal so regarding the results of the test, if the statistical significance does not exceed the critical level (i.e., nonsignificance) then the equality of the covariance matrices is supported and the assumption is respected. To do so, the test uses the F distribution to verify if we will accept the null hypothesis.

So in the case of this test, we expect that it turns out non significant so that we can accept the null hypothesis that the groups matrices do not differ, as DA implies.

However, and given that this is our case in several of our models, we are also interested in knowing what happens if this assumption is not met and how can this affect our results.

²⁵ Tables in pages 68 to 79 of Annex B.

According to Brown and Wicker (2000) in the case that this assumption is violated, even so DA maintains its robustness. In fact, according to Klecka (1975) the worst consequence is that cases are more likely to be classified into the group with the greatest dispersion. Brown and Wicker (2000) even state that: *“In short, the available literature indicates that violation of the homogeneity of covariance’s assumptions is not of major importance to conducting a valid discriminant analysis”*. What other authors as Hair, *et al.*, (2005) recommend is that, if possible, in the cases where the assumptions that DA implies cannot be me respected, the researchers should consider using a Logistic Regression model instead. However, this was not a possibility in our study, given our initial premise of having three states of the economy under analysis, what is impossible to do in a Logistic Regression.

That said and given that our sample is well balanced between the number of observations in each of the 3 categories we believe that in the cases were in fact the Box’s M test indicates the existence of differences in the group’s variances and covariance’s structures our final results should not be affected so that they became invalid, in what is also the opinion of Brown and Wicker (2000).

D. Outliers

Finally, we should mention the treatment that we gave to outliers. There is no clear and uncontested definition for an outlier, other than stating that it is an observation at an abnormal distance from other values, which leaves to the analyst what to consider as an outlier. However, this was an exercise we had to do, following the advice of Hair, *et al.*, (2005) because of the distortive effect that these observations have in DA results and on its interpretation.

In our case, our procedure implied identifying graphically each outlier, which we did based on SPSS’ algorithm. This algorithm identifies as an outlier any observation that distances itself more than 1.5 times the Interquartile Range²⁶ from the rest of the scores. Additionally, with this choice we maintained the coherence with the software we used (also there was no reason to consider SPSS’s choice as inadequate).

²⁶ The Interquartile Range, or IQR, represents the difference between the upper and the lower quartiles of a sample.

So once we had the outliers identified, given the distortion effect that these cause on DA, we had basically two options: eliminate that piece of data or replace the outlier with a value that contained valid information. We chose this option, so each outlier present in our sample was replaced by the maximum or minimum of its series according to the kind of outlier it was. This way we solved the problem associated with the instability of the results of DA in the presence of outliers, while simultaneously not losing the information from the moments in which the variables assumed extreme values.

3.4.4. Estimation of the Discriminant Functions

In what concerns the estimation process that we used, we choose a simultaneous estimation process leaving behind the possibility to use a stepwise estimation. Our choice has a theoretical reason behind it given that we wanted to include all the discriminator variables in the analysis and we were not interested in seeing intermediate results based only on the most discriminating variables.

Also if we take into consideration the size of our sample, choosing a stepwise estimation method would raise some concerns, given that for samples in which we have less observations per discriminator variable, this estimation method becomes less stable.

3.4.5. Interpretation of the Discriminant Functions

Once we have our estimation results ready, the more important step will be to analyze their quality and then to interpret them. Regarding the quality of the results there a number of aspects that we have to take into consideration. We will now run them one by one.

A. Evaluate group differences

The first thing to do is to evaluate if there are indeed group differences because otherwise the DA estimation process is worthless. In order to do that, a Wilks' Lambda test is performed on the group's differences.

B. Assessing Group Membership Prediction Accuracy

Given that in DA the discriminated variable is nonmetric, we cannot use a typical quality measure like the R^2 of a linear regression. Rather, each observation must be assessed as to whether it was correctly classified or not.

In order to do that we build classification matrices that give us both the correct classification of an observation in its due group and also the classification predicted by the discriminant functions.

So in DA the percentage correctly classified – also designated **hit ratio** – reveals how well the discriminant function classifies the observations. So this concept is use to take us one step further in evaluating our work, beyond just the statistical significance of our results.

C. Comparing the Hit Ratio.

However once we have our hit ratio computed we have to be able to classify its quality. So if we find a hit ratio of 20% is it good?

To evaluate this result, Hair, *et. al.* (2005) mentions the standard comparison measure that basically divides by one the number of groups under analysis,

$$C_{\text{EQUAL}} = 1 / \text{Number of groups}$$

So in our case in which we have three groups, we can consider 33.33% our limit level. Any hit ratio above that is *beating pure chance* and therefore means that our analysis is useful²⁷.

²⁷ Given the distribution of our observations through our 3 groups, we will not take into consideration the size of the groups.

However, if for example we had a sample of 100 observations with 90 of these in one group and the remaining 10 in another group, it would be recommendable to adjust the calculation of the minimum required hit ratio. One way to do that is to use the proportional chance criterion which gives us a threshold value using the following formula: $c_{\text{PRO}} = p^2 + (1 - p^2)$, where p stands for the proportion of individuals in group 1.

3.4.6. Validation of the Discrimination Results

To allow subsequent testing of the validity of the discriminant function, a holdout sample randomly selected was withheld from the initial analysis. To do so, the technique that we used was a split-sample one.

So while estimating our models we arbitrarily²⁸ choose 12 observations that stand for nearly 20% of our total sample of 64 observations. These observations were chosen arbitrarily according to Hair, *et al.*, (2005). Additionally, we believe it is preferable to selected the holdout sample this way due to structure shifts. If we selected for our holdout sample sequential observations and if these happened to coincide with a structural shift (as an example we can think about a trend inversion in the stock market) our valuation of the quality of the model would be inaccurate.

In order to create our models and compute our hit ratios, these 12 observations were used as an *alternative sample* that tested the results obtained with our remaining observations and allowed us to have both a “training” hit ratio and a “test” hit ratio.

Using a holdout sample to test the discriminant function adjusts for the upward bias that occurs if observations used in computing the discriminant function are also used for developing the classification matrix. Given a limited sample size, the decision was made to use a larger group for deriving the function to ensure stability of the coefficients.

²⁸ In Excel © we run the function “rand()” that created next to our 64 observations, 64 random numbers. We then sorted out our observations using as a criteria these random elements created and choose the first 12 elements.

4. EMPIRICAL RESULTS

4.1. Models estimated

4.1.1. Models estimated in Section A: Finding the most interesting sectors

In this section we wanted to assess which sectors were the ones containing the highest level of discriminatory power regarding the GDP evolution. To do, we estimated 18 models, one for each of our sectors. These models included our original variable and the remaining 8 lag variables we created for each sector. In order to identify these sectors, we looked at the Wilk's Lambda test that we performed on the discriminant functions generated in the models. With these results, we looked for the Discriminant Functions that were significant at a 5% level.

At this stage, we were trying to assess **which sectors** were the ones containing the highest level of discriminatory power regarding GDP evolution.

4.1.1.1. Estimations for the 18 sectors

We present the results of these 18 models in Annex C, namely the Standardized Discriminant Function Coefficients in Table C.1 and the Structure Matrices in Table C.2²⁹. These Standardized Discriminant Functions Coefficients indicate the partial contribution of each variable to the discriminant function, basically the same way beta weights do in multiple regressions. As for the Structure Matrices, they indicate the simple correlation between the variables and the discriminant functions. We also present the Box'M test results³⁰. This test is performed to evaluate the dispersion and

²⁹ Table C.1 in pages 80 to 84 and Table C.2 in pages 85 to 89 of Annex C.

³⁰ Table C.3 in page 89 to page 90 of Annex C.

covariance structures between the different categories of the discriminated variable. According to the null hypothesis of the test, if the statistical significance does not exceed the critical level (i.e., nonsignificance) then the equality of the covariance matrices is supported and the assumption of DA of non equality of the covariance matrices is respected. Comments on this assumptions were already made in section “3.4.3. Assumptions”.

After estimating our models the first step we took was to use a test of Equality of Group Means to verify which variables could help us find differences within our three groups of observations and therefore would be helpful in discriminating the evolution of GDP³¹. These results are presented in Table C.4 of Annex C³² and looking at the results indicates that no model contains the perfect mix of variables. However we can obtain some indications regarding which sectors contain more helpful information.

For example, variables from the financial industry present themselves as the most helpful (from the models containing the variable “*Financial Services*” we found 3 meaningful variables and from “*Banks*” we found 2). Then we have a wide range of variables from several sectors whose models contain also two meaningful variables (*Construction & Materials, Retail, Telecommunications, Travel*).

But this is just step one of the analysis of the results obtained. After using the test of Equality of Group Means to find if the variables help differentiate between the groups, we still have to verify if there is indeed discriminatory power in the discriminant functions that originate from the data presented.

To conclude on that, what we did was to analyze the quality of the results of the discriminant functions with a Wilks’ Lambda test. This test is used to verify if there are differences between the means of identified groups of subjects on a combination of dependent variables. This evaluates the significance of the discriminant function as a whole and if one rejects the null hypothesis that the two groups have the same mean

³¹ We recall that in order to allow for an effective discrimination, DA implies that the group means have to be distant from one another, otherwise the results will be poorer given that the algorithm will not be able to discriminate between the different groups. This will lead to misclassifications or observations that should be in one category but will be classified by the model in a different category, therefore deteriorating the results.

³² Table C.4 in pages 90 to 94 of Annex C.

discriminant function scores, then we can conclude that the model has discriminatory capabilities. So this step helped us choose which models indeed contained statistically more significant discriminant functions. It was with this information that we subsequently chose the sectors that we would use to generate further models.

We will now present the results of the estimation of discriminant functions, namely the Wilk's Lambda test that allowed us to check for statistically significant discriminatory functions.

Table 4.1: Wilks' Lambda of the models estimated in Section A

Sectors	Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig ³³ .
Auto	1 through 2	0,502	27236	16	0,04
	2	0,873	5372	7	0,62
Banks	1 through 2	0,362	39656	18	0,00
	2	0,781	9660	8	0,29
Basic Resources	1 through 2	0,755	10963	18	0,90
	2	0,901	4085	8	0,85
Chemicals	1 through 2	0,642	17260	18	0,51
	2	0,874	5264	8	0,73
Construction & Materials	1 through 2	0,425	33360	18	0,02
	2	0,789	9239	8	0,32
Financial Services	1 through 2	0,510	26296	18	0,09
	2	0,789	9250	8	0,32
Food	1 through 2	0,652	16706	18	0,54
	2	0,882	4897	8	0,77

³³ We used a 10% significance level, meaning that all discriminant functions computed that presented a Sig level under 0,10 were deemed statistically significant. Just for the sake of information, the majority of our results would be maintained if we used a 5% significance level (indeed, only one discriminant function now classified as significant would no longer have that status).

Health Care	1 through 2	0,759	10741	18	0,91
	2	0,930	2822	8	0,95
Industrial Goods & Services	1 through 2	0,612	19121	18	0,38
	2	0,830	7255	8	0,51
Insurance	1 through 2	0,590	20576	18	0,30
	2	0,796	8902	8	0,35
Media	1 through 2	0,646	16594	18	0,55
	2	0,918	3259	8	0,92
Oil	1 through 2	0,770	10198	18	0,93
	2	0,925	3051	8	0,93
Personal & Household Goods	1 through 2	0,581	21199	18	0,27
	2	0,908	3779	8	0,88
Retail	1 through 2	0,449	31222	18	0,03
	2	0,828	7345	8	0,50
Technology	1 through 2	0,577	21446	18	0,26
	2	0,839	6843	8	0,55
Telecoms	1 through 2	0,525	25107	18	0,12
	2	0,747	11401	8	0,18
Travel & Leisure	1 through 2	0,466	29749	18	0,04
	2	0,876	5155	8	0,74
Utilities	1 through 2	0,772	10078	18	0,93
	2	0,918	3324	8	0,91

So from the results presented we can now know which sectors present more informative value. Our criterion was that the models should have at least one significant discriminant function statistically significant and the sectors that had were:

- Auto
- Banks
- Construction & Materials
- Financial Services
- Retail
- Travel & Leisure

Now having these sectors in mind, we wanted to go to step two and figure out which **time frames** are more informative.

It seems reasonable that some of these sectors will have a higher discriminatory power when considered their non-lag variables (they should have an *in sync* evolution with GDP), while others will probably be more relevant through their lag variables. But before we could do so, we also have to analyze the performance of the global market index in the same way we did for the 18 sectors.

4.1.1.2. Estimations for the S&P500

We recall that our dissertation aims at finding out if there is a combination of sectors that contains more information regarding the future evolution of GDP than a global market index. So, if we are correct, the discriminatory capabilities of the model with the S&P500 should be weaker than those obtained with the different sectors.

Indeed our results show that this is the case.

Using for the S&P500 the same methodology that we used above for each individual sector, we find that that particular model has no discriminant function yielding statistical significance. We present our results below.

Table 4.2: Wilks' Lambda of the models estimated for the S&P500

Model	Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
S&P500	1 through 2	0,358	41603	36	0,24
	2	0,672	16088	17	0,52

We recall that both functions present are distant from the minimum significance level that we required of 10%.

So at this point, we may already conclude that our initial premise of more information contained in the sectors of the stock market is correct, given that we had several discriminatory functions with statistical significance in the models we estimated above.

However what we still have to analyze is how can the stock market sectors' discriminate the evolution of GDP. So after having already selected six sectors, we will now try to find out which time frames are more meaningful.

4.1.2. Models estimated in Section B: Finding the most interesting time frames

With the sectors we found in section A in mind, we wanted to go further and to try to find out if there was any specific time frame that could be more insightful regarding pattern finding on the market sectors' evolution and the GDP evolution. To do this for each of the above mentioned sectors we created the following models:

i. Models with just one discriminator variable. A model with just the original sector variable that had no lag. Then we created another model with just the 1 lag variable. Then we did the same for the 2 lag variable, for the 3 lag variable and so on until the last model estimated that contained only the 8 lag variable.

ii. Models with two discriminator variables. However there was no reason to limit our reasoning to just 1 lag period. So, in the same logic as the above mentioned, we

estimated models with two variables. First with just the original sector variable and the 1 lag variable. Then we estimated another model that contained the 1 lag variable and the 2 lag variables and went on until the final model that contained the 7 lag variable and the 8 lag variable.

iii. Models with three discriminator variables. We then repeated the same process but for 3 variable models. The first model had the original variable, the 1 lag variable and the 2 lag variable, the second one had the 1 lag variable, the 2 lag variable and the 3 lag variable and we proceeded until the final model that contained the 6 lag variable, the 7 lag variable and the 8 lag variable.

iv. Models with four discriminator variables. Finally, we repeated the same process for models with four variables beginning in one model with the original variable and the 1, 2 and 3 lag variables and we then ended with a model that contained the 5, 6, 7 and 8 lag variables.

At this stage, we were trying to assess **which time frames** were the ones containing the highest level of discriminatory power regarding GDP evolution.

4.1.2.1. Estimation of 180 models

We will now present the results of our estimation of 180 models, consisting of 30 models for each of the 6 sectors that we choose in the previous section.

For practical reasons however, we will present the results of the Test of Equality for Group Means and also the Wilk's Lambda Test in Tables D.1 and D.2 of Annex D³⁴. For now, we will only present the models that achieved the best results (meaning at least one statistically significant discriminant function), since these are the ones that we will pursue on. The results are in the table below.

³⁴ Table D.1 in pages 95 to 110 and Table D.2 in pages 111 to 122 of Annex D.

Table 4.3: Wilks' Lambda Test for models with at least one significant Discriminant Function out of the 180 models estimated

Sectors	Variables in the model	Test of Functions	Wilks' Lambda	Chi-square	df	Sig.	Hit Ratio (%)	
							Training	Test
Auto	USAutoVAR_Lag8Q	1	0,868	6.084	2	0,048	55,8	33,0
	USAutoVAR_Lag3Q , USAutoVAR_Lag4Q , USAutoVAR_Lag5Q	1 through 2	0,714	14.502	6	0,025	53,9	16,6
	USBanksVAR_Lag7Q	1	0,628	20.453	2	0,000	52,0	41,6
Banks	USBanksVAR_Lag6Q , USBanksVAR_Lag7Q	1 through 2	0,596	22.505	4	0,000	50,0	42,0
	USBanksVAR_Lag7Q , USBanksVAR_Lag8Q	1 through 2	0,616	20.559	4	0,000	54,0	33,0
	USBanksVAR_Lag5Q , USBanksVAR_Lag6Q , USBanksVAR_Lag7Q	1 through 2	0,559	25.041	6	0,000	52,0	33,0
	USBanksVAR_Lag6Q , USBanksVAR_Lag7Q , USBanksVAR_Lag8Q	1 through 2	0,575	23.266	6	0,001	54,0	42,0
	USBanksVAR_Lag4Q , USBanksVAR_Lag5Q , USBanksVAR_Lag6Q , USBanksVAR_Lag7Q	1 through 2	0,502	29.272	8	0,000	56,0	25,0
	USBanksVAR_Lag5Q , USBanksVAR_Lag6Q , USBanksVAR_Lag7Q , USBanksVAR_Lag8Q	1 through 2	0,537	25.836	8	0,001	56,0	42,0
Construction & Materials	USConsMatVAR_Lag7Q	1	0,774	11.287	2	0,004	52,0	50,0
	USConsMatVAR_Lag6Q , USConsMatVAR_Lag7Q	1 through 2	0,731	13.656	4	0,008	48,0	58,0
	USConsMatVAR_Lag7Q , USConsMatVAR_Lag8Q	1 through 2	0,736	13.009	4	0,011	54,0	50,0
	USConsMatVAR_Lag5Q , USConsMatVAR_Lag6Q , USConsMatVAR_Lag7Q	1 through 2	0,712	14.600	6	0,024	50,0	58,0
	USConsMatVAR_Lag6Q , USConsMatVAR_Lag7Q , USConsMatVAR_Lag8Q	1 through 2	0,691	15.502	6	0,017	54,0	58,0
	USConsMatVAR_Lag4Q , USConsMatVAR_Lag5Q , USConsMatVAR_Lag6Q , USConsMatVAR_Lag7Q	1 through 2	0,596	21.961	8	0,005	58,0	50,0

Financial Services	USConsMatVAR_Lag5Q , USConsMatVAR_Lag6Q , USConsMatVAR_Lag7Q , USConsMatVAR_Lag8Q	1 through 2	0,675	16.323	8	0,038	52,0	50,0
							0,0	0,0
	USFinSerVAR_Lag4Q	1	0,87	6.285	2	0,043	46,0	42,0
	USFinSerVAR_Lag7Q	1	0,829	8.245	2	0,016	46,0	50,0
	USFinSerVAR_Lag6Q , USFinSerVAR_Lag7Q	1 through 2	0,751	12.457	4	0,014	56,0	42,0
	USFinSerVAR_Lag6Q , USFinSerVAR_Lag7Q	2	0,909	4.144	1	0,042		
	USFinSerVAR_Lag7Q , USFinSerVAR_Lag8Q	1 through 2	0,788	10.102	4	0,039	48,0	50,0
	USFinSerVAR_Lag5Q , USFinSerVAR_Lag6Q , USFinSerVAR_Lag7Q	1 through 2	0,737	13.094	6	0,042	54,0	50,0
	USFinSerVAR_Lag6Q , USFinSerVAR_Lag7Q , USFinSerVAR_Lag8Q	1 through 2	0,709	14.469	6	0,025	56,0	50,0
	USFinSerVAR_Lag4Q , USFinSerVAR_Lag5Q , USFinSerVAR_Lag6Q , USFinSerVAR_Lag7Q	1 through 2	0,672	16.902	8	0,031	56,0	33,0
	USRetVAR_Lag2Q , USRetVAR_Lag3Q	1 through 2	0,802	10.045	4	0,04	48,0	42,0
	USRetVAR_Lag2Q , USRetVAR_Lag3Q , USRetVAR_Lag4Q	1 through 2	0,713	14.905	6	0,02	58,0	25,0
	USRetVAR_Lag2Q , USRetVAR_Lag3Q , USRetVAR_Lag4Q , USRetVAR_Lag5Q	1 through 2	0,661	17.626	8	0,02	52,0	33,0
	USRetVAR_Lag5Q , USRetVAR_Lag6Q , USRetVAR_Lag7Q , USRetVAR_Lag8Q	1 through 2	0,687	15.580	8	0,05	52,0	50,0
Travel	USTravelVAR_Lag7Q	1	0,869	6155	2	0,05	38,0	50,0
<i>Average</i>							52.20	42.83

So with these results, we were able to find the presented 29 models, corresponding to 30 discriminant functions (given that for the Financial Services sector we found two discriminant functions) that provide us a Wilk's Lambda test that is statistically significant at 95%.

First we should now clearly highlight the importance of the financial industry in discrimination of the different GDP observation groups as of the 29 models, 15 of them are with variables of either the Banks or the Financial Services sector.

The second sector of the economy that presents good discriminatory results is the Construction & Materials sector, which presents 7 of the 29 models and although it has one discriminant function less than the Financial Services sector, it has better discriminatory power (since its discriminant functions have lower Wilk's Lambda's).

After these sectors, we have Retail that has a lower number of discriminant functions, although two of these present interesting results (Wilk's Lambda below 0.70). After Retail, we have Auto that presents poorer results (only two discriminant functions and with above 0.70 Wilk's Lambda)

Finally, Travel is the least informative sector, presenting only one discriminant function with a poor discriminatory power (0.87 Wilk's Lambda).

But the assessment of the results should not be done looking only at the discriminatory power given by the Wilk's Lambda. We should also assess the hit ratios originated by these models to verify their capability to perform out of the sample used to create them.

From the data presented above we can conclude that our hit ratios are both (in train and in test) mostly well above the minimum threshold of 33.33% which is the hit ratio that we could expect by *pure chance*. Therefore we believe that these models are fit to discriminate the phenomenon at hand given their discriminatory power and hit ratio characteristics.

4.1.3. Model estimated in Section C: Achieving high quality information

In our last phase of estimation, we took the best variables and the best time frames and mixed together in one single model that constitutes the cornerstone of our work and that presents a high level of quality. This will be the last model to be presented.

To complete this task, we took the best model we had from Section B and we add it the variables that belonged to the second best model. If the model that resulted from this combination was better than the one we had previously, we repeated this process, otherwise we would stop.

4.1.3.1. Final Model Estimated

So going one step further we tried to combine the more relevant information from Section A and Section B and tried to put together in just one model the variables we believed had more discriminatory power.

In order to do so, we pursued the following strategy: we started by putting in just one model all the variables of the best model that we presented above. This model contained the variables “USBanksVAR_Lag4Q”, “USBanksVAR_Lag5Q”, “USBanksVAR_Lag6Q” and “USBanksVAR_Lag7Q” and presented a Wilk’s Lambda of 0.502, with a Sig. level of 0.000.

Then, we added the variables of the second best discriminant model, that in this case contained the same variables as above, plus also the Bank’s variable with 8 quarters of lag. So the variables we would need to introduce were “USBanksVAR_Lag4Q”, “USBanksVAR_Lag5Q”, “USBanksVAR_Lag6Q”, “USBanksVAR_Lag7Q” and “USBanksVAR_Lag8Q”. So in this case, to our initial model we only added the variable “USBanksVAR_Lag8Q” given that the other variables were already included. We then proceed as mentioned before, evaluating if this model had a higher or lower discriminatory ability than the one we had before, which it did given that it presented a Wilk’s Lambda of 0.489, while being statistically significant and therefore we continued.

Our third best performing model contained the Construction & Materials lag variables of 4, 5, 6 and 7 quarters of lag. Once again, we estimated a new model including these variables and we analyzed its Wilk’s Lambda and significance. Given that it improved our previous model we kept these variables and proceed with our estimation process.

We will now present a table with all the transformations we did following the process explained above.

Table 4.4: Inclusion of additional variables in our final model

Variables	Wilk's Lambda	Significance
USBanksVAR_Lag4Q , USBanksVAR_Lag5Q , USBanksVAR_Lag6Q , USBanksVAR_Lag7Q	0,502	0,000
USBanksVAR_Lag8Q	0,489	0,001
USConsMatVAR_Lag4Q , USConsMatVAR_Lag5Q , USConsMatVAR_Lag6Q , USConsMatVAR_Lag7Q	0,386	0,005
USRetVAR_Lag2Q , USRetVAR_Lag3Q , USRetVAR_Lag4Q , USRetVAR_Lag5Q	0,275	0,006
USFinSerVAR_Lag4Q , USFinSerVAR_Lag5Q , USFinSerVAR_Lag6Q , USFinSerVAR_Lag7Q	0,146	0,001
USConsMatVAR_Lag5Q , USConsMatVAR_Lag6Q , USConsMatVAR_Lag7Q , USConsMatVAR_Lag8Q	0,14	0,001
USRetVAR_Lag5Q , USRetVAR_Lag6Q , USRetVAR_Lag7Q , USRetVAR_Lag8Q	0,115	0,003
USFinSerVAR_Lag6Q , USFinSerVAR_Lag7Q , USFinSerVAR_Lag8Q	0,071	0,000
USAutoVAR_Lag3Q , USAutoVAR_Lag4Q , USAutoVAR_Lag5Q	0,048	0,000
USAutoVAR_Lag8Q	0,043	0,000
UStTravelVAR_Lag7Q	0,039	0,000

So as we can see in the table above, this process ended only with the inclusion of all variables from the models mentioned before. In the end, we had achieved the cornerstone equation of our study: a model that presented a 0.039 Wilk's Lambda stating its high discriminatory power, as we can see below.

Table 4.5: Wilks' Lambda test performed on both Discriminant Functions of the best model

Test of Functions	Wilks' Lambda	Chi-square	Df	Sig.
1 through 2	0,039	97,566	54	,000
2	,318	34,330	26	,127

We attained a model that presented a 90.4% hit ratio in train and 29.4% in test with the first one being extremely high and the second ratio being slightly below our benchmark, as Table 4.6 shows.

Table 4.6: Coincidence Matrix for GDP of the best model

Main Sample			
	1	2	3
1	11	1	1
2	0	22	0
3	0	3	14

Correct Classifications: 90,4%

Incorrect Classifications: 9,6%

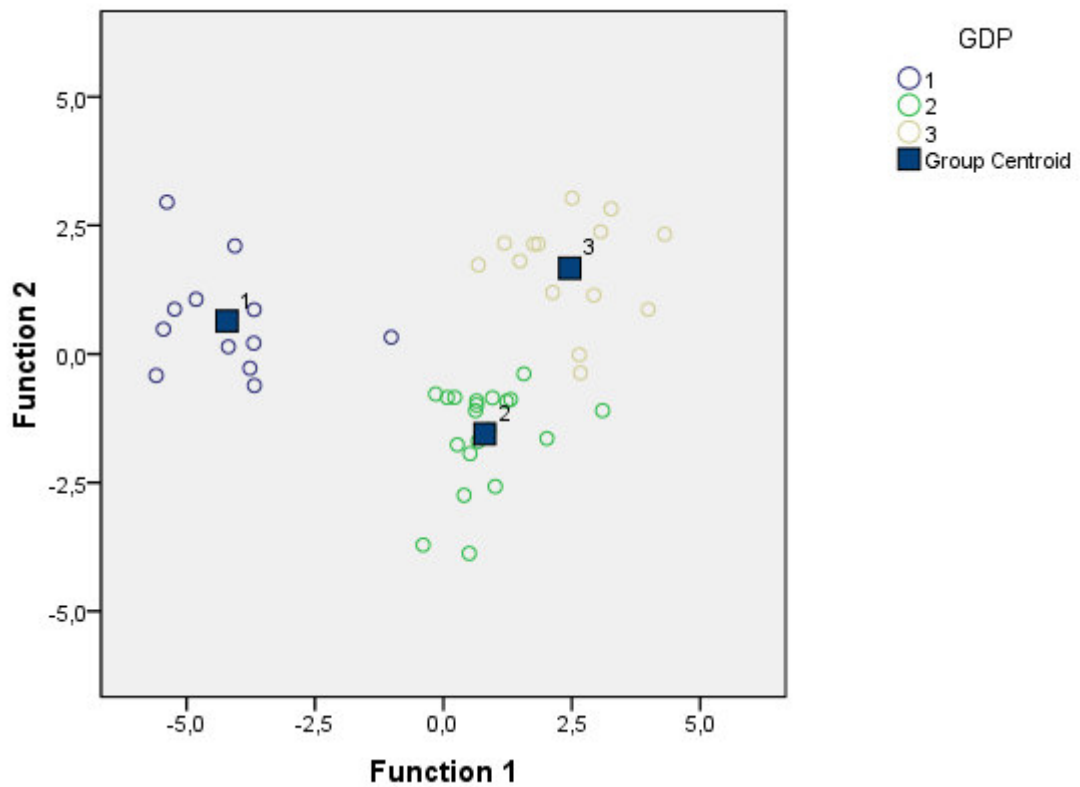
Holdout Sample			
	1	2	3
1	0	2	0
2	1	5	1
3	1	2	0

Correct Classifications: 29,4%

Incorrect Classifications: 70,6%

Additionally, we present below a graphic depicting how DA classified the different observations it analyzed. We can clearly see three groups of data, representing what was classified in each of the three categories created for GDP.

Image 4.1. Canonical Discriminant Functions of the best model



We also present the eigenvalues and canonical correlations of the two discriminant functions of the best model below³⁵.

Table 4.7: Eigenvalues of the two discriminant functions of the best model

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	7,231(a)	77,2	77,2	,937
2	2,140(a)	22,8	100,0	,826

a. First 2 canonical discriminant functions were used in the analysis.

This canonical correlation can be squared ($0.937^2 \Rightarrow 87.80\%$) and be interpreted as the percent of variance in the discriminated variable (GDP) that can be accounted for by

³⁵ We also present in page 123 to page 124 Table E.1 with the Structure Matrix of our best model.

this model. As we can see, it is a very relevant percentage that is explained by this model.

Table 4.8: Standardized Canonical Discriminant Function Coefficients of the best model

	Function	
	1	2
USAutoVAR_Lag3Q	,777	-,274
USAutoVAR_Lag4Q	,303	-,106
USAutoVAR_Lag5Q	1,268	-,260
USAutoVAR_Lag8Q	-,106	1,096
USBanksVAR_Lag4Q	-,010	,257
USBanksVAR_Lag5Q	1,059	1,013
USBanksVAR_Lag6Q	,918	,366
USBanksVAR_Lag7Q	2,299	-,134
USBanksVAR_Lag8Q	3,636	-,925
USConsMatVAR_Lag4Q	-,076	,253
USConsMatVAR_Lag5Q	-,185	,171
USConsMatVAR_Lag6Q	,078	-,572
USConsMatVAR_Lag7Q	,715	,879
USConsMatVAR_Lag8Q	-,347	-,339
USFinSerVAR_Lag4Q	,734	2,489
USFinSerVAR_Lag5Q	-,968	-1,804
USFinSerVAR_Lag6Q	-,008	,838
USFinSerVAR_Lag7Q	-1,143	-,133
USFinSerVAR_Lag8Q	-3,398	1,682
USRetVAR_Lag2Q	,252	-,839
USRetVAR_Lag3Q	-,120	,566
USRetVAR_Lag4Q	-,958	-2,765

USRetVAR_Lag5Q	-,386	,618
USRetVAR_Lag6Q	-,086	,150
USRetVAR_Lag7Q	-,988	-,641
USRetVAR_Lag8Q	,083	1,106
UStavelVAR_Lag7Q	,410	-,910

These standardized canonical discriminant function coefficients have the same purpose of the beta weights in the multiple regressions as we stated before, meaning that they indicate the relative importance of the discriminator variables in discriminating the dependent variable. So by looking at the above table we can see that the variable with the highest weight is the Bank's variable with a lag of 8 quarters, followed also by Financial Services variable also with a lag of 8 quarters and the third more relevant being again from Banks, with a lag of 7 quarters.

So at this point, what further use could we make of our model?

Given that our estimation was initially done only using information known to the model until the end of 2007, we now have an additional 5 observations (1Q08, 2Q08, 3Q08, 4Q08 and 1Q09) that can be used to verify if the model classified correctly data that we currently have available but that at the time at which we proceed with our estimations was still unknown.

4.2. An out-of-sample test: data from 2008 and early 2009

Although our results have been obtained only with data until the end of 2007, at the time of completion of this dissertation we have already five additional GDP observations available (and the respective stock market sectors' evolution).

So a further application we can obtain from our model is to verify if it discriminated correctly the five additional observations that we have available. In order to do so, we enlarged our initial database with information on these five additional periods.

We present below the model classification with the final numbers of US GDP for 2008 and the 1Q09. We recall however that the BEA (Bureau of Economic Analysis), which is the entity responsible for the national accounting numbers in the USA, releases three GDP readings. The first one or the “Advance GDP” number is released about a month after the quarter ends. The second one or the “Preliminary GDP” reading is released two months after the quarter ends. The third one or the “Final GDP” reading is released about three months after the end of the quarter. Additionally, as part of the NIPA (National Income and Product Accounts) revision process every year at July the quarterly estimates for the three preceding years are revised.

This highlights one of the interesting aspects of our model which is to give access to a estimate for the GDP on one given quarter exactly on the day that quarter ends, which is approximately one month before the first official estimate is released by the BEA (and nearly three months before the final official reading is released). This was what lead us to look at the current economic consensus number in order to assess what is the expectation for the 1Q09 US GDP and therefore assess our estimate. Given that the current estimate is of -4.00% (annualized real GDP growth rate) our model would have to estimate a classification in the first interval (nominal quarterly GDP growth below 2% or negative real quarterly GDP growth) in order to be correct.

Table 4.9: Model Accuracy

Period	Historical Nominal Values	Model classification	Decision
1Q08	0,85%	]2%, 4%[	Incorrect
2Q08	1,02%	]2%, 4%[	Incorrect
3Q08	0,83%	]2%, 4%[	Incorrect
4Q08	-1,47%	< 2%	Correct
1Q09	-4,00% ³⁶	< 2%	Correct

Model Accuracy: 40%

Benchmark³⁷: 33%

So as we can see, regarding the evolution of the stock markets during 2008 and early 2009 we had five opportunities to evaluate the classificatory capabilities of our model. Indeed it predicted the evolution of GDP correctly in two out of these five quarters or it presented a successful hit ratio of 40%. The model seems to have captured the trend correctly, as its results accompanied the downwards trajectory of the US economy during 2008 and the beginning of 2009.

We recall that this was a specially difficult year for the stock markets in the US (S&P was down -38% in FY08) and was also the confirmation of a clear trend inversion. Since the end of 2002 that we had been witnessing an upward trajectory of the US stock market and, in the summer of 2007, the first events that would trigger a trend inversion in both the equity markets and the real economy, took place.

Of course more observations would be necessary to state it without doubt, but it seems as our model has captured this new trend as its three initial predictions for 1Q08, 2Q08 and 3Q08 place GDP growing between]2%, 4%[and the last two (4Q08 and 1Q09) place it in the < 2% interval, which we believe helps validating its interest.

³⁶ This is a (real) consensus figure, as at the time of completion of this dissertation there is still no official BEA reading for the GDP evolution for the first quarter of 2009.

³⁷ We recall here the comments made on section “3.4.5. *Interpretation of the Discriminant Functions*” regarding the definition of the 33% benchmark for evaluating the quality of results in a model where the discriminated variable has 3 categories.

4.3. Implications for portfolio managers

Another important aspect of our results regards the classification of both sectors that belong to our last model and possible implications for portfolio managers.

By belonging to the last model presented the sectors “Auto”, “Banks”, “Construction & Materials”, “Financial Services”, “Retail” and “Travel & Leisure” presented themselves as cyclical sectors, given their high discriminatory powers over the evolution of GDP.

The distinction between cyclical and non-cyclical sectors has accompanied stock market investors’ for quite some long and specially in times of milder economic activity, it is usually brought up. This distinction lies mostly on the distinction between what are true necessities and luxuries for the consumers. Sectors that produce goods that satisfy basic consumer needs will probably not be as affected by economic downturns as sectors that produce luxury goods. So basically it is more expectable that a company that produces cars can be more affected than a company that produces tooth paste, because consumers can delay the purchase a new car, but will difficultly delaying purchasing tooth paste. So sectors like the food sector, utilities, health or pharma are typically considered non-cyclical goods. Opposing to these, we have the typical industrial sectors, also financials, technology and real estate as those whose investment projects are usually delayed in periods of low economic growth, therefore affecting the companies’ future earnings generation capabilities and consequently their current prices.

The argument underlying this investment idea is that during recessions it is preferable to hold stock from sectors that are less cyclical and therefore less exposed to the downturn, while in periods of strong growth it pays off to hold stocks that are more cyclical.

Therefore our results indicate that the six mentioned sectors present a cyclical nature. This fact is relevant as it allows portfolio managers to shift in and out of these sectors according to whatever perspective they have for the evolution of the economy. Economies near a bottom should lead to a portfolio sector rotation into these sectors, while investors in economies still in a downward trajectory should divest from them.

5. CONCLUSION

The central argument we proposed at the beginning of this dissertation was to study if there was more information on the stock market sector's regarding the evolution of the economy than the one that existed in an overall stock market index.

In order to do so, we applied a multivariate statistical technique called Discriminant Analysis that allowed us to find out if there was a combination of stock market sector's that indeed contained more information regarding the evolution of GDP than a global stock market index. According to our methodology we estimated 247 models and conclude that indeed there was information in the stock market sectors that we should not overlook. We could easily assess that when we looked for statistically significant discriminant functions in the models we generated.

At that time, we found that six of the analyzed sectors had at least one discriminant function that according to a Wilk's Lambda test was statistically significant. When we applied the same methodology to our overall stock market index, the S&P500, we found that the model had not generated any statistically significant discriminant function. From this point onwards, given that we did not have any statistically significant function, we proceeded our work with the sectorial models.

Comparing the results of the two streams of research we pursued, we can clearly conclude for the validity of our initial premise that there were stock market sectors' combinations that indeed had more discriminatory power over the real economy than a global stock market index.

Given that our initial database included information only until the end of 2007 and it had already became available information regarding the beginning of 2009, we decided to evaluate our model and see how it would predict GDP evolution for the 4 quarters of 2008 and the first quarter of 2009, based on the stock market evolution.

Our conclusion was that the model was right in two out of these five times, meaning a 40% hit ratio, above the minimum 33% threshold. Although this exercise has a limited scope due to the very short sample in which we used it, the fact that it spotted the

inversion is a good sign regarding its future accuracy, meaning that its results should be looked into with more detail.

Finally, we were also able to conclude on the cyclicity of the six sectors that belonged to our final model. Since the variables “Auto”, “Banks”, “Construction & Materials”, “Financial Services”, “Retail” and “Travel & Leisure” discriminated with accuracy the evolution of GDP, this indicated that these sectors have a cyclical nature. This fact is therefore quite important as it has implications over the decisions made by portfolio managers, who should invest in these sectors when they believe the economy will begin an upward trajectory and inversely divest from them when they believe the economic conditions will deteriorate.

So our results can be understood as a sign that it could make sense to further study the stock market sectors and maybe, using different techniques, direct further research in two directions.

First of all, it would be interesting to see if the relationships we have identified will maintain themselves robust over time. That is a question that unfortunately we will only have the possibility to answer once our historical database becomes more extensive. In the future it could then be possible to analyze if the evolution of the above mentioned sectors still retains the discriminatory power they have presented now.

Additionally we could also try to study, now that we have assessed that the sectors as a group have relevant information within, the reasons why some of these sectors tend to have a better role in discriminating the evolution of GDP.

The development of new statistical techniques and the world of possibilities that every day are unraveled by new algorithms and research regarding the treatment of comprehensive databases, can only make us hope that further research could bring additional relevant information in understanding the relationship between the stock markets and the real economy.

BIBLIOGRAPHY

ANNAERT, Jan, DE CEUSTER, Marc J. K. and VALCKX, Nico (2001), "*Financial Market Volatility: Informative In Predicting Recessions*", Bank of Finland Discussion Paper No. 14/2001. Available at SSRN: <http://ssrn.com/abstract=317921> or DOI: 10.2139/ssrn.317921

ANG, Andrew, PIAZZESI, Monika and WEI, Min (2006), "*What Does the Yield Curve Tell Us about Growth?*", Journal of Econometrics 131, 359-403.

ASHLEY, R., GRANGER, C. W. J., (1980), "*Advertising and aggregate consumption: an analysis of causality*", Econometrica 48, 1149-1168.

BARRO, R. (1990), "*The stock market and investment*", Review of Financial Studies, 3, pp. 115–131.

BASISTHA, Arabinda, KUROV, Alexander (2008) "*Macroeconomic Cycles and the Stock Market's Reaction to Monetary Policy*", available at SSRN: <http://ssrn.com/abstract=1092246>

BERNARD, H., Gerlach S. (1998), "*Does the term structure predict recessions? The international evidence,*" International Journal of Finance and Economics, vol. 3, pp. 195-215.

BERNANKE, Ben (1990), "*On the Predictive Power of Interest Rates and Interest Rate Spreads*" NBER Working Papers 3486, National Bureau of Economic Research, Inc.

BERNANKE, Ben, GERTLER, Mark, GILCHRIST, Simon (1996), "*The Financial Accelerator and the Flight to Quality*", Review of Economics and Statistics, 78, 1:1-15, 1996

BERNANKE, Ben, KUTTNER, Kenneth N. (2003), "*What explains the stock market's reaction to Federal Reserve policy?*", Staff Reports 174, Federal Reserve Bank of New York.

BERNANKE, Ben, GERTLER, Mark, GILCHRIST, Simon (1998), "*The Financial Accelerator in a Quantitative Business Cycle Framework*" NBER Working Papers 6455, National Bureau of Economic Research, Inc.

BINSWANGER, M. (1999), "*Stock Markets, Speculative Bubbles and Economic Growth*". Aldershot: Edward Elgar.

BINSWANGER, M. (2000), "*Stock market booms and real economic activity: Is this time different?*", International Review of Economics and Finance 9, pp. 387–415.

BLANCHARD, Olivier, RHEE, Changyong, SUMMERS, Lawrence (1993), "*The Stock Market, Profit, and Investment*", The Quarterly Journal of Economics, MIT Press, vol. 108(1), pages 115-36, February.

BODIE, Zvi, (1976), "*Common Stocks as a Hedge against Inflation*", Journal of Finance, Vol. 31, issue 2, pages 459-70

BRAINARD, William C., TOBIN, J. (1968), "*Pitfalls in Financial Modelling*", American Economic Review, LVIII, 2:99-122

BROWN, M. T., & TINSLEY, H. E. A. (1983), "*Discriminant analysis*", Journal of Leisure Research, 15 (4), 290-310

BROWN, Michael T. and WICKER, Lori R. (2000), "*Discriminant Analysis*", BROWN, Steven D. and TINSLEY, Howard E. A. (editors), "*Handbook of Applied Multivariate Statistics and Mathematical Modeling*", Elsevier Science & Technology Books

BUTTLER, Larry (1978), "*Recession? – A Market View*", Federal Reserve Bank of San Francisco Weekly Letter, December 15

CAMPBELL, John Y. (1998), "*Stock Returns and the Term Structure*", NBER Working Papers 1626, National Bureau of Economic Research, Inc.

CANOVA, Fabio, DE NICOLO', Gianni (1995), "*Stock returns and real activity: A structural approach*", European Economic Review, Elsevier, vol. 39(5), pages 981-1015, May.

CARROLL, Christopher D., FUHRER, Jeffrey C., WILCOX, David W. (1994), "*Does Consumer Sentiment Forecast Household Spending? If So, Why?*" American Economic Review, American Economic Association, vol. 84(5), pages 1397-1408, December

CHAUVET, Marcelle, POTTER, Simon (2005), “*Predicting a Recession: Evidence from the Yield Curve in the Presence of Structural Breaks*”, Journal of Forecasting 24, 77-103.

CHEN, Shiu-Sheng (2008), “*Predicting the Bear Stock Market: Macroeconomic Variables as Leading Indicators*” Available at SSRN: <http://ssrn.com/abstract=1106100>

CHOI, J. J., HAUSER, S. and KOPECKY, K. (1999): “*Does the stock market predict real activity? Time series evidence from the G-7 countries*”, Journal of Banking & Finance 23, pp. 1771–1792.

DAMODARAN, Aswath (1994), “*Damodaran on Valuation: Security Analysis for Investment and Corporate Finance*”, New York: John Wiley & Sons

DIEBOLD, Francis X., RUDEBUSCH, Glenn D. (1989), “*Scoring the Leading Indicators*” Journal of Business, University of Chicago Press, vol. 62(3), pages 369-91, July.

DOTSEY, Michael (1998), “*The Predictive Content of the Interest Rate Term Spread for Future Economic Growth*”, Federal Reserve Bank of Richmond Economic Quarterly, 84, 31-51.

DUONG, Manh Ha, SILIVERSTOV, Boriss (2006), “*On the role of the stock market for real economic activity: evidence for Europe*”, DIW Berlin, German Institute for Economic Research, Discussion Papers 599

EISENBEIS, Robert A. (1977), "*Pitfalls in the Application of Discriminant Analysis in Business, Finance, and Economics*", Journal of Finance, American Finance Association, vol. 32(3), pages 875-900, June.

ELWELL, Craig K (2006), "*Long Term Growth of the US Economy: Significance, Determinants and Policy*", Congressional Research Service – The Library of Congress, Report for Congress, May 2006

ESTRELLA, Arturo (2005), "*Why Does the Yield Curve Predict output and Inflation?*" The Economic Journal 115, 722-744.

ESTRELLA, Arturo (2005), "*The Yield Curve as a Leading Indicator: Frequently Asked Questions*" Federal Reserve Bank of New York, Capital Markets Web page.

ESTRELLA, Arturo, HARDOUVELIS, Gikas A., (1991), "*The Term Structure as a Predictor of Real Economic Activity*", The Journal of Finance, 46, 555-576.

ESTRELLA, A. and F. MISHKIN (1996), "*Predicting U.S. recessions: financial variables as leading indicators*", Federal Reserve Bank of New York Research paper No. 9609.

ESTRELLA, A., RODRIGUES, António P., SCHICH, Sebastian (2003), "*How stable is the predictive power of the yield curve? Evidence from Germany and the United States*" Review of Economics and Statistics 85: 629 - 644

FAMA, E. (1965), "*The Behavior of Stock-Market Prices*", The Journal of Business

FAMA, E. (1981), "*Stock returns, real activity, inflation, and money*", American Economic Review 71, 545–565.

FAMA, E. (1990), "*Stock returns, expected returns, and real activity*", Journal of Finance 45, pp. 1089–1108.

FAMA, E., SCHWERT, G. (1977), "*Asset Return and Inflation*", Journal of Financial Economics, 5, n.º 2, 115-146

FILARDO, Andrew J. (1999), "*How reliable are recession prediction models?*", Federal Reserve Bank of Kansas City - Economic Review, Second Quarter 1999

FILARDO, Andrew J. (2004), "*The 2001 US recession: what did recession prediction models tell us?*" BIS Working Papers 148, Bank for International Settlements.

FIXLER, Dennis J., GRIMM, Bruce T. (2008), "*The reliability of the GDP and GDI estimates*", Survey of Current Business, February 2008, pp. 16-32

FRENCH, Kenneth R., SCHWERT, G. William, STAMBAUGH, Robert F. (1987), "*Expected stock returns and volatility*", Journal of Financial Economics 19, 3-29.

FRIEDMAN, Benjamin M., KUTTNER, Kenneth N. (1994), "*Why Does the Paper-Bill Spread Predict Real Economic Activity?*" NBER Working Papers 3879, National Bureau of Economic Research, Inc.

FURLONG, Frederik T. (1989), "*The yield curve and recessions*", Federal Reserve Bank of San Francisco Weekly Letter, March 10

GERLACH, Stefan, BERNARD, Henri (1998), "*Does the Term Structure Predict Recessions? The International Evidence*". BIS Working Paper No. 37; CEPR Discussion Paper Series No. 1892. Available at SSRN: <http://ssrn.com/abstract=125508>

GESKE, Robert, ROLL, Richard (1983), "*The monetary and fiscal linkage between stock returns and inflation*", Journal of Finance 38, 1-33.

GRANGER, C. W. J. (1980), "*Testing for Causality: A Personal Viewpoint*", Journal of Economic Dynamics and Control, 329-52

HAIR, Joseph F. Hair, BLACK, Bill, RABIN, Barry, ANDERSON, Rolph E., TATHAM, Ronald L. (2005), "*Multivariate Data Analysis*", Prentice Hall (6th edition)

HALTMAIER, Jane (2008), "*Predicting Cycles in Economic Activity*", FRB International Finance Discussion Paper No. 926. Available at SSRN: <http://ssrn.com/abstract=1118978>

HARVEY, Campbell R. (1988), "*The real term structure and consumption growth*, "Journal of Financial Economics", vol. 22, pp. 305-333.

HARVEY, Campbell R. (1989), "*Forecasts of Economic Growth from the Bond and Stock Markets*", Financial Analysts Journal September/October, 38-45.

HARVEY, Campbell R. (1989), "*Does the Bond Market do Better than the Stock Market in Predicting Economic Growth?*", Available at SSRN: <http://ssrn.com/abstract=812927>

HAUBRICH, Joseph G., DOMBROSKY, Ann M. (1996), "*Predicting real growth using the yield curve*" Economic Review, Federal Reserve Bank of Cleveland, issue Q I, pages 26-35.

HUI, Guo (2002), "*Why are stock market returns correlated with future economic activities?*" Review, Federal Reserve Bank of St. Louis, issue Mar., pages 19-34.

KAUL, Gautam (1987), "*Stock returns and inflation: The role of the monetary sector*", Journal of Financial Economics 18, 253-276.

KAUL, Gautam (1990), "*Monetary regimes and the relation between stock returns and inflationary expectations*", Journal of Financial and Quantitative Analysis, 25, 307-321.

KESSEL, Reuben A. (1965), "*The cyclical behavior of the term structure of interest rates*", National Bureau of Economic Research (NBER) Occasional Paper N.º 91

KLECKA, W. (1975), "*Discriminant Analysis*" in NIE, N. Hull, H. JENKINS, J., STEINBRENNER, K. and BENT, D. (Eds.), SPSS: Statistical Package for the Social Sciences. New York, NY: McGraw-Hill Book Company

LEE, Bong-Soo (1992), "*Causal Relations among Stock Returns, Interest Rates, Real Activity, and Inflation*" *Journal of Finance*, American Finance Association, vol. 47(4), pages 1591-603, September.

MERIKAS, Andreas G., (2007) "*Stock Prices Response to Real Economic Variables: The Case of Germany*". EFMA 2002 London Meetings. Available at SSRN: <http://ssrn.com/abstract=314402> or DOI: 10.2139/ssrn.314402

MITCHELL, Wesley C. (1913), "*Business Cycles*", Berkeley: University of California Press

MONETA, Fabio (2005), "*Does the Yield Spread Predict Recessions in the Euro Area?*", *International Finance*, Vol. 8, No. 2, pp. 263-301, ECB Working Paper No. 294. Available at SSRN: <http://ssrn.com/abstract=487474>

MORCK, Randall, SHLEIFER, Andrei, VISHNY, Robert W. (1990), "*The Stock Market and Investment: Is the Market a Sideshow?*" *Brookings Papers on Economic Activity*, Economic Studies Program, The Brookings Institution, vol. 21(1990-2), pages 157-216.

MORRISON, Donald G. (1969), "*On the Interpretation of Discriminant Analysis*", *Journal of Marketing Research*, Vol. 6, No. 2 (May, 1969), pp. 156-163

MUNDELL, Robert (1963), "*Inflation and Real Interest*", *The Journal of Political Economy*, Vol. 71, No. 3 (Jun., 1963), pp. 280-283, The University of Chicago Press,

NELSON, Charles R (1976), "*Inflation and Rates of Return on Common Stocks*" Journal of Finance, American Finance Association, Vol. 31(2), pages 471-83, May.

PEIRO, A. (1996), "*Stock prices, production and interest rates: comparison of three European countries with the USA*", Empirical Economics 2, pp. 221–234.

PERRY, George L., SCHULTZE, Charles L. (1993), "*Was This Recession Different? Are They All Different*" Brookings Papers on Economic Activity, Economic Studies Program, The Brookings Institution, vol. 24(1993-1), pages 145-212.

POTERBA, James M. (2000), "*Stock Market Wealth and Consumption*", Journal of Economic Perspectives, American Economic Association, vol. 14(2), pages 99-118, Spring.

RITTER, Jay R. (2004), "*Economic Growth and Equity Returns*", EFA 2005 Moscow Meetings Paper. Available at SSRN: <http://ssrn.com/abstract=667507>

RUDEBUSCH, Glenn D., WILLIAMS, John C. (2007), "*Forecasting recessions: the puzzle of the enduring power of the yield curve*" Working Paper Series 2007-16, Federal Reserve Bank of San Francisco.

SCHWERT, G. William (1990), "*Stock Returns and Real Activity: A Century of Evidence*" NBER Working Papers 3296, National Bureau of Economic Research, Inc.

SHAH, Hemant (1989), "*Stock returns and anticipated aggregate real activity*", Graduate School of Business, University of Chicago.

STEVENS, J. (1996), "*Applied Multivariate Statistics for the Social Sciences*" (3rd ed.), Mahwah, NJ: Lawrence Erlbaum.

STOCK, James H., and WATSON, Mark W. (1989), "*New Indices of Coincident and Leading Indicators*", in NBER Macroeconomic Annual 4, edited by Oliver Blanchard and Stanley Fischer, 351-394.

STOCK, James H., WATSON, Mark W. (2003), "*Forecasting Output and Inflation: The Role of Asset Prices*", Journal of Economic Literature, American Economic Association, vol. 41(3), pages 788-829, September.

SHILLER, R. (2000), "*Irrational Exuberance*". Princeton University Press.

TAFFLER, R. J. (1982), "*Forecasting Company Failure in the UK Using Discriminant analysis and Financial Ratio Data*", Journal of the Royal Statistical Society. Series A (General), Vol. 145, No. 3 (1982), pp. 342-358

TOBIN, James (1961), "*Money, Capital and Other Stores of Value*", American Economic Review, 51, 2:26-37

WATSON, Mark (1991), "*Using econometric model to predict recessions.*" Federal Reserve Bank of Chicago Economic Perspectives 15: 14-25

WHITE, Eugene, MISHKIN, Frederic (2002), "*U.S. Stock Market Crashes and Their Aftermath: Implications for Monetary Policy*" Departmental Working Papers 200208, Rutgers University, Department of Economics.

WICKER, Lori R., BROWN, Michael T. (2000), “*Discriminant Analysis*”, in Handbook of Applied Multivariate Statistics and Mathematical Modeling, BROWN, Steven D., TINSLEY, Howard E. A. (editors), pp. 209-236, Elsevier Science & Technology Books

WILSON, Sandra, PRESS, S. James (1978), “*Choosing Between Logistic Regression and Discriminant Analysis*”, Journal of the American Statistical Association, Vol. 73, No. 364 (Dec., 1978), pp. 699-705

WRIGHT, Jonathan H. (2006), “*The Yield Curve and Predicting Recessions*”, FEDs Working Paper No. 2006-7. Available at SSRN: <http://ssrn.com/abstract=899538>

ANNEXES

Annex A: Average Core PCE evolution

Table A.1 shows the calculations made for the average core PCE evolution in the period analyzed.

Table A.1: Core PCE evolution in the period under analysis

Year	Personal consumption expenditures excluding food and energy	%
1991	83.29	-
1992	86.13	3.41%
1993	88.33	2.56%
1994	90.37	2.31%
1995	92.39	2.23%
1996	94.12	1.88%
1997	95.64	1.61%
1998	96.90	1.31%
1999	98.34	1.49%
2000	100.00	1.68%
2001	101.90	1.90%
2002	103.71	1.77%
2003	105.18	1.42%
2004	107.34	2.06%
2005	109.64	2.15%
2006	112.13	2.27%
2007	114.55	2.16%
1992- 2007		2.01%

Annex B: Assumptions of Discriminant Analysis (DA)

One of the assumptions implied by DA is the multivariate normality of the independent variables, which is accepted in the case that all variables independently follow a normal distribution. So in order to verify if our variables were normal, we did a One-Sample Kolmogorov-Smirnov Test. This is a test used to compare the probability distribution of a sample of data with a reference probability distribution.

In this test (unlike the majority of statistical tests) the null hypothesis implies that the variables indeed follow the normal distribution so if the Sig level is below the 0,05 threshold then the null hypotheses is confirmed and we can assume that the variables follow a normal distribution.

Table B.1: Normality of the variables: assumption check

One-Sample Kolmogorov-Smirnov Test *

Variables	N	Kolmogorov-Smirnov Z	Asymp. Sig. (2-tailed)	a. Test distribution is Normal.
GDP	64	0,4418	0,9898	Normal Variable
USAutoVAR	65	0,4637	0,9826	Normal Variable
USAutoVAR_Lag1Q	64	0,4557	0,9855	Normal Variable
USAutoVAR_Lag2Q	63	0,4625	0,9830	Normal Variable
USAutoVAR_Lag3Q	62	0,4614	0,9835	Normal Variable
USAutoVAR_Lag4Q	61	0,4973	0,9656	Normal Variable
USAutoVAR_Lag5Q	60	0,4990	0,9646	Normal Variable
USAutoVAR_Lag6Q	59	0,5540	0,9187	Normal Variable
USAutoVAR_Lag7Q	58	0,5098	0,9573	Normal Variable
USAutoVAR_Lag8Q	57	0,4691	0,9804	Normal Variable
USBanksVAR	65	0,6552	0,7839	Normal Variable
USBanksVAR_Lag1Q	64	0,6598	0,7766	Normal Variable
USBanksVAR_Lag2Q	63	0,5870	0,8811	Normal Variable
USBanksVAR_Lag3Q	62	0,5449	0,9279	Normal Variable
USBanksVAR_Lag4Q	61	0,5418	0,9308	Normal Variable
USBanksVAR_Lag5Q	60	0,5614	0,9110	Normal Variable
USBanksVAR_Lag6Q	59	0,5569	0,9158	Normal Variable
USBanksVAR_Lag7Q	58	0,5536	0,9191	Normal Variable
USBanksVAR_Lag8Q	57	0,5605	0,9119	Normal Variable
USBasRsVAR	65	0,4344	0,9916	Normal Variable
USBasRsVAR_Lag1Q	64	0,4626	0,9830	Normal Variable
USBasRsVAR_Lag2Q	63	0,5192	0,9503	Normal Variable
USBasRsVAR_Lag3Q	62	0,4871	0,9716	Normal Variable

USBasRsVAR_Lag4Q	61	0,4347	0,9916	Normal Variable
USBasRsVAR_Lag5Q	60	0,3874	0,9983	Normal Variable
USBasRsVAR_Lag6Q	59	0,3829	0,9986	Normal Variable
USBasRsVAR_Lag7Q	58	0,4364	0,9912	Normal Variable
USBasRsVAR_Lag8Q	57	0,4262	0,9934	Normal Variable
USChemVAR	65	1,0397	0,2299	Normal Variable
USChemVAR_Lag1Q	64	1,0388	0,2307	Normal Variable
USChemVAR_Lag2Q	63	1,0282	0,2410	Normal Variable
USChemVAR_Lag3Q	62	1,0246	0,2445	Normal Variable
USChemVAR_Lag4Q	61	1,0121	0,2572	Normal Variable
USChemVAR_Lag5Q	60	0,9880	0,2831	Normal Variable
USChemVAR_Lag6Q	59	0,9868	0,2844	Normal Variable
USChemVAR_Lag7Q	58	0,9591	0,3164	Normal Variable
USChemVAR_Lag8Q	57	1,0309	0,2384	Normal Variable
USConsMatVAR	65	0,4843	0,9731	Normal Variable
USConsMatVAR_Lag1Q	64	0,5161	0,9527	Normal Variable
USConsMatVAR_Lag2Q	63	0,5168	0,9521	Normal Variable
USConsMatVAR_Lag3Q	62	0,5150	0,9536	Normal Variable
USConsMatVAR_Lag4Q	61	0,5298	0,9416	Normal Variable
USConsMatVAR_Lag5Q	60	0,5360	0,9362	Normal Variable
USConsMatVAR_Lag6Q	59	0,5522	0,9206	Normal Variable
USConsMatVAR_Lag7Q	58	0,5286	0,9427	Normal Variable
USConsMatVAR_Lag8Q	57	0,5270	0,9441	Normal Variable
USFinSerVAR	65	0,7428	0,6393	Normal Variable
USFinSerVAR_Lag1Q	64	0,7088	0,6965	Normal Variable
USFinSerVAR_Lag2Q	63	0,6894	0,7288	Normal Variable
USFinSerVAR_Lag3Q	62	0,7260	0,6676	Normal Variable
USFinSerVAR_Lag4Q	61	0,7368	0,6494	Normal Variable
USFinSerVAR_Lag5Q	60	0,7647	0,6025	Normal Variable
USFinSerVAR_Lag6Q	59	0,7245	0,6701	Normal Variable
USFinSerVAR_Lag7Q	58	0,6916	0,7251	Normal Variable
USFinSerVAR_Lag8Q	57	0,7399	0,6441	Normal Variable
USFoodVAR	65	0,9294	0,3534	Normal Variable
USFoodVAR_Lag1Q	64	0,9971	0,2731	Normal Variable
USFoodVAR_Lag2Q	63	0,9847	0,2867	Normal Variable
USFoodVAR_Lag3Q	62	0,9822	0,2896	Normal Variable
USFoodVAR_Lag4Q	61	0,9761	0,2965	Normal Variable
USFoodVAR_Lag5Q	60	0,9522	0,3248	Normal Variable
USFoodVAR_Lag6Q	59	0,9309	0,3515	Normal Variable
USFoodVAR_Lag7Q	58	0,9261	0,3577	Normal Variable
USFoodVAR_Lag8Q	57	0,9124	0,3758	Normal Variable
USHealthVAR	65	0,8981	0,3954	Normal Variable
USHealthVAR_Lag1Q	64	0,8917	0,4043	Normal Variable
USHealthVAR_Lag2Q	63	0,8598	0,4506	Normal Variable
USHealthVAR_Lag3Q	62	0,8362	0,4864	Normal Variable
USHealthVAR_Lag4Q	61	0,8266	0,5016	Normal Variable
USHealthVAR_Lag5Q	60	0,7911	0,5587	Normal Variable
USHealthVAR_Lag6Q	59	0,7660	0,6003	Normal Variable
USHealthVAR_Lag7Q	58	0,7755	0,5845	Normal Variable
USHealthVAR_Lag8Q	57	0,8312	0,4943	Normal Variable
USIndVAR	65	0,7014	0,7089	Normal Variable
USIndVAR_Lag1Q	64	0,7605	0,6094	Normal Variable

USIndVAR_Lag2Q	63	0,8219	0,5090	Normal Variable
USIndVAR_Lag3Q	62	0,8191	0,5133	Normal Variable
USIndVAR_Lag4Q	61	0,8313	0,4942	Normal Variable
USIndVAR_Lag5Q	60	0,8113	0,5258	Normal Variable
USIndVAR_Lag6Q	59	0,8104	0,5272	Normal Variable
USIndVAR_Lag7Q	58	0,7763	0,5832	Normal Variable
USIndVAR_Lag8Q	57	0,7394	0,6450	Normal Variable
USInsVAR	65	0,8082	0,5308	Normal Variable
USInsVAR_Lag1Q	64	0,7663	0,5999	Normal Variable
USInsVAR_Lag2Q	63	0,8172	0,5165	Normal Variable
USInsVAR_Lag3Q	62	0,8579	0,4534	Normal Variable
USInsVAR_Lag4Q	61	0,8535	0,4600	Normal Variable
USInsVAR_Lag5Q	60	0,8260	0,5025	Normal Variable
USInsVAR_Lag6Q	59	0,8205	0,5112	Normal Variable
USInsVAR_Lag7Q	58	0,8083	0,5308	Normal Variable
USInsVAR_Lag8Q	57	0,8840	0,4152	Normal Variable
USMedVAR	65	0,4981	0,9652	Normal Variable
USMedVAR_Lag1Q	64	0,4957	0,9666	Normal Variable
USMedVAR_Lag2Q	63	0,5460	0,9267	Normal Variable
USMedVAR_Lag3Q	62	0,5148	0,9537	Normal Variable
USMedVAR_Lag4Q	61	0,5110	0,9565	Normal Variable
USMedVAR_Lag5Q	60	0,5009	0,9634	Normal Variable
USMedVAR_Lag6Q	59	0,5057	0,9602	Normal Variable
USMedVAR_Lag7Q	58	0,5113	0,9562	Normal Variable
USMedVAR_Lag8Q	57	0,5130	0,9550	Normal Variable
USOilVAR	65	0,5858	0,8826	Normal Variable
USOilVAR_Lag1Q	64	0,5791	0,8907	Normal Variable
USOilVAR_Lag2Q	63	0,6086	0,8526	Normal Variable
USOilVAR_Lag3Q	62	0,5481	0,9247	Normal Variable
USOilVAR_Lag4Q	61	0,5410	0,9316	Normal Variable
USOilVAR_Lag5Q	60	0,5379	0,9345	Normal Variable
USOilVAR_Lag6Q	59	0,5337	0,9382	Normal Variable
USOilVAR_Lag7Q	58	0,5823	0,8869	Normal Variable
USOilVAR_Lag8Q	57	0,5668	0,9050	Normal Variable
USPHGVAR	65	0,7320	0,6574	Normal Variable
USPHGVAR_Lag1Q	64	0,7477	0,6310	Normal Variable
USPHGVAR_Lag2Q	63	0,7709	0,5922	Normal Variable
USPHGVAR_Lag3Q	62	0,8184	0,5145	Normal Variable
USPHGVAR_Lag4Q	61	0,7659	0,6005	Normal Variable
USPHGVAR_Lag5Q	60	0,7092	0,6959	Normal Variable
USPHGVAR_Lag6Q	59	0,7387	0,6462	Normal Variable
USPHGVAR_Lag7Q	58	0,7718	0,5905	Normal Variable
USPHGVAR_Lag8Q	57	0,7529	0,6223	Normal Variable
USRetVAR	65	1,0812	0,1929	Normal Variable
USRetVAR_Lag1Q	64	1,0731	0,1997	Normal Variable
USRetVAR_Lag2Q	63	1,0681	0,2040	Normal Variable
USRetVAR_Lag3Q	62	1,0539	0,2166	Normal Variable
USRetVAR_Lag4Q	61	1,0178	0,2514	Normal Variable
USRetVAR_Lag5Q	60	0,9719	0,3013	Normal Variable
USRetVAR_Lag6Q	59	0,9269	0,3567	Normal Variable
USRetVAR_Lag7Q	58	0,8842	0,4149	Normal Variable
USRetVAR_Lag8Q	57	0,8704	0,4349	Normal Variable

USTechVAR	65	0,7796	0,5777	Normal Variable
USTechVAR_Lag1Q	64	0,7860	0,5671	Normal Variable
USTechVAR_Lag2Q	63	0,8560	0,4563	Normal Variable
USTechVAR_Lag3Q	62	0,8245	0,5048	Normal Variable
USTechVAR_Lag4Q	61	0,8031	0,5391	Normal Variable
USTechVAR_Lag5Q	60	0,8691	0,4368	Normal Variable
USTechVAR_Lag6Q	59	0,8332	0,4911	Normal Variable
USTechVAR_Lag7Q	58	0,8006	0,5432	Normal Variable
USTechVAR_Lag8Q	57	0,8376	0,4843	Normal Variable
USTelcoVAR	65	0,6038	0,8592	Normal Variable
USTelcoVAR_Lag1Q	64	0,5888	0,8787	Normal Variable
USTelcoVAR_Lag2Q	63	0,6425	0,8035	Normal Variable
USTelcoVAR_Lag3Q	62	0,6071	0,8547	Normal Variable
USTelcoVAR_Lag4Q	61	0,5954	0,8703	Normal Variable
USTelcoVAR_Lag5Q	60	0,5781	0,8919	Normal Variable
USTelcoVAR_Lag6Q	59	0,5613	0,9110	Normal Variable
USTelcoVAR_Lag7Q	58	0,5565	0,9162	Normal Variable
USTelcoVAR_Lag8Q	57	0,5256	0,9452	Normal Variable
USTRavelVAR	65	0,4641	0,9824	Normal Variable
USTRavelVAR_Lag1Q	64	0,4839	0,9733	Normal Variable
USTRavelVAR_Lag2Q	63	0,5319	0,9398	Normal Variable
USTRavelVAR_Lag3Q	62	0,5312	0,9404	Normal Variable
USTRavelVAR_Lag4Q	61	0,4998	0,9641	Normal Variable
USTRavelVAR_Lag5Q	60	0,4554	0,9856	Normal Variable
USTRavelVAR_Lag6Q	59	0,4626	0,9830	Normal Variable
USTRavelVAR_Lag7Q	58	0,4833	0,9736	Normal Variable
USTRavelVAR_Lag8Q	57	0,4210	0,9943	Normal Variable
USUtilVAR	65	0,9870	0,2842	Normal Variable
USUtilVAR_Lag1Q	64	0,9881	0,2830	Normal Variable
USUtilVAR_Lag2Q	63	0,9707	0,3027	Normal Variable
USUtilVAR_Lag3Q	62	0,9290	0,3540	Normal Variable
USUtilVAR_Lag4Q	61	0,9863	0,2850	Normal Variable
USUtilVAR_Lag5Q	60	0,9799	0,2921	Normal Variable
USUtilVAR_Lag6Q	59	0,9676	0,3063	Normal Variable
USUtilVAR_Lag7Q	58	0,9327	0,3492	Normal Variable
USUtilVAR_Lag8Q	57	0,9038	0,3876	Normal Variable

Another assumptions that DA implies is the lack of multicollinearity among independent variables. To verify this degree of multicollinearity we computed the correlation matrices only of our original variables; then for each of these original variables and the corresponding lags and finally for our final model. These results being in the next page and extend from Table B.2 to Table B.21.

Table B.2: Correlations between all “original” variables (lags excluded)

		USAutoVAR	USBanksVAR	USBasRsVAR	USChemVAR	USConsMatVAR	USFinSerVAR	USFoodVAR	USHealthVAR	USIndVAR	USInsVAR	USMedVAR	USOilVAR	USTelcoVAR	USPHGVAR	USRetVAR	USTechVAR	USTravelVAR	USUtilVAR
USAutoVAR	Pearson Correlation	1																	
	Sig. (2-tailed)																		
	N	64																	
USBanksVAR	Pearson Correlation	68,759%	1																
	Sig. (2-tailed)	0,000%																	
	N	64	64																
USBasRsVAR	Pearson Correlation	43,189%	30,225%	1															
	Sig. (2-tailed)	0,037%	1,521%																
	N	64	64	64															
USChemVAR	Pearson Correlation	45,922%	45,370%	73,967%	1														
	Sig. (2-tailed)	0,014%	0,017%	0,000%															
	N	64	64	64	64														
USConsMatVAR	Pearson Correlation	58,585%	60,456%	57,954%	68,009%	1													
	Sig. (2-tailed)	0,000%	0,000%	0,000%	0,000%														
	N	64	64	64	64	64													
USFinSerVAR	Pearson Correlation	62,465%	84,172%	23,171%	39,740%	54,431%	1												
	Sig. (2-tailed)	0,000%	0,000%	6,543%	0,115%	0,000%													
	N	64	64	64	64	64	64												
USFoodVAR	Pearson Correlation	32,692%	41,722%	27,157%	48,996%	57,294%	43,686%	1											
	Sig. (2-tailed)	0,837%	0,060%	2,995%	0,004%	0,000%	0,031%												
	N	64	64	64	64	64	64	64											
USHealthVAR	Pearson Correlation	26,056%	37,756%	9,130%	29,053%	35,450%	50,810%	68,599%	1										
	Sig. (2-tailed)	3,758%	0,210%	47,308%	1,986%	0,405%	0,002%	0,000%											
	N	64	64	64	64	64	64	64	64										
USIndVAR	Pearson Correlation	66,147%	62,555%	45,886%	58,632%	62,360%	78,470%	51,818%	49,222%	1									
	Sig. (2-tailed)	0,000%	0,000%	0,014%	0,000%	0,000%	0,000%	0,001%	0,004%										
	N	64	64	64	64	64	64	64	64	64									
USInsVAR	Pearson Correlation	55,463%	79,680%	23,374%	43,058%	62,885%	88,285%	61,379%	53,387%	68,862%	1								
	Sig. (2-tailed)	0,000%	0,000%	6,303%	0,038%	0,000%	0,000%	0,000%	0,001%	0,000%									
	N	64	64	64	64	64	64	64	64	64	64								
USMedVAR	Pearson Correlation	68,209%	54,835%	36,268%	50,847%	53,360%	71,054%	41,007%	44,646%	77,488%	58,882%	1							
	Sig. (2-tailed)	0,000%	0,000%	0,323%	0,002%	0,001%	0,000%	0,076%	0,022%	0,000%	0,000%								
	N	64	64	64	64	64	64	64	64	64	64	64							
USOilVAR	Pearson Correlation	34,121%	37,882%	36,697%	36,411%	47,569%	43,816%	19,185%	9,476%	50,590%	46,088%	31,624%	1						
	Sig. (2-tailed)	0,579%	0,202%	0,286%	0,310%	0,007%	0,029%	12,884%	45,640%	0,002%	0,013%	1,090%							
	N	64	64	64	64	64	64	64	64	64	64	64	64						
USTelcoVAR	Pearson Correlation	47,257%	48,269%	23,057%	32,223%	46,438%	56,781%	32,369%	37,707%	55,479%	52,719%	65,209%	29,943%	1					
	Sig. (2-tailed)	0,008%	0,005%	6,681%	0,941%	0,011%	0,000%	0,908%	0,213%	0,000%	0,001%	0,000%	1,623%						
	N	64	64	64	64	64	64	64	64	64	64	64	64	64					
USPHGVAR	Pearson Correlation	43,469%	53,737%	42,943%	62,712%	74,013%	55,974%	81,477%	62,460%	61,193%	67,871%	60,000%	30,790%	38,002%	1				
	Sig. (2-tailed)	0,033%	0,000%	0,040%	0,000%	0,000%	0,000%	0,000%	0,000%	0,000%	0,000%	0,000%	1,332%	0,195%					
	N	64	64	64	64	64	64	64	64	64	64	64	64	64	64				
USRetVAR	Pearson Correlation	62,446%	59,161%	33,365%	53,009%	57,864%	70,750%	45,609%	36,589%	72,120%	63,233%	77,245%	20,360%	46,581%	61,553%	1			
	Sig. (2-tailed)	0,000%	0,000%	0,705%	0,001%	0,000%	0,000%	0,015%	0,295%	0,000%	0,000%	0,000%	10,660%	0,010%	0,000%				
	N	64	64	64	64	64	64	64	64	64	64	64	64	64	64	64			
USTechVAR	Pearson Correlation	54,514%	39,589%	28,600%	36,468%	35,087%	65,761%	29,657%	37,424%	80,369%	48,414%	72,708%	36,499%	52,663%	36,640%	63,654%	1		
	Sig. (2-tailed)	0,000%	0,120%	2,196%	0,305%	0,447%	0,000%	1,733%	0,232%	0,000%	0,005%	0,000%	0,302%	0,001%	0,290%	0,000%			
	N	64	64	64	64	64	64	64	64	64	64	64	64	64	64	64	64		
USTravelVAR	Pearson Correlation	63,325%	63,249%	38,786%	53,485%	71,428%	69,520%	50,463%	41,951%	63,665%	65,575%	58,912%	37,355%	32,928%	64,690%	71,261%	44,722%	1	
	Sig. (2-tailed)	0,000%	0,000%	0,154%	0,001%	0,000%	0,000%	0,002%	0,056%	0,000%	0,000%	0,000%	0,236%	0,789%	0,000%	0,000%	0,021%		
	N	64	64	64	64	64	64	64	64	64	64	64	64	64	64	64	64	64	
USUtilVAR	Pearson Correlation	33,880%	41,415%	10,145%	13,642%	41,675%	43,014%	31,059%	26,321%	32,992%	47,805%	28,437%	52,492%	42,586%	39,901%	14,701%	21,242%	36,506%	1
	Sig. (2-tailed)	0,617%	0,067%	42,505%	28,242%	0,061%	0,039%	1,249%	3,561%	0,776%	0,006%	2,277%	0,001%	0,045%	0,109%	24,637%	9,196%	0,302%	
	N	64	64	64	64	64	64	64	64	64	64	64	64	64	64	64	64	64	64

Table B.3: Correlations between all variables (lags included) (for the sector Auto)

		USAutoVAR	USAutoVAR_La g1Q	USAutoVAR_La g2Q	USAutoVAR_La g3Q	USAutoVAR_La g4Q	USAutoVAR_La g5Q	USAutoVAR_La g6Q	USAutoVAR_La g7Q	USAutoVAR_La g8Q
USAutoVAR	Pearson Correlation	1								
	Sig. (2-tailed)									
	N	64								
USAutoVAR_Lag1Q	Pearson Correlation	100.000%	1							
	Sig. (2-tailed)	0.000%								
	N	63	63							
USAutoVAR_Lag2Q	Pearson Correlation	-3.339%	-3.339%	1						
	Sig. (2-tailed)	79.669%	79.669%							
	N	62	62	62						
USAutoVAR_Lag3Q	Pearson Correlation	3.120%	3.120%	-5.910%	1					
	Sig. (2-tailed)	81.136%	81.136%	65.094%						
	N	61	61	61	61					
USAutoVAR_Lag4Q	Pearson Correlation	-0.239%	-0.239%	2.416%	-7.364%	1				
	Sig. (2-tailed)	98.555%	98.555%	85.461%	57.605%					
	N	60	60	60	60	60				
USAutoVAR_Lag5Q	Pearson Correlation	-4.014%	-4.014%	1.393%	5.280%	-6.202%	1			
	Sig. (2-tailed)	76.280%	76.280%	91.658%	69.123%	64.073%				
	N	59	59	59	59	59	59			
USAutoVAR_Lag6Q	Pearson Correlation	-18.253%	-18.253%	-4.481%	0.924%	5.078%	-5.838%	1		
	Sig. (2-tailed)	17.024%	17.024%	73.836%	94.511%	70.503%	66.337%			
	N	58	58	58	58	58	58	58		
USAutoVAR_Lag7Q	Pearson Correlation	-3.117%	-3.117%	-18.934%	-3.741%	1.287%	4.394%	-5.700%	1	
	Sig. (2-tailed)	81.797%	81.797%	15.837%	78.231%	92.428%	74.553%	67.364%		
	N	57	57	57	57	57	57	57	57	
USAutoVAR_Lag8Q	Pearson Correlation	-12.406%	-12.406%	-1.685%	-17.641%	-2.026%	0.623%	3.933%	-6.200%	1
	Sig. (2-tailed)	36.230%	36.230%	90.190%	19.341%	88.216%	96.366%	77.348%	64.989%	
	N	56	56	56	56	56	56	56	56	56

Table B.4: Correlations between all variables (lags included) (for the sector Banks)

		USBanksVAR	USBanksVAR_L ag1Q	USBanksVAR_L ag2Q	USBanksVAR_L ag3Q	USBanksVAR_L ag4Q	USBanksVAR_L ag5Q	USBanksVAR_L ag6Q	USBanksVAR_L ag7Q	USBanksVAR_L ag8Q
USBanksVAR	Pearson Correlation	1								
	Sig. (2-tailed)									
	N	64								
USBanksVAR_Lag1Q	Pearson Correlation	0.732%	1							
	Sig. (2-tailed)	95.461%								
	N	63	63							
USBanksVAR_Lag2Q	Pearson Correlation	11.614%	-6.596%	1						
	Sig. (2-tailed)	36.868%	61.052%							
	N	62	62	62						
USBanksVAR_Lag3Q	Pearson Correlation	8.306%	10.041%	-9.661%	1					
	Sig. (2-tailed)	52.450%	44.131%	45.889%						
	N	61	61	61	61					
USBanksVAR_Lag4Q	Pearson Correlation	-4.874%	7.920%	9.708%	-9.914%	1				
	Sig. (2-tailed)	71.150%	54.750%	46.058%	45.107%					
	N	60	60	60	60	60				
USBanksVAR_Lag5Q	Pearson Correlation	10.836%	-7.254%	5.184%	8.966%	-10.208%	1			
	Sig. (2-tailed)	41.395%	58.509%	69.657%	49.949%	44.170%				
	N	59	59	59	59	59	59			
USBanksVAR_Lag6Q	Pearson Correlation	-4.156%	11.697%	-7.132%	0.549%	9.382%	-10.335%	1		
	Sig. (2-tailed)	75.675%	38.188%	59.473%	96.739%	48.359%	44.008%			
	N	58	58	58	58	58	58	58		
USBanksVAR_Lag7Q	Pearson Correlation	1.164%	-3.257%	13.792%	-6.806%	0.660%	9.869%	-14.456%	1	
	Sig. (2-tailed)	93.152%	80.991%	30.627%	61.493%	96.116%	46.515%	28.333%		
	N	57	57	57	57	57	57	57	57	
USBanksVAR_Lag8Q	Pearson Correlation	0.075%	0.345%	-4.639%	13.547%	-6.896%	0.311%	8.992%	-14.317%	1
	Sig. (2-tailed)	99.563%	97.984%	73.424%	31.949%	61.354%	98.185%	50.985%	29.249%	
	N	56	56	56	56	56	56	56	56	56

Table B.5: Correlations between all variables (lags included) (for the sector Basic Resources)

		USBasRsVAR	USBasRsVAR_L ag1Q	USBasRsVAR_L ag2Q	USBasRsVAR_L ag3Q	USBasRsVAR_L ag4Q	USBasRsVAR_L ag5Q	USBasRsVAR_L ag6Q	USBasRsVAR_L ag7Q	USBasRsVAR_L ag8Q
USBasRsVAR	Pearson Correlation	1								
	Sig. (2-tailed)									
	N	64								
USBasRsVAR_Lag1Q	Pearson Correlation	-14.491%	1							
	Sig. (2-tailed)	25.717%								
	N	63	63							
USBasRsVAR_Lag2Q	Pearson Correlation	2.720%	-14.499%	1						
	Sig. (2-tailed)	83.377%	26.085%							
	N	62	62	62						
USBasRsVAR_Lag3Q	Pearson Correlation	-22.731%	2.911%	-14.528%	1					
	Sig. (2-tailed)	7.811%	82.376%	26.393%						
	N	61	61	61	61					
USBasRsVAR_Lag4Q	Pearson Correlation	-1.775%	-22.640%	2.972%	-15.501%	1				
	Sig. (2-tailed)	89.289%	8.196%	82.166%	23.698%					
	N	60	60	60	60	60				
USBasRsVAR_Lag5Q	Pearson Correlation	-5.551%	-1.684%	-22.644%	2.595%	-16.058%	1			
	Sig. (2-tailed)	67.627%	89.929%	8.460%	84.532%	22.438%				
	N	59	59	59	59	59	59			
USBasRsVAR_Lag6Q	Pearson Correlation	10.015%	-5.363%	-1.652%	-23.879%	1.463%	-16.742%	1		
	Sig. (2-tailed)	45.446%	68.928%	90.203%	7.105%	91.322%	20.906%			
	N	58	58	58	58	58	58	58		
USBasRsVAR_Lag7Q	Pearson Correlation	-7.995%	9.819%	-5.447%	-0.522%	-22.877%	2.090%	-15.409%	1	
	Sig. (2-tailed)	55.439%	46.746%	68.737%	96.928%	8.696%	87.737%	25.245%		
	N	57	57	57	57	57	57	57	57	
USBasRsVAR_Lag8Q	Pearson Correlation	15.234%	-7.945%	9.837%	-5.722%	-0.816%	-23.043%	1.763%	-15.161%	1
	Sig. (2-tailed)	26.234%	56.050%	47.075%	67.531%	95.243%	8.752%	89.741%	26.466%	
	N	56	56	56	56	56	56	56	56	56

Table B.6: Correlations between all variables (lags included) (for the sector Chemicals)

		USChemVAR	USChemVAR_L ag1Q	USChemVAR_L ag2Q	USChemVAR_L ag3Q	USChemVAR_L ag4Q	USChemVAR_L ag5Q	USChemVAR_L ag6Q	USChemVAR_L ag7Q	USChemVAR_L ag8Q
USChemVAR	Pearson Correlation	1								
	Sig. (2-tailed)									
	N	64								
USChemVAR_Lag1Q	Pearson Correlation	-14.673%	1							
	Sig. (2-tailed)	25.116%								
	N	63	63							
USChemVAR_Lag2Q	Pearson Correlation	12.157%	-14.470%	1						
	Sig. (2-tailed)	34.656%	26.182%							
	N	62	62	62						
USChemVAR_Lag3Q	Pearson Correlation	-26.266%	12.598%	-16.143%	1					
	Sig. (2-tailed)	4.085%	33.331%	21.391%						
	N	61	61	61	61					
USChemVAR_Lag4Q	Pearson Correlation	26.537%	-26.128%	11.493%	-17.881%	1				
	Sig. (2-tailed)	4.044%	4.375%	38.190%	17.163%					
	N	60	60	60	60	60				
USChemVAR_Lag5Q	Pearson Correlation	-29.798%	26.778%	-27.038%	10.754%	-18.755%	1			
	Sig. (2-tailed)	2.189%	4.032%	3.835%	41.752%	15.490%				
	N	59	59	59	59	59	59			
USChemVAR_Lag6Q	Pearson Correlation	22.957%	-29.670%	25.869%	-28.905%	9.612%	-19.624%	1		
	Sig. (2-tailed)	8.301%	2.372%	4.991%	2.776%	47.289%	13.984%			
	N	58	58	58	58	58	58	58		
USChemVAR_Lag7Q	Pearson Correlation	-21.978%	23.085%	-30.246%	25.596%	-29.505%	9.420%	-20.153%	1	
	Sig. (2-tailed)	10.044%	8.404%	2.221%	5.463%	2.588%	48.582%	13.277%		
	N	57	57	57	57	57	57	57	57	
USChemVAR_Lag8Q	Pearson Correlation	32.269%	-22.152%	23.764%	-29.910%	26.327%	-29.299%	10.021%	-20.022%	1
	Sig. (2-tailed)	1.528%	10.084%	7.780%	2.513%	4.995%	2.842%	46.246%	13.900%	
	N	56	56	56	56	56	56	56	56	56

Table B.7: Correlations between all variables (lags included) (for the sector Construction & Materials)

		USConsMatVAR	USConsMatVAR_Lag1Q	USConsMatVAR_Lag2Q	USConsMatVAR_Lag3Q	USConsMatVAR_Lag4Q	USConsMatVAR_Lag5Q	USConsMatVAR_Lag6Q	USConsMatVAR_Lag7Q	USConsMatVAR_Lag8Q
USConsMatVAR	Pearson Correlation	1								
	Sig. (2-tailed)									
	N	64								
USConsMatVAR_Lag1Q	Pearson Correlation	-17.001%	1							
	Sig. (2-tailed)	18.282%								
	N	63	63							
USConsMatVAR_Lag2Q	Pearson Correlation	4.284%	-16.900%	1						
	Sig. (2-tailed)	74.095%	18.915%							
	N	62	62	62						
USConsMatVAR_Lag3Q	Pearson Correlation	-13.672%	4.617%	-16.932%	1					
	Sig. (2-tailed)	29.342%	72.387%	19.207%						
	N	61	61	61	61					
USConsMatVAR_Lag4Q	Pearson Correlation	5.089%	-11.285%	4.359%	-17.258%	1				
	Sig. (2-tailed)	69.938%	39.063%	74.086%	18.732%					
	N	60	60	60	60	60				
USConsMatVAR_Lag5Q	Pearson Correlation	-8.094%	6.305%	-11.437%	4.302%	-18.209%	1			
	Sig. (2-tailed)	54.227%	63.522%	38.841%	74.633%	16.750%				
	N	59	59	59	59	59	59			
USConsMatVAR_Lag6Q	Pearson Correlation	5.828%	-5.437%	6.005%	-11.750%	2.413%	-19.201%	1		
	Sig. (2-tailed)	66.389%	68.521%	65.433%	37.970%	85.729%	14.876%			
	N	58	58	58	58	58	58	58		
USConsMatVAR_Lag7Q	Pearson Correlation	-25.749%	4.653%	-5.295%	6.118%	-10.983%	2.774%	-18.518%	1	
	Sig. (2-tailed)	5.316%	73.106%	69.566%	65.122%	41.606%	83.771%	16.787%		
	N	57	57	57	57	57	57	57	57	
USConsMatVAR_Lag8Q	Pearson Correlation	20.287%	-28.587%	4.950%	-5.178%	7.751%	-10.452%	4.340%	-19.354%	1
	Sig. (2-tailed)	13.373%	3.270%	71.713%	70.470%	57.017%	44.331%	75.080%	15.295%	
	N	56	56	56	56	56	56	56	56	56

Table B.8: Correlations between all variables (lags included) (for the sector Financial Services)

		USFinSerVAR	USFinSerVAR_Lag1Q	USFinSerVAR_Lag2Q	USFinSerVAR_Lag3Q	USFinSerVAR_Lag4Q	USFinSerVAR_Lag5Q	USFinSerVAR_Lag6Q	USFinSerVAR_Lag7Q	USFinSerVAR_Lag8Q
USFinSerVAR	Pearson Correlation	1								
	Sig. (2-tailed)									
	N	64								
USFinSerVAR_Lag1Q	Pearson Correlation	1.588%	1							
	Sig. (2-tailed)	90.167%								
	N	63	63							
USFinSerVAR_Lag2Q	Pearson Correlation	3.746%	-4.930%	1						
	Sig. (2-tailed)	77.251%	70.357%							
	N	62	62	62						
USFinSerVAR_Lag3Q	Pearson Correlation	18.239%	0.601%	-8.105%	1					
	Sig. (2-tailed)	15.947%	96.334%	53.465%						
	N	61	61	61	61					
USFinSerVAR_Lag4Q	Pearson Correlation	-10.259%	18.846%	0.572%	-8.188%	1				
	Sig. (2-tailed)	43.537%	14.929%	96.540%	53.395%					
	N	60	60	60	60	60				
USFinSerVAR_Lag5Q	Pearson Correlation	-8.593%	-13.166%	17.227%	-0.554%	-8.244%	1			
	Sig. (2-tailed)	51.753%	32.021%	19.200%	96.679%	53.478%				
	N	59	59	59	59	59	59			
USFinSerVAR_Lag6Q	Pearson Correlation	15.563%	-6.880%	-11.739%	18.327%	-0.535%	-7.602%	1		
	Sig. (2-tailed)	24.338%	60.786%	38.015%	16.851%	96.822%	57.061%			
	N	58	58	58	58	58	58	58		
USFinSerVAR_Lag7Q	Pearson Correlation	-5.675%	17.542%	-5.822%	-11.212%	18.354%	-0.055%	-8.025%	1	
	Sig. (2-tailed)	67.500%	19.184%	66.706%	40.634%	17.173%	99.679%	55.289%		
	N	57	57	57	57	57	57	57	57	
USFinSerVAR_Lag8Q	Pearson Correlation	11.802%	-8.768%	15.633%	-7.146%	-11.272%	17.583%	0.719%	-7.546%	1
	Sig. (2-tailed)	38.634%	52.050%	24.992%	60.074%	40.817%	19.489%	95.806%	58.045%	
	N	56	56	56	56	56	56	56	56	56

Table B.9: Correlations between all variables (lags included) (for the sector Food)

		USFoodVAR	USFoodVAR_La g1Q	USFoodVAR_La g2Q	USFoodVAR_La g3Q	USFoodVAR_La g4Q	USFoodVAR_La g5Q	USFoodVAR_La g6Q	USFoodVAR_La g7Q	USFoodVAR_La g8Q
USFoodVAR	Pearson Correlation	1								
	Sig. (2-tailed)									
	N	64								
USFoodVAR_Lag1Q	Pearson Correlation	-.22.602%	1							
	Sig. (2-tailed)	7.488%								
	N	63	63							
USFoodVAR_Lag2Q	Pearson Correlation	26.174%	-.22.521%	1						
	Sig. (2-tailed)	3.988%	7.842%							
	N	62	62	62						
USFoodVAR_Lag3Q	Pearson Correlation	-.22.132%	26.786%	-.22.648%	1					
	Sig. (2-tailed)	8.650%	3.688%	7.923%						
	N	61	61	61	61					
USFoodVAR_Lag4Q	Pearson Correlation	28.378%	-.21.811%	26.729%	-.22.939%	1				
	Sig. (2-tailed)	2.800%	9.410%	3.896%	7.789%					
	N	60	60	60	60	60				
USFoodVAR_Lag5Q	Pearson Correlation	-.26.813%	28.450%	-.21.805%	26.791%	-.22.939%	1			
	Sig. (2-tailed)	4.005%	2.897%	9.711%	4.022%	8.052%				
	N	59	59	59	59	59	59			
USFoodVAR_Lag6Q	Pearson Correlation	32.584%	-.26.846%	28.438%	-.21.883%	26.776%	-.22.934%	1		
	Sig. (2-tailed)	1.256%	4.159%	3.050%	9.887%	4.214%	8.332%			
	N	58	58	58	58	58	58	58		
USFoodVAR_Lag7Q	Pearson Correlation	-.7754%	33.270%	-.26.961%	28.262%	-.22.172%	26.839%	-.23.006%	1	
	Sig. (2-tailed)	56.643%	1.145%	4.254%	3.316%	9.741%	4.353%	8.514%		
	N	57	57	57	57	57	57	57	57	
USFoodVAR_Lag8Q	Pearson Correlation	17.232%	-.7513%	33.245%	-.27.139%	28.170%	-.22.166%	26.824%	-.23.181%	1
	Sig. (2-tailed)	20.411%	58.211%	1.230%	4.305%	3.544%	10.063%	4.563%	8.560%	
	N	56	56	56	56	56	56	56	56	56

Table B.10: Correlations between all variables (lags included) (for the sector Health Care)

		USHealthVAR	USHealthVAR Lag1Q	USHealthVAR Lag2Q	USHealthVAR Lag3Q	USHealthVAR Lag4Q	USHealthVAR Lag5Q	USHealthVAR Lag6Q	USHealthVAR Lag7Q	USHealthVAR Lag8Q
USHealthVAR	Pearson Correlation	1								
	Sig. (2-tailed)									
	N	64								
USHealthVAR_Lag1Q	Pearson Correlation	4.975%	1							
	Sig. (2-tailed)	69.858%								
	N	63	63							
USHealthVAR_Lag2Q	Pearson Correlation	19.174%	5.082%	1						
	Sig. (2-tailed)	13.546%	69.485%							
	N	62	62	62						
USHealthVAR_Lag3Q	Pearson Correlation	3.932%	19.474%	5.170%	1					
	Sig. (2-tailed)	76.355%	13.260%	69.235%						
	N	61	61	61	61					
USHealthVAR_Lag4Q	Pearson Correlation	16.574%	4.855%	19.338%	5.218%	1				
	Sig. (2-tailed)	20.566%	71.259%	13.876%	69.215%					
	N	60	60	60	60	60				
USHealthVAR_Lag5Q	Pearson Correlation	8.010%	16.088%	5.516%	19.292%	5.348%	1			
	Sig. (2-tailed)	54.644%	22.352%	67.818%	14.322%	68.747%				
	N	59	59	59	59	59	59			
USHealthVAR_Lag6Q	Pearson Correlation	11.427%	8.004%	15.713%	5.501%	19.331%	5.307%	1		
	Sig. (2-tailed)	39.303%	55.033%	23.883%	68.172%	14.597%	69.235%			
	N	58	58	58	58	58	58	58		
USHealthVAR_Lag7Q	Pearson Correlation	15.331%	14.970%	10.053%	16.065%	5.201%	20.017%	5.499%	1	
	Sig. (2-tailed)	25.488%	26.636%	45.684%	23.255%	70.083%	13.546%	68.455%		
	N	57	57	57	57	57	57	57	57	
USHealthVAR_Lag8Q	Pearson Correlation	3.902%	12.577%	13.748%	9.867%	16.532%	4.662%	19.982%	7.064%	1
	Sig. (2-tailed)	77.527%	35.568%	31.231%	46.939%	22.336%	73.296%	13.980%	60.490%	
	N	56	56	56	56	56	56	56	56	56

Table B.11: Correlations between all variables (lags included) (for the sector Industrials)

		USIndVAR	USIndVAR_Lag 1Q	USIndVAR_Lag 2Q	USIndVAR_Lag 3Q	USIndVAR_Lag 4Q	USIndVAR_Lag 5Q	USIndVAR_Lag 6Q	USIndVAR_Lag 7Q	USIndVAR_Lag 8Q
USIndVAR	Pearson Correlation	1								
	Sig. (2-tailed)									
	N	64								
USIndVAR_Lag1Q	Pearson Correlation	-15.984%	1							
	Sig. (2-tailed)	21.079%								
	N	63	63							
USIndVAR_Lag2Q	Pearson Correlation	10.881%	-17.864%	1						
	Sig. (2-tailed)	39.987%	16.479%							
	N	62	62	62						
USIndVAR_Lag3Q	Pearson Correlation	1.424%	11.446%	-17.552%	1					
	Sig. (2-tailed)	91.326%	37.975%	17.604%						
	N	61	61	61	61					
USIndVAR_Lag4Q	Pearson Correlation	-7.136%	2.878%	13.074%	-18.074%	1				
	Sig. (2-tailed)	58.794%	82.720%	31.940%	16.697%					
	N	60	60	60	60	60				
USIndVAR_Lag5Q	Pearson Correlation	-11.887%	-7.395%	2.702%	13.138%	-18.015%	1			
	Sig. (2-tailed)	36.988%	57.787%	83.904%	32.127%	17.215%				
	N	59	59	59	59	59	59			
USIndVAR_Lag6Q	Pearson Correlation	21.638%	-11.371%	-6.830%	2.527%	12.687%	-17.956%	1		
	Sig. (2-tailed)	10.280%	39.537%	61.045%	85.064%	34.260%	17.743%			
	N	58	58	58	58	58	58	58		
USIndVAR_Lag7Q	Pearson Correlation	-9.289%	21.174%	-12.156%	-6.653%	3.142%	12.615%	-17.749%	1	
	Sig. (2-tailed)	49.192%	11.384%	36.770%	62.291%	81.650%	34.978%	18.656%		
	N	57	57	57	57	57	57	57	57	
USIndVAR_Lag8Q	Pearson Correlation	18.163%	-10.138%	20.617%	-11.969%	-6.032%	3.053%	12.935%	-18.129%	1
	Sig. (2-tailed)	18.034%	45.720%	12.739%	37.960%	65.879%	82.326%	34.204%	18.117%	
	N	56	56	56	56	56	56	56	56	56

Table B.12: Correlations between all variables (lags included) (for the sector Insurance)

		USInsVAR	USInsVAR_Lag 1Q	USInsVAR_Lag 2Q	USInsVAR_Lag 3Q	USInsVAR_Lag 4Q	USInsVAR_Lag 5Q	USInsVAR_Lag 6Q	USInsVAR_Lag 7Q	USInsVAR_Lag 8Q
USInsVAR	Pearson Correlation	1								
	Sig. (2-tailed)									
	N	64								
USInsVAR_Lag1Q	Pearson Correlation	0.186%	1							
	Sig. (2-tailed)	98.849%								
	N	63	63							
USInsVAR_Lag2Q	Pearson Correlation	10.026%	-3.778%	1						
	Sig. (2-tailed)	43.813%	77.065%							
	N	62	62	62						
USInsVAR_Lag3Q	Pearson Correlation	2.796%	8.206%	-4.363%	1					
	Sig. (2-tailed)	83.063%	52.955%	73.846%						
	N	61	61	61	61					
USInsVAR_Lag4Q	Pearson Correlation	3.612%	4.082%	8.756%	-4.008%	1				
	Sig. (2-tailed)	78.411%	75.679%	50.591%	76.107%					
	N	60	60	60	60	60				
USInsVAR_Lag5Q	Pearson Correlation	-29.815%	1.966%	3.026%	8.648%	-3.749%	1			
	Sig. (2-tailed)	2.182%	88.250%	82.005%	51.487%	77.800%				
	N	59	59	59	59	59	59			
USInsVAR_Lag6Q	Pearson Correlation	18.018%	-29.588%	3.120%	3.704%	8.404%	-3.421%	1		
	Sig. (2-tailed)	17.592%	2.413%	81.613%	78.251%	53.054%	79.880%			
	N	58	58	58	58	58	58	58		
USInsVAR_Lag7Q	Pearson Correlation	-4.585%	19.629%	-29.308%	2.979%	3.532%	8.636%	-3.642%	1	
	Sig. (2-tailed)	73.489%	14.336%	2.693%	82.591%	79.421%	52.296%	78.798%		
	N	57	57	57	57	57	57	57	57	
USInsVAR_Lag8Q	Pearson Correlation	9.747%	-7.020%	18.686%	-30.043%	3.352%	3.136%	9.114%	-3.381%	1
	Sig. (2-tailed)	47.484%	60.718%	16.789%	2.446%	80.627%	81.855%	50.412%	80.461%	
	N	56	56	56	56	56	56	56	56	56

Table B.13: Correlations between all variables (lags included) (for the sector Media)

		USMedVAR	USMedVAR_La g1Q	USMedVAR_La g2Q	USMedVAR_La g3Q	USMedVAR_La g4Q	USMedVAR_La g5Q	USMedVAR_La g6Q	USMedVAR_La g7Q	USMedVAR_La g8Q
USMedVAR	Pearson Correlation	1								
	Sig. (2-tailed)									
	N	64								
USMedVAR_Lag1Q	Pearson Correlation	0.266%	1							
	Sig. (2-tailed)	98.346%								
	N	63	63							
USMedVAR_Lag2Q	Pearson Correlation	12.941%	-2.376%	1						
	Sig. (2-tailed)	31.610%	85.455%							
	N	62	62	62						
USMedVAR_Lag3Q	Pearson Correlation	8.691%	11.221%	-4.310%	1					
	Sig. (2-tailed)	50.542%	38.926%	74.156%						
	N	61	61	61	61					
USMedVAR_Lag4Q	Pearson Correlation	8.422%	9.025%	11.565%	-4.189%	1				
	Sig. (2-tailed)	52.229%	49.284%	37.888%	75.063%					
	N	60	60	60	60	60				
USMedVAR_Lag5Q	Pearson Correlation	-19.589%	7.665%	8.308%	11.029%	-4.131%	1			
	Sig. (2-tailed)	13.704%	56.392%	53.158%	40.566%	75.607%				
	N	59	59	59	59	59	59			
USMedVAR_Lag6Q	Pearson Correlation	21.377%	-17.343%	10.497%	10.468%	10.986%	-3.305%	1		
	Sig. (2-tailed)	10.713%	19.295%	43.293%	43.422%	41.166%	80.548%			
	N	58	58	58	58	58	58	58		
USMedVAR_Lag7Q	Pearson Correlation	-4.205%	25.328%	-15.131%	12.710%	7.193%	11.873%	-5.527%	1	
	Sig. (2-tailed)	75.829%	5.964%	26.562%	35.058%	59.832%	38.346%	68.577%		
	N	56	56	56	56	56	56	56	56	
USMedVAR_Lag8Q	Pearson Correlation	40.312%	-3.836%	26.097%	-14.937%	12.688%	7.334%	11.620%	-11.068%	1
	Sig. (2-tailed)	0.228%	78.099%	5.430%	27.639%	35.595%	59.463%	39.821%	42.561%	
	N	55	55	55	55	55	55	55	54	55

Table B.14: Correlations between all variables (lags included) (for the sector Oil and Gas)

		USOiVAR	USOiVAR_Lag 1Q	USOiVAR_Lag 2Q	USOiVAR_Lag 3Q	USOiVAR_Lag 4Q	USOiVAR_Lag 5Q	USOiVAR_Lag 6Q	USOiVAR_Lag 7Q	USOiVAR_Lag 8Q
USOiVAR	Pearson Correlation	1								
	Sig. (2-tailed)									
	N	64								
USOiVAR_Lag1Q	Pearson Correlation	-5.602%	1							
	Sig. (2-tailed)	66.279%								
	N	63	63							
USOiVAR_Lag2Q	Pearson Correlation	15.449%	-5.241%	1						
	Sig. (2-tailed)	23.056%	68.578%							
	N	62	62	62						
USOiVAR_Lag3Q	Pearson Correlation	3.285%	17.932%	-5.578%	1					
	Sig. (2-tailed)	80.154%	16.672%	66.939%						
	N	61	61	61	61					
USOiVAR_Lag4Q	Pearson Correlation	-7.186%	6.907%	17.731%	-7.839%	1				
	Sig. (2-tailed)	58.534%	60.001%	17.532%	55.163%					
	N	60	60	60	60	60				
USOiVAR_Lag5Q	Pearson Correlation	12.256%	-7.530%	6.938%	17.986%	-7.765%	1			
	Sig. (2-tailed)	35.510%	57.083%	60.158%	17.284%	55.882%				
	N	59	59	59	59	59	59			
USOiVAR_Lag6Q	Pearson Correlation	-12.537%	15.836%	-8.108%	5.141%	15.421%	-7.718%	1		
	Sig. (2-tailed)	34.839%	23.511%	54.517%	70.154%	24.776%	56.471%			
	N	58	58	58	58	58	58	58		
USOiVAR_Lag7Q	Pearson Correlation	13.042%	-15.675%	16.418%	-6.494%	8.019%	15.467%	-5.440%	1	
	Sig. (2-tailed)	33.356%	24.424%	22.233%	63.126%	55.321%	25.063%	68.777%		
	N	57	57	57	57	57	57	57	57	
USOiVAR_Lag8Q	Pearson Correlation	-13.756%	13.409%	-15.697%	16.473%	-6.718%	8.025%	15.603%	-5.419%	1
	Sig. (2-tailed)	31.202%	32.449%	24.795%	22.504%	62.278%	55.655%	25.084%	69.160%	
	N	56	56	56	56	56	56	56	56	56

Table B.15: Correlations between all variables (lags included) (for the sector Producer and Household Goods)

		USPHGVAR	USPHGVAR_La g1Q	USPHGVAR_La g2Q	USPHGVAR_La g3Q	USPHGVAR_La g4Q	USPHGVAR_La g5Q	USPHGVAR_La g6Q	USPHGVAR_La g7Q	USPHGVAR_La g8Q
USPHGVAR	Pearson Correlation	1								
	Sig. (2-tailed)									
	N	64								
USPHGVAR_Lag1Q	Pearson Correlation	-15.446%	1							
	Sig. (2-tailed)	22.678%								
	N	63	63							
USPHGVAR_Lag2Q	Pearson Correlation	10.133%	-15.488%	1						
	Sig. (2-tailed)	43.323%	22.937%							
	N	62	62	62						
USPHGVAR_Lag3Q	Pearson Correlation	-6.300%	10.748%	-15.519%	1					
	Sig. (2-tailed)	62.957%	40.968%	23.237%						
	N	61	61	61	61					
USPHGVAR_Lag4Q	Pearson Correlation	22.885%	-6.838%	10.779%	-15.400%	1				
	Sig. (2-tailed)	7.861%	60.368%	41.235%	24.008%					
	N	60	60	60	60	60				
USPHGVAR_Lag5Q	Pearson Correlation	-19.395%	22.716%	-6.823%	10.907%	-15.531%	1			
	Sig. (2-tailed)	14.105%	8.359%	60.764%	41.092%	24.016%				
	N	59	59	59	59	59	59			
USPHGVAR_Lag6Q	Pearson Correlation	14.075%	-18.301%	22.780%	-7.261%	11.348%	-15.306%	1		
	Sig. (2-tailed)	29.196%	16.910%	8.546%	58.807%	39.634%	25.136%			
	N	58	58	58	58	58	58	58		
USPHGVAR_Lag7Q	Pearson Correlation	-14.303%	15.566%	-18.393%	22.535%	-6.941%	11.678%	-16.358%	1	
	Sig. (2-tailed)	28.852%	24.758%	17.082%	9.191%	60.791%	38.700%	22.404%		
	N	57	57	57	57	57	57	57	57	
USPHGVAR_Lag8Q	Pearson Correlation	24.184%	-16.005%	15.663%	-18.125%	22.254%	-7.303%	12.883%	-15.536%	1
	Sig. (2-tailed)	7.254%	23.869%	24.900%	18.128%	9.925%	59.271%	34.402%	25.290%	
	N	56	56	56	56	56	56	56	56	56

Table B.16: Correlations between all variables (lags included) (for the sector Retail)

		USRetVAR	USRetVAR_Lag 1Q	USRetVAR_Lag 2Q	USRetVAR_Lag 3Q	USRetVAR_Lag 4Q	USRetVAR_Lag 5Q	USRetVAR_Lag 6Q	USRetVAR_Lag 7Q	USRetVAR_Lag 8Q
USRetVAR	Pearson Correlation	1								
	Sig. (2-tailed)									
	N	64								
USRetVAR_Lag1Q	Pearson Correlation	0.443%	1							
	Sig. (2-tailed)	97.249%								
	N	63	63							
USRetVAR_Lag2Q	Pearson Correlation	-13.685%	-0.695%	1						
	Sig. (2-tailed)	28.887%	95.728%							
	N	62	62	62						
USRetVAR_Lag3Q	Pearson Correlation	13.006%	-14.652%	-1.700%	1					
	Sig. (2-tailed)	31.778%	25.985%	89.653%						
	N	61	61	61	61					
USRetVAR_Lag4Q	Pearson Correlation	19.851%	12.915%	-14.933%	-1.846%	1				
	Sig. (2-tailed)	12.840%	32.537%	25.479%	88.869%					
	N	60	60	60	60	60				
USRetVAR_Lag5Q	Pearson Correlation	-14.881%	20.050%	13.121%	-14.898%	-1.827%	1			
	Sig. (2-tailed)	26.064%	12.785%	32.188%	26.010%	89.074%				
	N	59	59	59	59	59	59			
USRetVAR_Lag6Q	Pearson Correlation	0.197%	-14.807%	20.355%	13.299%	-14.877%	-1.841%	1		
	Sig. (2-tailed)	98.828%	26.733%	12.539%	31.964%	26.504%	89.090%			
	N	58	58	58	58	58	58	58		
USRetVAR_Lag7Q	Pearson Correlation	0.915%	0.270%	-14.826%	20.491%	13.311%	-14.886%	-1.851%	1	
	Sig. (2-tailed)	94.617%	98.410%	27.106%	12.626%	32.360%	26.911%	89.132%		
	N	57	57	57	57	57	57	57	57	
USRetVAR_Lag8Q	Pearson Correlation	12.040%	-4.950%	-9.438%	-18.542%	26.367%	4.199%	-15.639%	3.399%	1
	Sig. (2-tailed)	37.676%	71.712%	48.898%	17.127%	4.959%	75.861%	24.971%	80.358%	
	N	56	56	56	56	56	56	56	56	56

Table B.17: Correlations between all variables (lags included) (for the sector Technologies)

		USTechVAR	USTechVAR_La g1Q	USTechVAR_La g2Q	USTechVAR_La g3Q	USTechVAR_La g4Q	USTechVAR_La g5Q	USTechVAR_La g6Q	USTechVAR_La g7Q	USTechVAR_La g8Q
USTechVAR	Pearson Correlation	1								
	Sig. (2-tailed)									
	N	64								
USTechVAR_Lag1Q	Pearson Correlation	0.779%	1							
	Sig. (2-tailed)	95.169%								
	N	63	63							
USTechVAR_Lag2Q	Pearson Correlation	13.181%	0.257%	1						
	Sig. (2-tailed)	30.714%	98.420%							
	N	62	62	62						
USTechVAR_Lag3Q	Pearson Correlation	5.186%	13.891%	0.348%	1					
	Sig. (2-tailed)	69.145%	28.568%	97.874%						
	N	61	61	61	61					
USTechVAR_Lag4Q	Pearson Correlation	-6.105%	6.340%	14.125%	0.182%	1				
	Sig. (2-tailed)	64.311%	63.032%	28.171%	98.900%					
	N	60	60	60	60	60				
USTechVAR_Lag5Q	Pearson Correlation	-5.712%	-7.002%	6.200%	14.266%	0.455%	1			
	Sig. (2-tailed)	66.741%	59.821%	64.086%	28.110%	97.269%				
	N	59	59	59	59	59	59			
USTechVAR_Lag6Q	Pearson Correlation	20.990%	-5.410%	-6.936%	6.144%	14.163%	0.561%	1		
	Sig. (2-tailed)	11.379%	68.668%	60.491%	64.681%	28.892%	96.667%			
	N	58	58	58	58	58	58	58		
USTechVAR_Lag7Q	Pearson Correlation	-0.365%	21.905%	-5.309%	-7.035%	5.962%	14.348%	0.491%	1	
	Sig. (2-tailed)	97.853%	10.161%	69.492%	60.308%	65.954%	28.699%	97.108%		
	N	57	57	57	57	57	57	57	57	
USTechVAR_Lag8Q	Pearson Correlation	12.102%	-2.450%	21.684%	-5.023%	-6.385%	5.441%	14.689%	0.876%	1
	Sig. (2-tailed)	37.430%	85.774%	10.844%	71.313%	64.013%	69.043%	28.000%	94.891%	
	N	56	56	56	56	56	56	56	56	56

Table B.18: Correlations between all variables (lags included) (for the sector Telecoms)

		USTelcoVAR	USTelcoVAR_L ag1Q	USTelcoVAR_L ag2Q	USTelcoVAR_L ag3Q	USTelcoVAR_L ag4Q	USTelcoVAR_L ag5Q	USTelcoVAR_L ag6Q	USTelcoVAR_L ag7Q	USTelcoVAR_L ag8Q
USTelcoVAR	Pearson Correlation	1								
	Sig. (2-tailed)									
	N	64								
USTelcoVAR_Lag1Q	Pearson Correlation	6.272%	1							
	Sig. (2-tailed)	62.534%								
	N	63	63							
USTelcoVAR_Lag2Q	Pearson Correlation	30.751%	4.746%	1						
	Sig. (2-tailed)	1.505%	71.411%							
	N	62	62	62						
USTelcoVAR_Lag3Q	Pearson Correlation	-2.613%	31.686%	4.848%	1					
	Sig. (2-tailed)	84.158%	1.285%	71.061%						
	N	61	61	61	61					
USTelcoVAR_Lag4Q	Pearson Correlation	8.192%	-1.052%	32.465%	4.772%	1				
	Sig. (2-tailed)	53.380%	93.639%	1.138%	71.733%					
	N	60	60	60	60	60				
USTelcoVAR_Lag5Q	Pearson Correlation	12.223%	9.994%	-0.912%	32.471%	4.373%	1			
	Sig. (2-tailed)	35.639%	45.139%	94.537%	1.210%	74.228%				
	N	59	59	59	59	59	59			
USTelcoVAR_Lag6Q	Pearson Correlation	-2.931%	14.031%	10.581%	-1.011%	32.098%	3.896%	1		
	Sig. (2-tailed)	82.712%	29.350%	42.924%	93.997%	1.402%	77.155%			
	N	58	58	58	58	58	58	58		
USTelcoVAR_Lag7Q	Pearson Correlation	2.696%	-0.048%	15.129%	10.204%	-1.584%	31.081%	3.051%	1	
	Sig. (2-tailed)	84.222%	99.719%	26.127%	45.009%	90.692%	1.861%	82.175%		
	N	57	57	57	57	57	57	57	57	
USTelcoVAR_Lag8Q	Pearson Correlation	5.905%	2.173%	-0.250%	15.182%	10.464%	-0.730%	31.373%	3.415%	1
	Sig. (2-tailed)	66.550%	87.368%	98.540%	26.401%	44.278%	95.742%	1.854%	80.267%	
	N	56	56	56	56	56	56	56	56	56

Table B.19: Correlations between all variables (lags included) (for the sector Travel)

		UStTravelVAR	UStTravelVAR_Lag1Q	UStTravelVAR_Lag2Q	UStTravelVAR_Lag3Q	UStTravelVAR_Lag4Q	UStTravelVAR_Lag5Q	UStTravelVAR_Lag6Q	UStTravelVAR_Lag7Q	UStTravelVAR_Lag8Q
UStTravelVAR	Pearson Correlation	1								
	Sig. (2-tailed)									
	N	64								
UStTravelVAR_Lag1Q	Pearson Correlation	-1.636%	1							
	Sig. (2-tailed)	89.872%								
	N	63	63							
UStTravelVAR_Lag2Q	Pearson Correlation	-22.338%	-3.123%	1						
	Sig. (2-tailed)	8.095%	80.958%							
	N	62	62	62						
UStTravelVAR_Lag3Q	Pearson Correlation	-12.296%	-21.591%	-2.240%	1					
	Sig. (2-tailed)	34.514%	9.468%	86.396%						
	N	61	61	61	61					
UStTravelVAR_Lag4Q	Pearson Correlation	0.379%	-12.510%	-21.850%	-2.174%	1				
	Sig. (2-tailed)	97.705%	34.089%	9.349%	86.902%					
	N	60	60	60	60	60				
UStTravelVAR_Lag5Q	Pearson Correlation	-5.727%	-0.123%	-13.076%	-21.622%	-2.216%	1			
	Sig. (2-tailed)	66.656%	99.260%	32.357%	10.002%	86.768%				
	N	59	59	59	59	59	59			
UStTravelVAR_Lag6Q	Pearson Correlation	2.020%	-4.322%	1.246%	-14.147%	-21.647%	-1.748%	1		
	Sig. (2-tailed)	88.034%	74.735%	92.603%	28.946%	10.265%	89.638%			
	N	58	58	58	58	58	58	58		
UStTravelVAR_Lag7Q	Pearson Correlation	-7.379%	1.921%	-4.459%	1.324%	-14.157%	-21.706%	-1.651%	1	
	Sig. (2-tailed)	58.543%	88.723%	74.188%	92.211%	29.352%	10.484%	90.297%		
	N	57	57	57	57	57	57	57	57	
UStTravelVAR_Lag8Q	Pearson Correlation	14.623%	-8.023%	1.400%	-4.108%	1.288%	-14.371%	-21.334%	-1.699%	1
	Sig. (2-tailed)	28.219%	55.669%	91.842%	76.369%	92.493%	29.067%	11.440%	90.111%	
	N	56	56	56	56	56	56	56	56	56

Table B.20: Correlations between all variables (lags included) (for the sector Utilities)

		USUtilVAR	USUtilVAR_Lag1Q	USUtilVAR_Lag2Q	USUtilVAR_Lag3Q	USUtilVAR_Lag4Q	USUtilVAR_Lag5Q	USUtilVAR_Lag6Q	USUtilVAR_Lag7Q	USUtilVAR_Lag8Q
USUtilVAR	Pearson Correlation	1								
	Sig. (2-tailed)									
	N	64								
USUtilVAR_Lag1Q	Pearson Correlation	19.236%	1							
	Sig. (2-tailed)	13.095%								
	N	63	63							
USUtilVAR_Lag2Q	Pearson Correlation	15.630%	21.340%	1						
	Sig. (2-tailed)	22.508%	9.584%							
	N	62	62	62						
USUtilVAR_Lag3Q	Pearson Correlation	3.860%	16.508%	21.567%	1					
	Sig. (2-tailed)	76.775%	20.359%	9.505%						
	N	61	61	61	61					
USUtilVAR_Lag4Q	Pearson Correlation	-24.309%	2.985%	16.833%	21.755%	1				
	Sig. (2-tailed)	6.127%	82.087%	19.857%	9.497%					
	N	60	60	60	60	60				
USUtilVAR_Lag5Q	Pearson Correlation	-13.179%	-22.394%	2.013%	16.569%	22.622%	1			
	Sig. (2-tailed)	31.973%	8.818%	87.973%	20.979%	8.492%				
	N	59	59	59	59	59	59			
USUtilVAR_Lag6Q	Pearson Correlation	-5.936%	-11.246%	-22.627%	1.654%	17.262%	21.398%	1		
	Sig. (2-tailed)	65.806%	40.061%	8.764%	90.192%	19.506%	10.677%			
	N	58	58	58	58	58	58	58		
USUtilVAR_Lag7Q	Pearson Correlation	-17.152%	-4.977%	-11.495%	-22.868%	1.924%	16.687%	20.917%	1	
	Sig. (2-tailed)	20.205%	71.315%	39.453%	8.708%	88.703%	21.474%	11.840%		
	N	57	57	57	57	57	57	57	57	
USUtilVAR_Lag8Q	Pearson Correlation	0.499%	-16.138%	-5.358%	-11.773%	-22.628%	0.987%	16.003%	20.601%	1
	Sig. (2-tailed)	97.087%	23.474%	69.489%	38.752%	9.355%	94.247%	23.873%	12.770%	
	N	56	56	56	56	56	56	56	56	56

Table B.21: Correlations between all variables included in the final model

[illegible]

*, Correlation is significant at the 0.05 level (2-tailed).

Annex C: Results of the estimation of 18 models described in section “4.1.1. Models estimated in Section A: Finding the most interesting sectors”

Our Discriminant Functions are defined by the Standardized Canonical Discriminant Function Coefficients we now present. These have the same purpose of the beta weights in typical multiple regressions, therefore indicating the relative importance of the discriminator variables in discriminating the dependent variable.

Table C.1: Standardized Canonical Discriminant Function Coefficients

Variables	Function	
	1	2
USAutoVAR	0,333	-0,414
USAutoVAR_Lag2Q	0,455	0,159
USAutoVAR_Lag3Q	0,756	0,345
USAutoVAR_Lag4Q	0,635	0,185
USAutoVAR_Lag5Q	0,459	-0,133
USAutoVAR_Lag6Q	0,093	0,536
USAutoVAR_Lag7Q	0,463	-0,461
USAutoVAR_Lag8Q	0,699	-0,181

Variables	Function	
	1	2
USBanksVAR	-0,168	0,472
USBanksVAR_Lag1Q	-0,107	-0,415
USBanksVAR_Lag2Q	0,445	-0,282
USBanksVAR_Lag3Q	0,500	-0,361
USBanksVAR_Lag4Q	0,271	0,498
USBanksVAR_Lag5Q	0,260	-0,261
USBanksVAR_Lag6Q	0,292	0,391
USBanksVAR_Lag7Q	0,981	0,135
USBanksVAR_Lag8Q	0,105	0,245

Variables	Function	
	1	2
USBasRsVAR	0,012	0,624
USBasRsVAR_Lag1Q	0,502	-0,084
USBasRsVAR_Lag2Q	0,263	0,529
USBasRsVAR_Lag3Q	0,746	-0,047
USBasRsVAR_Lag4Q	0,062	0,244
USBasRsVAR_Lag5Q	0,675	0,493
USBasRsVAR_Lag6Q	0,757	0,034
USBasRsVAR_Lag7Q	0,155	-0,318
USBasRsVAR_Lag8Q	0,446	-0,086

Variables	Function	
-----------	----------	--

	1	2
USChemVAR	0,158	0,087
USChemVAR_Lag1Q	-0,013	0,784
USChemVAR_Lag2Q	0,595	0,045
USChemVAR_Lag3Q	0,527	0,624
USChemVAR_Lag4Q	0,216	-0,361
USChemVAR_Lag5Q	0,337	0,095
USChemVAR_Lag6Q	0,381	0,320
USChemVAR_Lag7Q	0,918	-0,391
USChemVAR_Lag8Q	0,196	0,130

Variables	Function	
	1	2
USConsMatVAR	0,096	0,498
USConsMatVAR_Lag1Q	0,262	0,111
USConsMatVAR_Lag2Q	0,374	0,835
USConsMatVAR_Lag3Q	0,579	0,615
USConsMatVAR_Lag4Q	0,659	-0,204
USConsMatVAR_Lag5Q	0,107	0,230
USConsMatVAR_Lag6Q	0,630	0,271
USConsMatVAR_Lag7Q	1,050	-0,052
USConsMatVAR_Lag8Q	0,165	-0,444

Variables	Function	
	1	2
USFinSerVAR	0,179	0,320
USFinSerVAR_Lag1Q	-0,395	0,052
USFinSerVAR_Lag2Q	0,548	-0,190
USFinSerVAR_Lag3Q	0,401	-0,151
USFinSerVAR_Lag4Q	0,427	0,477
USFinSerVAR_Lag5Q	-0,030	-0,220
USFinSerVAR_Lag6Q	-0,004	0,627
USFinSerVAR_Lag7Q	0,798	-0,023
USFinSerVAR_Lag8Q	-0,206	0,436

Variables	Function	
	1	2
USFoodVAR	-0,339	-0,550
USFoodVAR_Lag1Q	0,070	0,044
USFoodVAR_Lag2Q	-0,232	0,164
USFoodVAR_Lag3Q	0,302	0,516
USFoodVAR_Lag4Q	0,224	-0,139
USFoodVAR_Lag5Q	-0,145	0,479
USFoodVAR_Lag6Q	0,566	0,053
USFoodVAR_Lag7Q	0,829	-0,519
USFoodVAR_Lag8Q	0,616	0,139

Variables	Function	
	1	2
USHealthVAR	0,106	0,848
USHealthVAR_Lag1Q	0,053	-0,130

USHealthVAR_Lag2Q	-0,017	0,163
USHealthVAR_Lag3Q	0,044	-0,270
USHealthVAR_Lag4Q	0,711	-0,459
USHealthVAR_Lag5Q	-0,264	-0,113
USHealthVAR_Lag6Q	-0,249	-0,163
USHealthVAR_Lag7Q	0,624	0,257
USHealthVAR_Lag8Q	0,291	-0,070

Variables	Function	
	1	2
USIndVAR	0,215	-0,058
USIndVAR_Lag1Q	-0,110	-0,021
USIndVAR_Lag2Q	0,598	-0,224
USIndVAR_Lag3Q	0,720	-0,188
USIndVAR_Lag4Q	0,445	0,104
USIndVAR_Lag5Q	-0,194	-0,158
USIndVAR_Lag6Q	-0,179	0,468
USIndVAR_Lag7Q	0,661	0,639
USIndVAR_Lag8Q	-0,033	0,742

Variables	Function	
	1	2
USInsVAR	0,381	-0,163
USInsVAR_Lag1Q	-0,173	-0,360
USInsVAR_Lag2Q	0,030	0,489
USInsVAR_Lag3Q	0,421	0,071
USInsVAR_Lag4Q	0,363	-0,071
USInsVAR_Lag5Q	-0,164	0,538
USInsVAR_Lag6Q	0,284	-0,552
USInsVAR_Lag7Q	0,702	0,704
USInsVAR_Lag8Q	0,385	-0,171

Variables	Function	
	1	2
USMedVAR	0,177	0,132
USMedVAR_Lag1Q	-0,165	0,340
USMedVAR_Lag2Q	0,148	0,751
USMedVAR_Lag3Q	0,591	0,161
USMedVAR_Lag4Q	0,765	-0,026
USMedVAR_Lag5Q	-0,004	0,004
USMedVAR_Lag6Q	-0,017	0,037
USMedVAR_Lag7Q	0,352	-0,093
USMedVAR_Lag8Q	0,055	-1,172

Variables	Function	
	1	2
USOilVAR	0,378	0,077
USOilVAR_Lag1Q	0,351	0,110
USOilVAR_Lag2Q	0,630	-0,185
USOilVAR_Lag3Q	0,287	0,643
USOilVAR_Lag4Q	-0,132	0,171

USOilVAR_Lag5Q	-0,569	-0,596
USOilVAR_Lag6Q	0,091	0,248
USOilVAR_Lag7Q	-0,632	0,603
USOilVAR_Lag8Q	0,069	0,016

Variables	Function	
	1	2
USPHGVAR	-0,175	-0,095
USPHGVAR_Lag1Q	-0,009	0,289
USPHGVAR_Lag2Q	0,138	0,691
USPHGVAR_Lag3Q	0,659	0,515
USPHGVAR_Lag4Q	0,266	-0,051
USPHGVAR_Lag5Q	-0,085	0,302
USPHGVAR_Lag6Q	0,570	0,308
USPHGVAR_Lag7Q	0,959	-0,261
USPHGVAR_Lag8Q	0,607	-0,361

Variables	Function	
	1	2
USRetVAR	0,199	0,206
USRetVAR_Lag1Q	0,065	0,303
USRetVAR_Lag2Q	0,749	-0,013
USRetVAR_Lag3Q	0,675	0,206
USRetVAR_Lag4Q	0,492	0,128
USRetVAR_Lag5Q	0,106	-0,549
USRetVAR_Lag6Q	-0,037	0,784
USRetVAR_Lag7Q	0,533	0,137
USRetVAR_Lag8Q	-0,386	0,431

Variables	Function	
	1	2
USTechVAR	0,390	0,275
USTechVAR_Lag1Q	-0,325	0,704
USTechVAR_Lag2Q	0,308	-0,005
USTechVAR_Lag3Q	0,330	0,147
USTechVAR_Lag4Q	0,421	0,486
USTechVAR_Lag5Q	0,120	0,168
USTechVAR_Lag6Q	-0,626	0,148
USTechVAR_Lag7Q	0,225	0,167
USTechVAR_Lag8Q	-0,473	0,180

Variables	Function	
	1	2
USTelcoVAR	0,068	0,418
USTelcoVAR_Lag1Q	0,466	-0,253
USTelcoVAR_Lag2Q	-0,445	0,120
USTelcoVAR_Lag3Q	-0,242	0,981
USTelcoVAR_Lag4Q	0,932	0,265
USTelcoVAR_Lag5Q	0,073	-0,038
USTelcoVAR_Lag6Q	-0,353	0,168
USTelcoVAR_Lag7Q	0,528	-0,048

USTelcoVAR_Lag8Q	0,335	-0,984
------------------	-------	--------

Variables	Function	
	1	2
UStTravelVAR	0,168	-0,060
UStTravelVAR_Lag1Q	0,361	0,374
UStTravelVAR_Lag2Q	0,788	0,663
UStTravelVAR_Lag3Q	0,807	0,153
UStTravelVAR_Lag4Q	0,920	0,049
UStTravelVAR_Lag5Q	0,155	0,399
UStTravelVAR_Lag6Q	0,584	-0,374
UStTravelVAR_Lag7Q	0,760	-0,339
UStTravelVAR_Lag8Q	-0,234	-0,243

Variables	Function	
	1	2
USUtilVAR	0,289	0,176
USUtilVAR_Lag1Q	-0,466	-0,301
USUtilVAR_Lag2Q	0,403	0,020
USUtilVAR_Lag3Q	0,544	-0,273
USUtilVAR_Lag4Q	-0,541	0,729
USUtilVAR_Lag5Q	-0,039	0,327
USUtilVAR_Lag6Q	0,142	-0,369
USUtilVAR_Lag7Q	1,001	0,383
USUtilVAR_Lag8Q	-0,702	0,166

Another input of our DA models are Structure Matrices. These indicate the simple correlation between our variables and the Standardized Discriminant Function, therefore indicating the partial contribution of each variable of each variable to the Discriminant Function. The variables are ordered by absolute size of correlation within function. The * indicates the largest absolute correlation between each variable and any discriminant function.

Table C.2: Structure Matrices

Variables	Function	
	1	2
USAutoVAR_Lag8Q	0,442(*)	-0,225
USAutoVAR_Lag5Q	0,321(*)	-0,231
USAutoVAR_Lag4Q	0,275(*)	0,186
USAutoVAR_Lag6Q	0,088	0,609(*)
USAutoVAR_Lag7Q	0,108	-0,470(*)
USAutoVAR_Lag3Q	0,328	0,459(*)
USAutoVAR	0,114	-0,390(*)
USAutoVAR_Lag1Q(a)	0,114	-0,390(*)
USAutoVAR_Lag2Q	0,055	0,197(*)

Variables	Function	
	1	2
USBanksVAR_Lag7Q	0,710(*)	0,081
USBanksVAR_Lag2Q	0,311(*)	-0,182
USBanksVAR_Lag4Q	0,155	0,507(*)
USBanksVAR_Lag6Q	-0,033	0,465(*)
USBanksVAR_Lag3Q	0,184	-0,416(*)
USBanksVAR_Lag1Q	-0,044	-0,286(*)
USBanksVAR	0,065	0,279(*)
USBanksVAR_Lag5Q	0,189	-0,245(*)
USBanksVAR_Lag8Q	-0,022	0,156(*)

Variables	Function	
	1	2
USBasRsVAR_Lag3Q	0,437(*)	-0,405
USBasRsVAR_Lag1Q	0,294(*)	-0,166
USBasRsVAR_Lag6Q	0,289(*)	0,067
USBasRsVAR_Lag8Q	0,212(*)	0,002
USBasRsVAR	-0,108	0,626(*)
USBasRsVAR_Lag5Q	0,332	0,420(*)
USBasRsVAR_Lag7Q	0,008	-0,403(*)
USBasRsVAR_Lag2Q	-0,003	0,338(*)
USBasRsVAR_Lag4Q	-0,160	0,246(*)

Variables	Function
-----------	----------

	1	2
USChemVAR_Lag7Q	0,679(*)	-0,128
USChemVAR_Lag2Q	0,271(*)	-0,005
USChemVAR_Lag1Q	0,041	0,726(*)
USChemVAR_Lag3Q	0,356	0,497(*)
USChemVAR_Lag4Q	0,043	-0,404(*)
USChemVAR_Lag5Q	-0,003	0,259(*)
USChemVAR_Lag6Q	0,026	-0,204(*)
USChemVAR_Lag8Q	0,044	-0,199(*)
USChemVAR	0,009	-0,098(*)

Variables	Function	
	1	2
USConsMatVAR_Lag7Q	0,596(*)	-0,123
USConsMatVAR_Lag1Q	0,084(*)	0,056
USConsMatVAR_Lag6Q	0,072(*)	-0,034
USConsMatVAR_Lag2Q	0,051	0,490(*)
USConsMatVAR_Lag5Q	-0,055	0,381(*)
USConsMatVAR_Lag4Q	0,328	-0,368(*)
USConsMatVAR_Lag3Q	0,165	0,301(*)
USConsMatVAR_Lag8Q	-0,022	-0,262(*)
USConsMatVAR	-0,145	0,247(*)

Variables	Function	
	1	2
USFinSerVAR_Lag7Q	0,626(*)	0,029
USFinSerVAR_Lag2Q	0,284(*)	-0,255
USFinSerVAR_Lag3Q	0,183(*)	-0,120
USFinSerVAR_Lag6Q	-0,073	0,645(*)
USFinSerVAR_Lag4Q	0,396	0,492(*)
USFinSerVAR_Lag8Q	-0,220	0,351(*)
USFinSerVAR	0,154	0,316(*)
USFinSerVAR_Lag5Q	-0,012	-0,168(*)
USFinSerVAR_Lag1Q	-0,074	0,080(*)

Variables	Function	
	1	2
USFoodVAR_Lag7Q	0,504(*)	-0,284
USFoodVAR_Lag8Q	0,342(*)	0,014
USFoodVAR_Lag1Q	0,328(*)	0,221
USFoodVAR_Lag6Q	0,254(*)	-0,106
USFoodVAR_Lag2Q	-0,183(*)	-0,019
USFoodVAR	-0,171	-0,606(*)
USFoodVAR_Lag3Q	0,263	0,543(*)
USFoodVAR_Lag5Q	0,007	0,442(*)
USFoodVAR_Lag4Q	0,118	-0,171(*)

Variables	Function	
	1	2
USHealthVAR_Lag4Q	0,675(*)	-0,383
USHealthVAR_Lag7Q	0,596(*)	0,211

USHealthVAR_Lag8Q	0,305(*)	-0,027
USHealthVAR_Lag2Q	0,262(*)	0,145
USHealthVAR_Lag1Q	0,185(*)	-0,007
USHealthVAR	0,225	0,726(*)
USHealthVAR_Lag3Q	0,162	-0,292(*)
USHealthVAR_Lag6Q	-0,056	-0,222(*)
USHealthVAR_Lag5Q	-0,034	-0,120(*)

Variables	Function	
	1	2
USIndVAR_Lag7Q	0,554(*)	0,371
USIndVAR_Lag2Q	0,353(*)	-0,129
USIndVAR_Lag4Q	0,310(*)	0,240
USIndVAR	0,143(*)	0,090
USIndVAR_Lag8Q	-0,129	0,543(*)
USIndVAR_Lag6Q	-0,288	0,463(*)
USIndVAR_Lag3Q	0,300	-0,321(*)
USIndVAR_Lag5Q	0,073	-0,225(*)
USIndVAR_Lag1Q	0,028	0,059(*)

Variables	Function	
	1	2
USInsVAR_Lag7Q	0,580(*)	0,468
USInsVAR	0,407(*)	-0,232
USInsVAR_Lag4Q	0,392(*)	-0,138
USInsVAR_Lag8Q	0,259(*)	-0,227
USInsVAR_Lag1Q	-0,044(*)	-0,002
USInsVAR_Lag6Q	0,296	-0,436(*)
USInsVAR_Lag5Q	-0,165	0,413(*)
USInsVAR_Lag2Q	-0,096	0,218(*)
USInsVAR_Lag3Q	0,190	0,196(*)

Variables	Function	
	1	2
USMedVAR_Lag4Q	0,712(*)	-0,083
USMedVAR_Lag3Q	0,425(*)	0,248
USMedVAR_Lag7Q	0,365(*)	0,085
USMedVAR_Lag5Q	0,083(*)	0,065
USMedVAR_Lag8Q	0,141	-0,712(*)
USMedVAR	0,331	-0,332(*)
USMedVAR_Lag6Q	0,108	-0,278(*)
USMedVAR_Lag1Q	0,037	0,241(*)
USMedVAR_Lag2Q	0,117	0,137(*)

Variables	Function	
	1	2
USOilVAR_Lag5Q	-0,411(*)	-0,384
USOilVAR_Lag1Q	0,409(*)	0,217
USOilVAR_Lag2Q	0,370(*)	-0,198
USOilVAR	0,141(*)	0,067
USOilVAR_Lag7Q	-0,492	0,495(*)

USOilVAR_Lag3Q	0,092	0,464(*)
USOilVAR_Lag6Q	0,029	0,262(*)
USOilVAR_Lag4Q	-0,001	0,261(*)
USOilVAR_Lag8Q	-0,060	-0,073(*)

Variables	Function	
	1	2
USPHGVAR_Lag7Q	0,523(*)	-0,243
USPHGVAR_Lag4Q	0,293(*)	-0,059
USPHGVAR_Lag2Q	0,009	0,454(*)
USPHGVAR_Lag5Q	0,012	0,428(*)
USPHGVAR_Lag3Q	0,296	0,399(*)
USPHGVAR_Lag8Q	0,232	-0,327(*)
USPHGVAR_Lag1Q	0,092	0,278(*)
USPHGVAR	-0,089	-0,271(*)
USPHGVAR_Lag6Q	0,122	0,198(*)

Variables	Function	
	1	2
USRetVAR_Lag3Q	0,486(*)	0,156
USRetVAR_Lag7Q	0,404(*)	0,263
USRetVAR_Lag2Q	0,307(*)	-0,276
USRetVAR_Lag1Q	-0,020(*)	-0,019
USRetVAR_Lag6Q	-0,066	0,530(*)
USRetVAR_Lag8Q	-0,179	0,464(*)
USRetVAR	0,220	0,400(*)
USRetVAR_Lag5Q	0,159	-0,372(*)
USRetVAR_Lag4Q	0,196	0,247(*)

Variables	Function	
	1	2
USTechVAR_Lag6Q	-0,452(*)	0,284
USTechVAR_Lag8Q	-0,400(*)	0,270
USTechVAR_Lag2Q	0,326(*)	0,129
USTechVAR_Lag3Q	0,270(*)	0,183
USTechVAR_Lag5Q	0,125(*)	0,078
USTechVAR_Lag1Q	-0,223	0,687(*)
USTechVAR_Lag4Q	0,317	0,464(*)
USTechVAR_Lag7Q	0,113	0,426(*)
USTechVAR	0,234	0,327(*)

Variables	Function	
	1	2
USTelcoVAR_Lag4Q	0,748(*)	0,075
USTelcoVAR_Lag7Q	0,329(*)	0,089
USTelcoVAR_Lag1Q	0,275(*)	0,191
USTelcoVAR_Lag8Q	0,251	-0,553(*)
USTelcoVAR_Lag3Q	0,065	0,485(*)
USTelcoVAR_Lag5Q	0,099	0,312(*)
USTelcoVAR_Lag6Q	0,163	-0,272(*)
USTelcoVAR	0,097	0,147(*)

USTelcoVAR_Lag2Q	0,052	0,072(*)
Variables	Function	
	1	2
USTRavelVAR_Lag7Q	0,400(*)	-0,387
USTRavelVAR_Lag4Q	0,365(*)	-0,153
USTRavelVAR_Lag3Q	0,227(*)	0,004
USTRavelVAR_Lag2Q	0,175	0,595(*)
USTRavelVAR_Lag5Q	-0,113	0,428(*)
USTRavelVAR_Lag6Q	0,075	-0,389(*)
USTRavelVAR_Lag1Q	-0,034	0,283(*)
USTRavelVAR_Lag8Q	-0,188	-0,203(*)
USTRavelVAR	-0,112	-0,156(*)
Variables	Function	
	1	2
USUtilVAR_Lag8Q	-0,329(*)	0,216
USUtilVAR	0,169(*)	-0,076
USUtilVAR_Lag2Q	0,144(*)	0,078
USUtilVAR_Lag4Q	-0,225	0,660(*)
USUtilVAR_Lag7Q	0,462	0,474(*)
USUtilVAR_Lag5Q	0,069	0,464(*)
USUtilVAR_Lag1Q	-0,036	-0,361(*)
USUtilVAR_Lag3Q	0,124	-0,238(*)
USUtilVAR_Lag6Q	-0,025	0,031(*)

The Box's M test is performed to evaluate the dispersion and covariance structures between the different categories of the discriminated variable. According to the null hypothesis of the test, if the statistical significance does not exceed the critical level (i.e., nonsignificance) then the equality of the covariance matrices is supported and the assumption is respected. To do so, the test uses the F distribution to verify if we will accept the null hypothesis. Consequences of disrespecting this assumption were already discussed in detail in section "3.4.3. Assumptions" of this dissertation.

Table C.3: Box's M Test results for the 18 models estimated

Sectors	Box's M	Approx.	df1	df2	Sig.
USAutoVAR	108,8	1,065	72	3.755,3	0,333
USBanksVAR	124,8	0,925	90	3.696,2	0,678
USBasRsVAR	172,8	1,280	90	3.696,2	0,040
USChemVAR	177,4	1,314	90	3.696,2	0,026
USConsMatVAR	239,4	1,773	90	3.696,2	0,000
USFinSerVAR	128,1	0,949	90	3.696,2	0,616
USFoodVAR	203,8	1,510	90	3.696,2	0,002
USHealthVAR	149,6	1,108	90	3.696,2	0,230
USIndVAR	174,5	1,292	90	3.696,2	0,034

USInsVAR	158,1	1,171	90	3.696,2	0,131
USMedVAR	168,5	1,216	90	3.174,2	0,084
USOilVAR	176,8	1,310	90	3.696,2	0,028
USPHGVAR	199,6	1,478	90	3.696,2	0,003
USRetVAR	213,6	1,582	90	3.696,2	0,000
USTechVAR	188,3	1,395	90	3.696,2	0,009
USTelcoVAR	166,3	1,232	90	3.696,2	0,070
USTravelVAR	139,6	1,175	90	3.696,2	0,126
USUtilVAR	158,7	1,175	90	3.696,2	0,126

To evaluate the quality of results attained in DA we performed a Test for Equality of Group Means. This test verifies which variables could help find differences within our three groups of observations and therefore are meaningful in discriminating the evolution of GDP. We recall that in order to allow for an effective discrimination, DA implies that the group means have to be distant from one another, otherwise the results will be poorer given that the algorithm will not be able to discriminate between the different groups. This will lead to misclassifications or observations that should be in one category but will be classified by the model in a different category, therefore deteriorating the results.

Table C.4: Test of Equality of Group Means

Sectors		Wilks' Lambda	F	df1	df2	Sig.
Auto	USAutoVAR	0,969	0,683	2	43	0,510
	USAutoVAR_Lag1Q	0,969	0,678	2	43	0,513
	USAutoVAR_Lag2Q	0,992	0,170	2	43	0,845
	USAutoVAR_Lag3Q	0,901	2,369	2	43	0,106
	USAutoVAR_Lag4Q	0,943	1,307	2	43	0,281
	USAutoVAR_Lag5Q	0,922	1,809	2	43	0,176
	USAutoVAR_Lag6Q	0,944	1,283	2	43	0,288
	USAutoVAR_Lag7Q	0,961	0,877	2	43	0,424
	USAutoVAR_Lag8Q	0,868	3,268	2	43	0,048
Banks	USBanksVAR	0,974	0,578	2	43	0,565
	USBanksVAR_Lag1Q	0,975	0,543	2	43	0,585
	USBanksVAR_Lag2Q	0,892	2,612	2	43	0,085
	USBanksVAR_Lag3Q	0,919	1,894	2	43	0,163

	USBanksVAR_Lag4Q	0,909	2,149	2	43	0,129
	USBanksVAR_Lag5Q	0,945	1,248	2	43	0,297
	USBanksVAR_Lag6Q	0,941	1,336	2	43	0,274
	USBanksVAR_Lag7Q	0,631	1,258	2	43	0,000
	USBanksVAR_Lag8Q	0,993	0,160	2	43	0,853
Basic Resources	USBasRsVAR	0,956	0,979	2	43	0,384
	USBasRsVAR_Lag1Q	0,981	0,424	2	43	0,657
	USBasRsVAR_Lag2Q	0,988	0,272	2	43	0,763
	USBasRsVAR_Lag3Q	0,948	1,181	2	43	0,317
	USBasRsVAR_Lag4Q	0,988	0,250	2	43	0,780
	USBasRsVAR_Lag5Q	0,961	0,875	2	43	0,424
	USBasRsVAR_Lag6Q	0,984	0,356	2	43	0,702
	USBasRsVAR_Lag7Q	0,982	0,385	2	43	0,683
	USBasRsVAR_Lag8Q	0,991	0,186	2	43	0,831
Chemicals	USChemVAR	0,999	0,030	2	43	0,970
	USChemVAR_Lag1Q	0,929	1,651	2	43	0,204
	USChemVAR_Lag2Q	0,974	0,569	2	43	0,570
	USChemVAR_Lag3Q	0,925	1,753	2	43	0,185
	USChemVAR_Lag4Q	0,976	0,522	2	43	0,597
	USChemVAR_Lag5Q	0,990	0,209	2	43	0,812
	USChemVAR_Lag6Q	0,994	0,135	2	43	0,874
	USChemVAR_Lag7Q	0,856	3,618	2	43	0,035
	USChemVAR_Lag8Q	0,994	0,138	2	43	0,871
Construction & Materials	USConsMatVAR	0,967	0,734	2	43	0,486
	USConsMatVAR_Lag1Q	0,993	0,148	2	43	0,863
	USConsMatVAR_Lag2Q	0,938	1,429	2	43	0,251
	USConsMatVAR_Lag3Q	0,955	1,019	2	43	0,369
	USConsMatVAR_Lag4Q	0,886	2,763	2	43	0,074
	USConsMatVAR_Lag5Q	0,960	0,890	2	43	0,418
	USConsMatVAR_Lag6Q	0,995	0,101	2	43	0,904
	USConsMatVAR_Lag7Q	0,765	6,618	2	43	0,003
	USConsMatVAR_Lag8Q	0,982	0,405	2	43	0,670
Financial Services	USFinSerVAR	0,962	0,854	2	43	0,433
	USFinSerVAR_Lag1Q	0,995	0,101	2	43	0,904
	USFinSerVAR_Lag2Q	0,942	1,322	2	43	0,277
	USFinSerVAR_Lag3Q	0,978	0,476	2	43	0,624
	USFinSerVAR_Lag4Q	0,869	3,240	2	43	0,049
	USFinSerVAR_Lag5Q	0,992	0,164	2	43	0,850

	USFinSerVAR_Lag6Q	0,897	2,459	2	43	0,097
	USFinSerVAR_Lag7Q	0,823	4,624	2	43	0,015
	USFinSerVAR_Lag8Q	0,944	1,278	2	43	0,289
Food	USFoodVAR	0,944	1,279	2	43	0,289
	USFoodVAR_Lag1Q	0,957	0,957	2	43	0,392
	USFoodVAR_Lag2Q	0,988	0,257	2	43	0,775
	USFoodVAR_Lag3Q	0,940	1,372	2	43	0,264
	USFoodVAR_Lag4Q	0,991	0,190	2	43	0,828
	USFoodVAR_Lag5Q	0,974	0,563	2	43	0,573
	USFoodVAR_Lag6Q	0,976	0,521	2	43	0,598
	USFoodVAR_Lag7Q	0,909	2,162	2	43	0,127
	USFoodVAR_Lag8Q	0,960	0,891	2	43	0,418
Health Care	USHealthVAR	0,952	1,094	2	43	0,344
	USHealthVAR_Lag1Q	0,992	0,166	2	43	0,847
	USHealthVAR_Lag2Q	0,983	0,367	2	43	0,695
	USHealthVAR_Lag3Q	0,988	0,266	2	43	0,768
	USHealthVAR_Lag4Q	0,898	2,440	2	43	0,099
	USHealthVAR_Lag5Q	0,999	0,029	2	43	0,971
	USHealthVAR_Lag6Q	0,996	0,095	2	43	0,910
	USHealthVAR_Lag7Q	0,923	1,791	2	43	0,179
	USHealthVAR_Lag8Q	0,979	0,453	2	43	0,639
Industrial Goods & Services	USIndVAR	0,991	0,191	2	43	0,827
	USIndVAR_Lag1Q	0,999	0,021	2	43	0,979
	USIndVAR_Lag2Q	0,955	1,025	2	43	0,367
	USIndVAR_Lag3Q	0,950	1,139	2	43	0,329
	USIndVAR_Lag4Q	0,956	0,990	2	43	0,380
	USIndVAR_Lag5Q	0,988	0,264	2	43	0,769
	USIndVAR_Lag6Q	0,932	1,573	2	43	0,219
	USIndVAR_Lag7Q	0,879	2,949	2	43	0,063
	USIndVAR_Lag8Q	0,938	1,423	2	43	0,252
Insurance	USInsVAR	0,933	1,543	2	43	0,225
	USInsVAR_Lag1Q	0,999	0,014	2	43	0,986
	USInsVAR_Lag2Q	0,985	0,331	2	43	0,720
	USInsVAR_Lag3Q	0,978	0,481	2	43	0,621
	USInsVAR_Lag4Q	0,945	1,259	2	43	0,294
	USInsVAR_Lag5Q	0,949	1,144	2	43	0,328
	USInsVAR_Lag6Q	0,926	1,706	2	43	0,194
	USInsVAR_Lag7Q	0,852	3,727	2	43	0,032

	USInsVAR_Lag8Q	0,965	0,789	2	43	0,461
Media	USMedVAR	0,947	1,177	2	42	0,318
	USMedVAR_Lag1Q	0,994	0,121	2	42	0,886
	USMedVAR_Lag2Q	0,993	0,156	2	42	0,856
	USMedVAR_Lag3Q	0,925	1,714	2	42	0,192
	USMedVAR_Lag4Q	0,824	4,485	2	42	0,017
	USMedVAR_Lag5Q	0,997	0,068	2	42	0,934
	USMedVAR_Lag6Q	0,988	0,249	2	42	0,781
	USMedVAR_Lag7Q	0,946	1,191	2	42	0,314
	USMedVAR_Lag8Q	0,949	1,128	2	42	0,333
Oil	USOilVAR	0,996	0,094	2	43	0,910
	USOilVAR_Lag1Q	0,964	0,805	2	43	0,454
	USOilVAR_Lag2Q	0,970	0,661	2	43	0,521
	USOilVAR_Lag3Q	0,981	0,413	2	43	0,665
	USOilVAR_Lag4Q	0,994	0,119	2	43	0,888
	USOilVAR_Lag5Q	0,956	0,988	2	43	0,381
	USOilVAR_Lag6Q	0,994	0,124	2	43	0,884
	USOilVAR_Lag7Q	0,936	1,477	2	43	0,240
	USOilVAR_Lag8Q	0,999	0,025	2	43	0,975
Personal & Household Goods	USPHGVAR	0,988	0,257	2	43	0,774
	USPHGVAR_Lag1Q	0,987	0,272	2	43	0,763
	USPHGVAR_Lag2Q	0,979	0,452	2	43	0,639
	USPHGVAR_Lag3Q	0,938	1,410	2	43	0,255
	USPHGVAR_Lag4Q	0,953	1,049	2	43	0,359
	USPHGVAR_Lag5Q	0,982	0,402	2	43	0,672
	USPHGVAR_Lag6Q	0,988	0,267	2	43	0,767
	USPHGVAR_Lag7Q	0,862	3,441	2	43	0,041
	USPHGVAR_Lag8Q	0,961	0,882	2	43	0,421
Retail	USRetVAR	0,931	1,591	2	43	0,215
	USRetVAR_Lag1Q	1,000	0,009	2	43	0,991
	USRetVAR_Lag2Q	0,913	2,046	2	43	0,142
	USRetVAR_Lag3Q	0,830	4,405	2	43	0,018
	USRetVAR_Lag4Q	0,957	0,968	2	43	0,388
	USRetVAR_Lag5Q	0,952	1,076	2	43	0,350
	USRetVAR_Lag6Q	0,942	1,331	2	43	0,275
	USRetVAR_Lag7Q	0,868	3,277	2	43	0,047
	USRetVAR_Lag8Q	0,933	1,540	2	43	0,226

Technology	USTechVAR	0,957	0,975	2	43	0,385
	USTechVAR_Lag1Q	0,898	2,433	2	43	0,100
	USTechVAR_Lag2Q	0,951	1,109	2	43	0,339
	USTechVAR_Lag3Q	0,962	0,852	2	43	0,434
	USTechVAR_Lag4Q	0,920	1,870	2	43	0,166
	USTechVAR_Lag5Q	0,992	0,177	2	43	0,838
	USTechVAR_Lag6Q	0,902	2,328	2	43	0,110
	USTechVAR_Lag7Q	0,961	0,874	2	43	0,425
	USTechVAR_Lag8Q	0,920	1,866	2	43	0,167
Telecoms	USTelcoVAR	0,989	0,245	2	43	0,784
	USTelcoVAR_Lag1Q	0,958	0,953	2	43	0,394
	USTelcoVAR_Lag2Q	0,997	0,062	2	43	0,940
	USTelcoVAR_Lag3Q	0,925	1,754	2	43	0,185
	USTelcoVAR_Lag4Q	0,808	5,100	2	43	0,010
	USTelcoVAR_Lag5Q	0,964	0,800	2	43	0,456
	USTelcoVAR_Lag6Q	0,965	0,782	2	43	0,464
	USTelcoVAR_Lag7Q	0,954	1,035	2	43	0,364
	USTelcoVAR_Lag8Q	0,885	2,807	2	43	0,072
Travel & Leisure	USTRavelVAR	0,986	0,311	2	43	0,735
	USTRavelVAR_Lag1Q	0,988	0,265	2	43	0,768
	USTRavelVAR_Lag2Q	0,928	1,656	2	43	0,203
	USTRavelVAR_Lag3Q	0,957	0,970	2	43	0,387
	USTRavelVAR_Lag4Q	0,893	2,584	2	43	0,087
	USTRavelVAR_Lag5Q	0,964	0,799	2	43	0,456
	USTRavelVAR_Lag6Q	0,974	0,566	2	43	0,572
	USTRavelVAR_Lag7Q	0,861	3,479	2	43	0,040
	USTRavelVAR_Lag8Q	0,964	0,795	2	43	0,458
Utilities	USUtilVAR	0,994	0,128	2	43	0,881
	USUtilVAR_Lag1Q	0,988	0,254	2	43	0,777
	USUtilVAR_Lag2Q	0,996	0,096	2	43	0,908
	USUtilVAR_Lag3Q	0,992	0,171	2	43	0,844
	USUtilVAR_Lag4Q	0,954	1,038	2	43	0,363
	USUtilVAR_Lag5Q	0,980	0,432	2	43	0,652
	USUtilVAR_Lag6Q	1,000	0,004	2	43	0,996
	USUtilVAR_Lag7Q	0,943	1,297	2	43	0,284
	USUtilVAR_Lag8Q	0,976	0,530	2	43	0,593

Annex D: Results of the estimation of the models described in section “4.1.2. Models estimated in Section B: Finding the most interesting time frames”

We will start by presenting the results for the Test of Equality of Group Means estimated for our models. As we mentioned before, this test verifies which variables could help find differences within our three groups of observations and therefore are meaningful in discriminating the evolution of GDP.

Table D.1: Test of Equality of Group Means

	Models	Variables	Wilks' Lambda	F	df1	df2	Sig.	
USAutoVAR	USAutoVAR	USAutoVAR	0,96	1.029	2	49	0,365	Non Sig. Var.
	USAutoVAR_Lag1Q	USAutoVAR_Lag1Q	0,968	0,797	2	48	0,456	Non Sig. Var.
	USAutoVAR_Lag2Q	USAutoVAR_Lag2Q	0,997	0,07	2	47	0,932	Non Sig. Var.
	USAutoVAR_Lag3Q	USAutoVAR_Lag3Q	0,936	1.565	2	46	0,220	Non Sig. Var.
	1Q USAutoVAR_Lag4Q	USAutoVAR_Lag4Q	0,921	1.939	2	45	0,156	Non Sig. Var.
	USAutoVAR_Lag5Q	USAutoVAR_Lag5Q	0,907	2.245	2	44	0,118	Non Sig. Var.
	USAutoVAR_Lag6Q	USAutoVAR_Lag6Q	0,95	1.159	2	44	0,323	Non Sig. Var.
	USAutoVAR_Lag7Q	USAutoVAR_Lag7Q	0,979	0,477	2	44	0,624	Non Sig. Var.
	USAutoVAR_Lag8Q	USAutoVAR_Lag8Q	0,868	3.268	2	43	0,048	Sig. Var.
	2Q USAutoVAR ,	USAutoVAR	0,968	1	2	48	0,454	Non Sig. Var.
	USAutoVAR_Lag1Q	USAutoVAR_Lag1Q	0,968	1	2	48	0,456	Non Sig. Var.
	USAutoVAR_Lag1Q ,	USAutoVAR_Lag1Q	0,974	0,616	2	47	0,544	Non Sig. Var.
	USAutoVAR_Lag2Q	USAutoVAR_Lag2Q	0,997	0,07	2	47	0,932	Non Sig. Var.
	USAutoVAR_Lag2Q ,	USAutoVAR_Lag2Q	0,997	0,078	2	46	0,925	Non Sig. Var.
	USAutoVAR_Lag3Q	USAutoVAR_Lag3Q	0,936	1.565	2	46	0,220	Non Sig. Var.
	USAutoVAR_Lag3Q ,	USAutoVAR_Lag3Q	0,928	1.737	2	45	0,188	Non Sig. Var.
	USAutoVAR_Lag4Q	USAutoVAR_Lag4Q	0,921	1.939	2	45	0,156	Non Sig. Var.
	USAutoVAR_Lag4Q ,	USAutoVAR_Lag4Q	0,939	1.438	2	44	0,248	Non Sig. Var.
	USAutoVAR_Lag5Q	USAutoVAR_Lag5Q	0,907	2.245	2	44	0,118	Non Sig.

3Q	USAutoVAR_Lag5Q , USAutoVAR_Lag6Q	USAutoVAR_Lag5Q	0,907	2.245	2	44	0,118	Var. Non Sig. Var.
		USAutoVAR_Lag6Q	0,95	1.159	2	44	0,323	Non Sig. Var.
	USAutoVAR_Lag6Q , USAutoVAR_Lag7Q	USAutoVAR_Lag6Q	0,95	1.159	2	44	0,323	Non Sig. Var.
		USAutoVAR_Lag7Q	0,979	0,477	2	44	0,624	Non Sig. Var.
	USAutoVAR_Lag7Q , USAutoVAR_Lag8Q	USAutoVAR_Lag7Q	0,961	0,877	2	43	0,424	Non Sig. Var.
		USAutoVAR_Lag8Q	0,868	3.268	2	43	0,048	Sig. Var.
		USAutoVAR	0,974	0,621	2	47	0,542	Non Sig. Var.
	USAutoVAR , USAutoVAR_Lag1Q , USAutoVAR_Lag2Q	USAutoVAR_Lag1Q	0,974	0,616	2	47	0,544	Non Sig. Var.
		USAutoVAR_Lag2Q	0,997	0,07	2	47	0,932	Non Sig. Var.
		USAutoVAR_Lag1Q	0,967	0,778	2	46	0,465	Non Sig. Var.
	USAutoVAR_Lag1Q , USAutoVAR_Lag2Q , USAutoVAR_Lag3Q	USAutoVAR_Lag2Q	0,997	0,078	2	46	0,925	Non Sig. Var.
		USAutoVAR_Lag3Q	0,936	1.565	2	46	0,220	Non Sig. Var.
		USAutoVAR_Lag2Q	0,998	0,055	2	45	0,947	Non Sig. Var.
	USAutoVAR_Lag2Q , USAutoVAR_Lag3Q , USAutoVAR_Lag4Q	USAutoVAR_Lag3Q	0,928	1.737	2	45	0,188	Non Sig. Var.
		USAutoVAR_Lag4Q	0,921	1.939	2	45	0,156	Non Sig. Var.
		USAutoVAR_Lag3Q	0,901	2.426	2	44	0,100	Non Sig. Var.
	USAutoVAR_Lag3Q , USAutoVAR_Lag4Q , USAutoVAR_Lag5Q	USAutoVAR_Lag4Q	0,939	1.438	2	44	0,248	Non Sig. Var.
		USAutoVAR_Lag5Q	0,907	2.245	2	44	0,118	Non Sig. Var.
		USAutoVAR_Lag4Q	0,939	1.438	2	44	0,248	Non Sig. Var.
	USAutoVAR_Lag4Q , USAutoVAR_Lag5Q , USAutoVAR_Lag6Q	USAutoVAR_Lag5Q	0,907	2.245	2	44	0,118	Non Sig. Var.
		USAutoVAR_Lag6Q	0,95	1.159	2	44	0,323	Non Sig. Var.
		USAutoVAR_Lag5Q	0,907	2.245	2	44	0,118	Non Sig. Var.
	USAutoVAR_Lag5Q , USAutoVAR_Lag6Q , USAutoVAR_Lag7Q	USAutoVAR_Lag6Q	0,95	1.159	2	44	0,323	Non Sig. Var.
		USAutoVAR_Lag7Q	0,979	0,477	2	44	0,624	Non Sig. Var.
4Q		USAutoVAR_Lag6Q	0,944	1.283	2	43	0,288	Non Sig. Var.
	USAutoVAR_Lag6Q , USAutoVAR_Lag7Q , USAutoVAR_Lag8Q	USAutoVAR_Lag7Q	0,961	0,877	2	43	0,424	Non Sig. Var.
		USAutoVAR_Lag8Q	0,868	3.268	2	43	0,048	Sig. Var.
	USAutoVAR , USAutoVAR_Lag1Q , USAutoVAR_Lag2Q , USAutoVAR_Lag3Q	USAutoVAR	0,967	0,784	2	46	0,463	Non Sig. Var.
		USAutoVAR_Lag1Q	0,967	0,778	2	46	0,465	Non Sig. Var.

	USBanksVAR_Lag8Q	USBanksVAR_Lag8Q	0,993	0	2	43	0,853	Non Sig. Var.
	USBanksVAR ,	USBanksVAR	0,977	1	2	48	0,576	Non Sig. Var.
	USBanksVAR_Lag1Q	USBanksVAR_Lag1Q	0,981	0	2	48	0,637	Non Sig. Var.
	USBanksVAR_Lag1Q ,	USBanksVAR_Lag1Q	0,983	0,411	2	47	0,666	Non Sig. Var.
	USBanksVAR_Lag2Q	USBanksVAR_Lag2Q	0,93	1765	2	47	0,182	Non Sig. Var.
	USBanksVAR_Lag2Q ,	USBanksVAR_Lag2Q	0,934	1638	2	46	0,206	Non Sig. Var.
	USBanksVAR_Lag3Q	USBanksVAR_Lag3Q	0,909	2.311	2	46	0,111	Non Sig. Var.
	USBanksVAR_Lag3Q ,	USBanksVAR_Lag3Q	0,907	2.319	2	45	0,110	Non Sig. Var.
2Q	USBanksVAR_Lag4Q	USBanksVAR_Lag4Q	0,902	2.456	2	45	0,097	Sig. Var.
	USBanksVAR_Lag4Q ,	USBanksVAR_Lag4Q	0,897	2.539	2	44	0,090	Sig. Var.
	USBanksVAR_Lag5Q	USBanksVAR_Lag5Q	0,944	1.293	2	44	0,285	Non Sig. Var.
	USBanksVAR_Lag5Q ,	USBanksVAR_Lag5Q	0,944	1.293	2	44	0,285	Non Sig. Var.
	USBanksVAR_Lag6Q	USBanksVAR_Lag6Q	0,957	1	2	44	0,377	Non Sig. Var.
	USBanksVAR_Lag6Q ,	USBanksVAR_Lag6Q	0,957	1	2	44	0,377	Non Sig. Var.
	USBanksVAR_Lag7Q	USBanksVAR_Lag7Q	0,628	13019	2	44	0,000	Sig. Var.
	USBanksVAR_Lag7Q ,	USBanksVAR_Lag7Q	0,631	12577	2	43	0,000	Sig. Var.
	USBanksVAR_Lag8Q	USBanksVAR_Lag8Q	0,993	0	2	43	0,853	Non Sig. Var.
3Q	USBanksVAR ,	USBanksVAR	0,98	0,474	2	47	0,625	Non Sig. Var.
	USBanksVAR_Lag1Q ,	USBanksVAR_Lag1Q	0,983	0,411	2	47	0,666	Non Sig. Var.
	USBanksVAR_Lag2Q	USBanksVAR_Lag2Q	0,93	1765	2	47	0,182	Non Sig. Var.
	USBanksVAR_Lag1Q ,	USBanksVAR_Lag1Q	0,978	0,508	2	46	0,605	Non Sig. Var.
	USBanksVAR_Lag2Q ,	USBanksVAR_Lag2Q	0,934	1638	2	46	0,206	Non Sig. Var.
	USBanksVAR_Lag3Q	USBanksVAR_Lag3Q	0,909	2.311	2	46	0,111	Non Sig. Var.
	USBanksVAR_Lag2Q ,	USBanksVAR_Lag2Q	0,927	1761	2	45	0,184	Non Sig. Var.
	USBanksVAR_Lag3Q ,	USBanksVAR_Lag3Q	0,907	2.319	2	45	0,110	Non Sig. Var.
	USBanksVAR_Lag4Q	USBanksVAR_Lag4Q	0,902	2.456	2	45	0,097	Sig. Var.
	USBanksVAR_Lag3Q ,	USBanksVAR_Lag3Q	0,917	1.982	2	44	0,150	Non Sig. Var.
	USBanksVAR_Lag4Q ,	USBanksVAR_Lag4Q	0,897	2.539	2	44	0,090	Sig. Var.
	USBanksVAR_Lag5Q	USBanksVAR_Lag5Q	0,944	1.293	2	44	0,285	Non Sig. Var.
	USBanksVAR_Lag4Q ,	USBanksVAR_Lag4Q	0,897	2.539	2	44	0,090	Sig. Var.
	USBanksVAR_Lag5Q ,	USBanksVAR_Lag5Q	0,944	1.293	2	44	0,285	Non Sig. Var.
	USBanksVAR_Lag6Q	USBanksVAR_Lag6Q	0,957	1	2	44	0,377	Non Sig. Var.

USConsMatVAR	4Q	USBanksVAR_Lag5Q , USBanksVAR_Lag6Q , USBanksVAR_Lag7Q	USBanksVAR_Lag5Q	0,944	1.293	2	44	0,285	Non Sig. Var.
			USBanksVAR_Lag6Q	0,957	1	2	44	0,377	Non Sig. Var.
			USBanksVAR_Lag7Q	0,628	13019	2	44	0,000	Sig. Var.
		USBanksVAR_Lag6Q , USBanksVAR_Lag7Q , USBanksVAR_Lag8Q	USBanksVAR_Lag6Q	0,941	1.336	2	43	0,274	Non Sig. Var.
			USBanksVAR_Lag7Q	0,631	12577	2	43	0,000	Sig. Var.
			USBanksVAR_Lag8Q	0,993	0	2	43	0,853	Non Sig. Var.
			USBanksVAR	0,975	0,598	2	46	0,554	Non Sig. Var.
		USBanksVAR , USBanksVAR_Lag1Q , USBanksVAR_Lag2Q , USBanksVAR_Lag3Q	USBanksVAR_Lag1Q	0,978	0,508	2	46	0,605	Non Sig. Var.
			USBanksVAR_Lag2Q	0,934	1638	2	46	0,206	Non Sig. Var.
			USBanksVAR_Lag3Q	0,909	2.311	2	46	0,111	Non Sig. Var.
		USBanksVAR_Lag1Q , USBanksVAR_Lag2Q , USBanksVAR_Lag3Q , USBanksVAR_Lag4Q	USBanksVAR_Lag1Q	0,966	0,78	2	45	0,465	Non Sig. Var.
			USBanksVAR_Lag2Q	0,927	1761	2	45	0,184	Non Sig. Var.
			USBanksVAR_Lag3Q	0,907	2.319	2	45	0,110	Non Sig. Var.
			USBanksVAR_Lag4Q	0,902	2.456	2	45	0,097	Sig. Var.
			USBanksVAR_Lag2Q	0,893	2649	2	44	0,082	Sig. Var.
		USBanksVAR_Lag2Q , USBanksVAR_Lag3Q , USBanksVAR_Lag4Q , USBanksVAR_Lag5Q	USBanksVAR_Lag3Q	0,917	1.982	2	44	0,150	Non Sig. Var.
			USBanksVAR_Lag4Q	0,897	2.539	2	44	0,090	Sig. Var.
			USBanksVAR_Lag5Q	0,944	1.293	2	44	0,285	Non Sig. Var.
			USBanksVAR_Lag3Q	0,917	1.982	2	44	0,150	Non Sig. Var.
		USBanksVAR_Lag3Q , USBanksVAR_Lag4Q , USBanksVAR_Lag5Q , USBanksVAR_Lag6Q	USBanksVAR_Lag4Q	0,897	2.539	2	44	0,090	Sig. Var.
			USBanksVAR_Lag5Q	0,944	1.293	2	44	0,285	Non Sig. Var.
			USBanksVAR_Lag6Q	0,957	1	2	44	0,377	Non Sig. Var.
			USBanksVAR_Lag4Q	0,897	2.539	2	44	0,090	Sig. Var.
		USBanksVAR_Lag4Q , USBanksVAR_Lag5Q , USBanksVAR_Lag6Q , USBanksVAR_Lag7Q	USBanksVAR_Lag5Q	0,944	1.293	2	44	0,285	Non Sig. Var.
			USBanksVAR_Lag6Q	0,957	1	2	44	0,377	Non Sig. Var.
			USBanksVAR_Lag7Q	0,628	13019	2	44	0,000	Sig. Var.
			USBanksVAR_Lag5Q	0,945	1.248	2	43	0,297	Non Sig. Var.
		USBanksVAR_Lag5Q , USBanksVAR_Lag6Q , USBanksVAR_Lag7Q , USBanksVAR_Lag8Q	USBanksVAR_Lag6Q	0,941	1.336	2	43	0,274	Non Sig. Var.
			USBanksVAR_Lag7Q	0,631	12577	2	43	0,000	Sig. Var.
			USBanksVAR_Lag8Q	0,993	0	2	43	0,853	Non Sig. Var.
	1Q	USConsMatVAR	USConsMatVAR	0,973	1	2	49	0,506	Non Sig. Var.
		USConsMatVAR_Lag1Q	USConsMatVAR_Lag1Q	0,996	0,103	2	48	0,903	Non Sig. Var.
		USConsMatVAR_Lag2Q	USConsMatVAR_Lag2Q	0,954	1125	2	47	0,333	Non Sig. Var.

	USConsMatVAR_Lag3Q	USConsMatVAR_Lag3Q	0,954	1.107	2	46	0,339	Non Sig. Var.
	USConsMatVAR_Lag4Q	USConsMatVAR_Lag4Q	0,878	3.137	2	45	0,053	Sig. Var.
	USConsMatVAR_Lag5Q	USConsMatVAR_Lag5Q	0,973	1	2	44	0,549	Non Sig. Var.
	USConsMatVAR_Lag6Q	USConsMatVAR_Lag6Q	0,996	0	2	44	0,911	Non Sig. Var.
	USConsMatVAR_Lag7Q	USConsMatVAR_Lag7Q	0,774	6433	2	44	0,004	Sig. Var.
	USConsMatVAR_Lag8Q	USConsMatVAR_Lag8Q	0,982	0	2	43	0,670	Non Sig. Var.
	USConsMatVAR ,	USConsMatVAR	0,974	1	2	48	0,526	Non Sig. Var.
	USConsMatVAR_Lag1Q	USConsMatVAR_Lag1Q	0,996	0	2	48	0,903	Non Sig. Var.
	USConsMatVAR_Lag1Q	USConsMatVAR_Lag1Q	0,996	0,105	2	47	0,901	Non Sig. Var.
	USConsMatVAR_Lag2Q	USConsMatVAR_Lag2Q	0,954	1125	2	47	0,333	Non Sig. Var.
	USConsMatVAR_Lag2Q	USConsMatVAR_Lag2Q	0,95	1208	2	46	0,308	Non Sig. Var.
	USConsMatVAR_Lag3Q	USConsMatVAR_Lag3Q	0,954	1.107	2	46	0,339	Non Sig. Var.
	USConsMatVAR_Lag3Q	USConsMatVAR_Lag3Q	0,955	1.070	2	45	0,352	Non Sig. Var.
2Q	USConsMatVAR_Lag4Q	USConsMatVAR_Lag4Q	0,878	3.137	2	45	0,053	Sig. Var.
	USConsMatVAR_Lag4Q	USConsMatVAR_Lag4Q	0,876	3.117	2	44	0,054	Sig. Var.
	USConsMatVAR_Lag5Q	USConsMatVAR_Lag5Q	0,973	1	2	44	0,549	Non Sig. Var.
	USConsMatVAR_Lag5Q	USConsMatVAR_Lag5Q	0,973	1	2	44	0,549	Non Sig. Var.
	USConsMatVAR_Lag6Q	USConsMatVAR_Lag6Q	0,996	0	2	44	0,911	Non Sig. Var.
	USConsMatVAR_Lag6Q	USConsMatVAR_Lag6Q	0,996	0	2	44	0,911	Non Sig. Var.
	USConsMatVAR_Lag7Q	USConsMatVAR_Lag7Q	0,774	6433	2	44	0,004	Sig. Var.
	USConsMatVAR_Lag7Q	USConsMatVAR_Lag7Q	0,765	6618	2	43	0,003	Sig. Var.
	USConsMatVAR_Lag8Q	USConsMatVAR_Lag8Q	0,982	0	2	43	0,670	Non Sig. Var.
3Q	USConsMatVAR ,	USConsMatVAR	0,973	0,65	2	47	0,527	Non Sig. Var.
	USConsMatVAR_Lag1Q	USConsMatVAR_Lag1Q	0,996	0,105	2	47	0,901	Non Sig. Var.
	USConsMatVAR_Lag2Q	USConsMatVAR_Lag2Q	0,954	1125	2	47	0,333	Non Sig. Var.
	USConsMatVAR_Lag1Q	USConsMatVAR_Lag1Q	0,995	0,104	2	46	0,901	Non Sig. Var.
	USConsMatVAR_Lag2Q	USConsMatVAR_Lag2Q	0,95	1208	2	46	0,308	Non Sig. Var.
	USConsMatVAR_Lag3Q	USConsMatVAR_Lag3Q	0,954	1.107	2	46	0,339	Non Sig. Var.
	USConsMatVAR_Lag2Q	USConsMatVAR_Lag2Q	0,95	1190	2	45	0,314	Non Sig. Var.
	USConsMatVAR_Lag3Q	USConsMatVAR_Lag3Q	0,955	1.070	2	45	0,352	Non Sig. Var.
	USConsMatVAR_Lag4Q	USConsMatVAR_Lag4Q	0,878	3.137	2	45	0,053	Sig. Var.
	USConsMatVAR_Lag3Q	USConsMatVAR_Lag3Q	0,953	1.077	2	44	0,349	Non Sig. Var.

4Q	USConsMatVAR_Lag4Q	USConsMatVAR_Lag4Q	0,876	3.117	2	44	0,054	Sig. Var.
	USConsMatVAR_Lag5Q	USConsMatVAR_Lag5Q	0,973	1	2	44	0,549	Non Sig. Var.
	USConsMatVAR_Lag4Q	USConsMatVAR_Lag4Q	0,876	3.117	2	44	0,054	Sig. Var.
	USConsMatVAR_Lag5Q	USConsMatVAR_Lag5Q	0,973	1	2	44	0,549	Non Sig. Var.
	USConsMatVAR_Lag6Q	USConsMatVAR_Lag6Q	0,996	0	2	44	0,911	Non Sig. Var.
	USConsMatVAR_Lag5Q	USConsMatVAR_Lag5Q	0,973	1	2	44	0,549	Non Sig. Var.
	USConsMatVAR_Lag6Q	USConsMatVAR_Lag6Q	0,996	0	2	44	0,911	Non Sig. Var.
	USConsMatVAR_Lag7Q	USConsMatVAR_Lag7Q	0,774	6433	2	44	0,004	Sig. Var.
	USConsMatVAR_Lag6Q	USConsMatVAR_Lag6Q	0,995	0	2	43	0,904	Non Sig. Var.
	USConsMatVAR_Lag7Q	USConsMatVAR_Lag7Q	0,765	6618	2	43	0,003	Sig. Var.
	USConsMatVAR_Lag8Q	USConsMatVAR_Lag8Q	0,982	0	2	43	0,670	Non Sig. Var.
	USConsMatVAR ,	USConsMatVAR	0,977	0,552	2	46	0,579	Non Sig. Var.
	USConsMatVAR_Lag1Q	USConsMatVAR_Lag1Q	0,995	0,104	2	46	0,901	Non Sig. Var.
	USConsMatVAR_Lag2Q	USConsMatVAR_Lag2Q	0,95	1208	2	46	0,308	Non Sig. Var.
	USConsMatVAR_Lag3Q	USConsMatVAR_Lag3Q	0,954	1.107	2	46	0,339	Non Sig. Var.
	USConsMatVAR_Lag1Q	USConsMatVAR_Lag1Q	0,997	0,071	2	45	0,932	Non Sig. Var.
	USConsMatVAR_Lag2Q	USConsMatVAR_Lag2Q	0,95	1190	2	45	0,314	Non Sig. Var.
	USConsMatVAR_Lag3Q	USConsMatVAR_Lag3Q	0,955	1.070	2	45	0,352	Non Sig. Var.
	USConsMatVAR_Lag4Q	USConsMatVAR_Lag4Q	0,878	3.137	2	45	0,053	Sig. Var.
	USConsMatVAR_Lag2Q	USConsMatVAR_Lag2Q	0,943	1328	2	44	0,275	Non Sig. Var.
	USConsMatVAR_Lag3Q	USConsMatVAR_Lag3Q	0,953	1.077	2	44	0,349	Non Sig. Var.
	USConsMatVAR_Lag4Q	USConsMatVAR_Lag4Q	0,876	3.117	2	44	0,054	Sig. Var.
	USConsMatVAR_Lag5Q	USConsMatVAR_Lag5Q	0,973	1	2	44	0,549	Non Sig. Var.
	USConsMatVAR_Lag3Q	USConsMatVAR_Lag3Q	0,953	1.077	2	44	0,349	Non Sig. Var.
	USConsMatVAR_Lag4Q	USConsMatVAR_Lag4Q	0,876	3.117	2	44	0,054	Sig. Var.
	USConsMatVAR_Lag5Q	USConsMatVAR_Lag5Q	0,973	1	2	44	0,549	Non Sig. Var.
	USConsMatVAR_Lag6Q	USConsMatVAR_Lag6Q	0,996	0	2	44	0,911	Non Sig. Var.
	USConsMatVAR_Lag4Q	USConsMatVAR_Lag4Q	0,876	3.117	2	44	0,054	Sig. Var.
	USConsMatVAR_Lag5Q	USConsMatVAR_Lag5Q	0,973	1	2	44	0,549	Non Sig. Var.
	USConsMatVAR_Lag6Q	USConsMatVAR_Lag6Q	0,996	0	2	44	0,911	Non Sig. Var.
	USConsMatVAR_Lag7Q	USConsMatVAR_Lag7Q	0,774	6433	2	44	0,004	Sig. Var.
	USConsMatVAR_Lag5Q	USConsMatVAR_Lag5Q	0,96	1	2	43	0,418	Non Sig. Var.
	USConsMatVAR_Lag6Q	USConsMatVAR_Lag6Q	0,995	0	2	43	0,904	Non Sig.

USFinServVAR	1Q	USConsMatVAR_Lag7Q	USConsMatVAR_Lag7Q	0,765	6618	2	43	0,003	Var.
		USConsMatVAR_Lag8Q	USConsMatVAR_Lag8Q	0,982	0	2	43	0,670	Sig. Var.
		USFinSerVAR	USFinSerVAR	0,98	1	2	49	0,607	Non Sig. Var.
		USFinSerVAR_Lag1Q	USFinSerVAR_Lag1Q	0,994	0,15	2	48	0,861	Non Sig. Var.
		USFinSerVAR_Lag2Q	USFinSerVAR_Lag2Q	0,962	0,94	2	47	0,398	Non Sig. Var.
		USFinSerVAR_Lag3Q	USFinSerVAR_Lag3Q	0,977	1	2	46	0,589	Non Sig. Var.
		USFinSerVAR_Lag4Q	USFinSerVAR_Lag4Q	0,87	3.373	2	45	0,043	Sig. Var.
		USFinSerVAR_Lag5Q	USFinSerVAR_Lag5Q	0,996	0	2	44	0,923	Non Sig. Var.
		USFinSerVAR_Lag6Q	USFinSerVAR_Lag6Q	0,904	2.328	2	44	0,109	Non Sig. Var.
		USFinSerVAR_Lag7Q	USFinSerVAR_Lag7Q	0,829	4534	2	44	0,016	Sig. Var.
	2Q	USFinSerVAR_Lag8Q	USFinSerVAR_Lag8Q	0,944	1.278	2	43	0,289	Non Sig. Var.
		USFinSerVAR , USFinSerVAR_Lag1Q	USFinSerVAR	0,978	1	2	48	0,582	Non Sig. Var.
		USFinSerVAR_Lag1Q , USFinSerVAR_Lag2Q	USFinSerVAR_Lag1Q	0,994	0	2	48	0,861	Non Sig. Var.
		USFinSerVAR_Lag1Q , USFinSerVAR_Lag2Q	USFinSerVAR_Lag2Q	0,962	0,141	2	47	0,868	Non Sig. Var.
		USFinSerVAR_Lag2Q , USFinSerVAR_Lag3Q	USFinSerVAR_Lag2Q	0,962	0,94	2	47	0,398	Non Sig. Var.
		USFinSerVAR_Lag2Q , USFinSerVAR_Lag3Q	USFinSerVAR_Lag3Q	0,96	0,964	2	46	0,389	Non Sig. Var.
		USFinSerVAR_Lag3Q , USFinSerVAR_Lag4Q	USFinSerVAR_Lag3Q	0,977	1	2	46	0,589	Non Sig. Var.
		USFinSerVAR_Lag3Q , USFinSerVAR_Lag4Q	USFinSerVAR_Lag4Q	0,977	1	2	45	0,586	Non Sig. Var.
		USFinSerVAR_Lag4Q , USFinSerVAR_Lag5Q	USFinSerVAR_Lag4Q	0,87	3.373	2	45	0,043	Sig. Var.
		USFinSerVAR_Lag4Q , USFinSerVAR_Lag5Q	USFinSerVAR_Lag5Q	0,869	3.313	2	44	0,046	Sig. Var.
	3Q	USFinSerVAR_Lag5Q , USFinSerVAR_Lag6Q	USFinSerVAR_Lag5Q	0,996	0	2	44	0,923	Non Sig. Var.
		USFinSerVAR_Lag5Q , USFinSerVAR_Lag6Q	USFinSerVAR_Lag6Q	0,996	0	2	44	0,923	Non Sig. Var.
		USFinSerVAR_Lag6Q , USFinSerVAR_Lag7Q	USFinSerVAR_Lag6Q	0,904	2.328	2	44	0,109	Non Sig. Var.
		USFinSerVAR_Lag6Q , USFinSerVAR_Lag7Q	USFinSerVAR_Lag7Q	0,904	2.328	2	44	0,109	Non Sig. Var.
		USFinSerVAR_Lag7Q , USFinSerVAR_Lag8Q	USFinSerVAR_Lag7Q	0,829	4534	2	44	0,016	Sig. Var.
		USFinSerVAR_Lag7Q , USFinSerVAR_Lag8Q	USFinSerVAR_Lag7Q	0,823	4624	2	43	0,015	Sig. Var.
		USFinSerVAR , USFinSerVAR_Lag1Q , USFinSerVAR_Lag2Q	USFinSerVAR_Lag8Q	0,944	1.278	2	43	0,289	Non Sig. Var.
		USFinSerVAR , USFinSerVAR_Lag1Q , USFinSerVAR_Lag2Q	USFinSerVAR	0,978	0,518	2	47	0,599	Non Sig. Var.
		USFinSerVAR_Lag1Q , USFinSerVAR_Lag2Q	USFinSerVAR_Lag1Q	0,994	0,141	2	47	0,868	Non Sig. Var.
		USFinSerVAR_Lag1Q , USFinSerVAR_Lag2Q , USFinSerVAR_Lag3Q	USFinSerVAR_Lag2Q	0,962	0,94	2	47	0,398	Non Sig. Var.
		USFinSerVAR_Lag1Q , USFinSerVAR_Lag2Q , USFinSerVAR_Lag3Q	USFinSerVAR_Lag1Q	0,994	0,129	2	46	0,879	Non Sig. Var.
		USFinSerVAR_Lag1Q , USFinSerVAR_Lag2Q , USFinSerVAR_Lag3Q	USFinSerVAR_Lag2Q	0,96	0,964	2	46	0,389	Non Sig. Var.

								Var.
		USFinSerVAR_Lag3Q	0,977	1	2	46	0,589	Non Sig. Var.
	USFinSerVAR_Lag2Q ,	USFinSerVAR_Lag2Q	0,959	0,96	2	45	0,391	Non Sig. Var.
	USFinSerVAR_Lag3Q ,	USFinSerVAR_Lag3Q	0,977	1	2	45	0,586	Non Sig. Var.
	USFinSerVAR_Lag4Q	USFinSerVAR_Lag4Q	0,87	3.373	2	45	0,043	Sig. Var.
	USFinSerVAR_Lag3Q ,	USFinSerVAR_Lag3Q	0,978	0	2	44	0,619	Non Sig. Var.
	USFinSerVAR_Lag4Q ,	USFinSerVAR_Lag4Q	0,869	3.313	2	44	0,046	Sig. Var.
	USFinSerVAR_Lag5Q	USFinSerVAR_Lag5Q	0,996	0	2	44	0,923	Non Sig. Var.
		USFinSerVAR_Lag4Q	0,869	3.313	2	44	0,046	Sig. Var.
	USFinSerVAR_Lag4Q ,	USFinSerVAR_Lag5Q	0,996	0	2	44	0,923	Non Sig. Var.
	USFinSerVAR_Lag5Q ,	USFinSerVAR_Lag6Q	0,904	2.328	2	44	0,109	Non Sig. Var.
	USFinSerVAR_Lag6Q	USFinSerVAR_Lag5Q	0,996	0	2	44	0,923	Non Sig. Var.
	USFinSerVAR_Lag5Q ,	USFinSerVAR_Lag6Q	0,904	2.328	2	44	0,109	Non Sig. Var.
	USFinSerVAR_Lag6Q ,	USFinSerVAR_Lag7Q	0,829	4534	2	44	0,016	Sig. Var.
	USFinSerVAR_Lag7Q ,	USFinSerVAR_Lag6Q	0,897	2.459	2	43	0,097	Sig. Var.
	USFinSerVAR_Lag8Q	USFinSerVAR_Lag7Q	0,823	4624	2	43	0,015	Sig. Var.
		USFinSerVAR_Lag8Q	0,944	1.278	2	43	0,289	Non Sig. Var.
4Q		USFinSerVAR	0,973	0,635	2	46	0,534	Non Sig. Var.
	USFinSerVAR ,	USFinSerVAR_Lag1Q	0,994	0,129	2	46	0,879	Non Sig. Var.
	USFinSerVAR_Lag1Q ,	USFinSerVAR_Lag2Q	0,96	0,964	2	46	0,389	Non Sig. Var.
	USFinSerVAR_Lag2Q ,	USFinSerVAR_Lag3Q	0,977	1	2	46	0,589	Non Sig. Var.
	USFinSerVAR_Lag3Q	USFinSerVAR_Lag1Q	0,992	0,17	2	45	0,844	Non Sig. Var.
	USFinSerVAR_Lag1Q ,	USFinSerVAR_Lag2Q	0,959	0,96	2	45	0,391	Non Sig. Var.
	USFinSerVAR_Lag2Q ,	USFinSerVAR_Lag3Q	0,977	1	2	45	0,586	Non Sig. Var.
	USFinSerVAR_Lag3Q ,	USFinSerVAR_Lag4Q	0,87	3.373	2	45	0,043	Sig. Var.
	USFinSerVAR_Lag4Q	USFinSerVAR_Lag2Q	0,941	1382	2	44	0,262	Non Sig. Var.
	USFinSerVAR_Lag2Q ,	USFinSerVAR_Lag3Q	0,978	0	2	44	0,619	Non Sig. Var.
	USFinSerVAR_Lag3Q ,	USFinSerVAR_Lag4Q	0,869	3.313	2	44	0,046	Sig. Var.
	USFinSerVAR_Lag4Q ,	USFinSerVAR_Lag5Q	0,996	0	2	44	0,923	Non Sig. Var.
	USFinSerVAR_Lag5Q	USFinSerVAR_Lag3Q	0,978	0	2	44	0,619	Non Sig. Var.
	USFinSerVAR_Lag3Q ,	USFinSerVAR_Lag4Q	0,869	3.313	2	44	0,046	Sig. Var.
	USFinSerVAR_Lag4Q ,	USFinSerVAR_Lag5Q	0,996	0	2	44	0,923	Non Sig. Var.
	USFinSerVAR_Lag5Q ,	USFinSerVAR_Lag6Q	0,904	2.328	2	44	0,109	Non Sig. Var.
	USFinSerVAR_Lag6Q	USFinSerVAR_Lag4Q	0,869	3.313	2	44	0,046	Sig. Var.

USRetailVAR	1Q	USFinSerVAR_Lag5Q , USFinSerVAR_Lag6Q , USFinSerVAR_Lag7Q	USFinSerVAR_Lag5Q	0,996	0	2	44	0,923	Non Sig. Var.
			USFinSerVAR_Lag6Q	0,904	2.328	2	44	0,109	Non Sig. Var.
			USFinSerVAR_Lag7Q	0,829	4534	2	44	0,016	Sig. Var.
		USFinSerVAR_Lag5Q , USFinSerVAR_Lag6Q , USFinSerVAR_Lag7Q , USFinSerVAR_Lag8Q	USFinSerVAR_Lag5Q	0,992	0	2	43	0,850	Non Sig. Var.
			USFinSerVAR_Lag6Q	0,897	2.459	2	43	0,097	Sig. Var.
			USFinSerVAR_Lag7Q	0,823	4624	2	43	0,015	Sig. Var.
			USFinSerVAR_Lag8Q	0,944	1.278	2	43	0,289	Non Sig. Var.
		USRetVAR	USRetVAR	0,95	1.295	2	49	0,283	Non Sig. Var.
	2Q	USRetVAR_Lag1Q	USRetVAR_Lag1Q	1000	0,011	2	48	0,989	Non Sig. Var.
		USRetVAR_Lag2Q	USRetVAR_Lag2Q	0,944	1382	2	47	0,261	Non Sig. Var.
		USRetVAR_Lag3Q	USRetVAR_Lag3Q	0,889	2.878	2	46	0,066	Sig. Var.
		USRetVAR_Lag4Q	USRetVAR_Lag4Q	0,952	1.133	2	45	0,331	Non Sig. Var.
		USRetVAR_Lag5Q	USRetVAR_Lag5Q	0,957	1	2	44	0,383	Non Sig. Var.
		USRetVAR_Lag6Q	USRetVAR_Lag6Q	0,938	1.443	2	44	0,247	Non Sig. Var.
		USRetVAR_Lag7Q	USRetVAR_Lag7Q	0,887	2811	2	44	0,071	Sig. Var.
		USRetVAR_Lag8Q	USRetVAR_Lag8Q	0,933	1.540	2	43	0,226	Non Sig. Var.
	3Q	USRetVAR , USRetVAR_Lag1Q	USRetVAR	0,939	1.570	2	48	0,219	Non Sig. Var.
			USRetVAR_Lag1Q	1000	0	2	48	0,989	Non Sig. Var.
		USRetVAR_Lag1Q , USRetVAR_Lag2Q	USRetVAR_Lag1Q	1000	0,001	2	47	0,999	Non Sig. Var.
			USRetVAR_Lag2Q	0,944	1382	2	47	0,261	Non Sig. Var.
		USRetVAR_Lag2Q , USRetVAR_Lag3Q	USRetVAR_Lag2Q	0,935	1600	2	46	0,213	Non Sig. Var.
			USRetVAR_Lag3Q	0,889	2.878	2	46	0,066	Sig. Var.
		USRetVAR_Lag3Q , USRetVAR_Lag4Q	USRetVAR_Lag3Q	0,875	3.207	2	45	0,050	Sig. Var.
			USRetVAR_Lag4Q	0,952	1.133	2	45	0,331	Non Sig. Var.
		USRetVAR_Lag4Q , USRetVAR_Lag5Q	USRetVAR_Lag4Q	0,958	1	2	44	0,393	Non Sig. Var.
			USRetVAR_Lag5Q	0,957	1	2	44	0,383	Non Sig. Var.
		USRetVAR_Lag5Q , USRetVAR_Lag6Q	USRetVAR_Lag5Q	0,957	1	2	44	0,383	Non Sig. Var.
			USRetVAR_Lag6Q	0,938	1.443	2	44	0,247	Non Sig. Var.
		USRetVAR_Lag6Q , USRetVAR_Lag7Q	USRetVAR_Lag6Q	0,938	1.443	2	44	0,247	Non Sig. Var.
			USRetVAR_Lag7Q	0,887	2811	2	44	0,071	Sig. Var.
		USRetVAR_Lag7Q , USRetVAR_Lag8Q	USRetVAR_Lag7Q	0,868	3277	2	43	0,047	Sig. Var.
			USRetVAR_Lag8Q	0,933	1.540	2	43	0,226	Non Sig. Var.
		USRetVAR , USRetVAR_Lag1Q ,	USRetVAR	0,938	1566	2	47	0,220	Non Sig. Var.

4Q	USRetVAR_Lag2Q	USRetVAR_Lag1Q	1000	0,001	2	47	0,999	Non Sig. Var.
		USRetVAR_Lag2Q	0,944	1382	2	47	0,261	Non Sig. Var.
	USRetVAR_Lag1Q ,	USRetVAR_Lag1Q	1000	0,006	2	46	0,994	Non Sig. Var.
	USRetVAR_Lag2Q ,	USRetVAR_Lag2Q	0,935	1600	2	46	0,213	Non Sig. Var.
	USRetVAR_Lag3Q	USRetVAR_Lag3Q	0,889	2.878	2	46	0,066	Sig. Var.
		USRetVAR_Lag2Q	0,935	1553	2	45	0,223	Non Sig. Var.
	USRetVAR_Lag2Q ,	USRetVAR_Lag3Q	0,875	3.207	2	45	0,050	Sig. Var.
	USRetVAR_Lag3Q ,	USRetVAR_Lag4Q	0,952	1.133	2	45	0,331	Non Sig. Var.
	USRetVAR_Lag4Q	USRetVAR_Lag3Q	0,854	3.760	2	44	0,031	Sig. Var.
	USRetVAR_Lag3Q ,	USRetVAR_Lag4Q	0,958	1	2	44	0,393	Non Sig. Var.
	USRetVAR_Lag4Q ,	USRetVAR_Lag5Q	0,957	1	2	44	0,383	Non Sig. Var.
	USRetVAR_Lag5Q	USRetVAR_Lag4Q	0,958	1	2	44	0,393	Non Sig. Var.
	USRetVAR_Lag4Q ,	USRetVAR_Lag5Q	0,957	1	2	44	0,383	Non Sig. Var.
	USRetVAR_Lag5Q ,	USRetVAR_Lag6Q	0,938	1.443	2	44	0,247	Non Sig. Var.
	USRetVAR_Lag6Q ,	USRetVAR_Lag5Q	0,957	1	2	44	0,383	Non Sig. Var.
	USRetVAR_Lag7Q	USRetVAR_Lag6Q	0,938	1.443	2	44	0,247	Non Sig. Var.
		USRetVAR_Lag7Q	0,887	2811	2	44	0,071	Sig. Var.
	USRetVAR_Lag6Q ,	USRetVAR_Lag6Q	0,942	1.331	2	43	0,275	Non Sig. Var.
	USRetVAR_Lag7Q ,	USRetVAR_Lag7Q	0,868	3277	2	43	0,047	Sig. Var.
	USRetVAR_Lag8Q	USRetVAR_Lag8Q	0,933	1.540	2	43	0,226	Non Sig. Var.
		USRetVAR	0,934	1617	2	46	0,210	Non Sig. Var.
	USRetVAR ,	USRetVAR_Lag1Q	1000	0,006	2	46	0,994	Non Sig. Var.
	USRetVAR_Lag1Q ,	USRetVAR_Lag2Q	0,935	1600	2	46	0,213	Non Sig. Var.
	USRetVAR_Lag2Q ,	USRetVAR_Lag3Q	0,889	2.878	2	46	0,066	Sig. Var.
	USRetVAR_Lag3Q	USRetVAR_Lag1Q	1000	0,007	2	45	0,993	Non Sig. Var.
	USRetVAR_Lag1Q ,	USRetVAR_Lag2Q	0,935	1553	2	45	0,223	Non Sig. Var.
	USRetVAR_Lag2Q ,	USRetVAR_Lag3Q	0,875	3.207	2	45	0,050	Sig. Var.
	USRetVAR_Lag3Q ,	USRetVAR_Lag4Q	0,952	1.133	2	45	0,331	Non Sig. Var.
	USRetVAR_Lag4Q	USRetVAR_Lag2Q	0,913	2088	2	44	0,136	Non Sig. Var.
	USRetVAR_Lag2Q ,	USRetVAR_Lag3Q	0,854	3.760	2	44	0,031	Sig. Var.
	USRetVAR_Lag3Q ,	USRetVAR_Lag4Q	0,958	1	2	44	0,393	Non Sig. Var.
	USRetVAR_Lag4Q ,	USRetVAR_Lag5Q	0,957	1	2	44	0,383	Non Sig. Var.
	USRetVAR_Lag5Q	USRetVAR_Lag3Q	0,854	3.760	2	44	0,031	Sig. Var.

USTravelVAR	1Q	USRetVAR_Lag4Q , USRetVAR_Lag5Q , USRetVAR_Lag6Q , USRetVAR_Lag7Q , USRetVAR_Lag8Q	USRetVAR_Lag4Q	0,958	1	2	44	0,393	Non Sig. Var.	
			USRetVAR_Lag5Q	0,957	1	2	44	0,383	Non Sig. Var.	
			USRetVAR_Lag6Q	0,938	1.443	2	44	0,247	Non Sig. Var.	
			USRetVAR_Lag4Q	0,958	1	2	44	0,393	Non Sig. Var.	
			USRetVAR_Lag5Q	0,957	1	2	44	0,383	Non Sig. Var.	
			USRetVAR_Lag6Q	0,938	1.443	2	44	0,247	Non Sig. Var.	
			USRetVAR_Lag7Q	0,887	2811	2	44	0,071	Sig. Var.	
			USRetVAR_Lag5Q	0,952	1.076	2	43	0,350	Non Sig. Var.	
			USRetVAR_Lag6Q	0,942	1.331	2	43	0,275	Non Sig. Var.	
			USRetVAR_Lag7Q	0,868	3277	2	43	0,047	Sig. Var.	
			USRetVAR_Lag8Q	0,933	1.540	2	43	0,226	Non Sig. Var.	
			USTravelVAR	USTravelVAR	0,991	0	2	49	0,794	Non Sig. Var.
			USTravelVAR_Lag1Q	USTravelVAR_Lag1Q	0,995	0,133	2	48	0,876	Non Sig. Var.
			USTravelVAR_Lag2Q	USTravelVAR_Lag2Q	0,95	1243	2	47	0,298	Non Sig. Var.
			USTravelVAR_Lag3Q	USTravelVAR_Lag3Q	0,958	1.018	2	46	0,369	Non Sig. Var.
			USTravelVAR_Lag4Q	USTravelVAR_Lag4Q	0,892	2.730	2	45	0,076	Sig. Var.
	2Q	USTravelVAR_Lag5Q	USTravelVAR_Lag5Q	0,975	1	2	44	0,573	Non Sig. Var.	
		USTravelVAR_Lag6Q	USTravelVAR_Lag6Q	0,981	0	2	44	0,650	Non Sig. Var.	
		USTravelVAR_Lag7Q	USTravelVAR_Lag7Q	0,869	3303	2	44	0,046	Sig. Var.	
		USTravelVAR_Lag8Q	USTravelVAR_Lag8Q	0,964	1	2	43	0,458	Non Sig. Var.	
		USTravelVAR , USTravelVAR_Lag1Q	USTravelVAR	0,991	0	2	48	0,804	Non Sig. Var.	
		USTravelVAR_Lag1Q	USTravelVAR_Lag1Q	0,995	0	2	48	0,876	Non Sig. Var.	
		USTravelVAR_Lag1Q , USTravelVAR_Lag2Q	USTravelVAR_Lag1Q	0,994	0,146	2	47	0,865	Non Sig. Var.	
		USTravelVAR_Lag2Q	USTravelVAR_Lag2Q	0,95	1243	2	47	0,298	Non Sig. Var.	
		USTravelVAR_Lag2Q , USTravelVAR_Lag3Q	USTravelVAR_Lag2Q	0,944	1363	2	46	0,266	Non Sig. Var.	
		USTravelVAR_Lag3Q	USTravelVAR_Lag3Q	0,958	1.018	2	46	0,369	Non Sig. Var.	
		USTravelVAR_Lag3Q , USTravelVAR_Lag4Q	USTravelVAR_Lag3Q	0,956	1.045	2	45	0,360	Non Sig. Var.	
		USTravelVAR_Lag4Q	USTravelVAR_Lag4Q	0,892	2.730	2	45	0,076	Sig. Var.	
		USTravelVAR_Lag4Q , USTravelVAR_Lag5Q	USTravelVAR_Lag4Q	0,889	2.758	2	44	0,074	Sig. Var.	
		USTravelVAR_Lag5Q	USTravelVAR_Lag5Q	0,975	1	2	44	0,573	Non Sig. Var.	
		USTravelVAR_Lag5Q , USTravelVAR_Lag6Q	USTravelVAR_Lag5Q	0,975	1	2	44	0,573	Non Sig. Var.	
		USTravelVAR_Lag6Q	USTravelVAR_Lag6Q	0,981	0	2	44	0,650	Non Sig.	

									Var.
	UStTravelVAR_Lag6Q , UStTravelVAR_Lag7Q	UStTravelVAR_Lag6Q	0,981	0	2	44	0,650	Non Sig.	Var.
		UStTravelVAR_Lag7Q	0,869	3303	2	44	0,046	Sig. Var.	
	UStTravelVAR_Lag7Q , UStTravelVAR_Lag8Q	UStTravelVAR_Lag7Q	0,861	3479	2	43	0,040	Sig. Var.	
		UStTravelVAR_Lag8Q	0,964	1	2	43	0,458	Non Sig.	Var.
		UStTravelVAR	0,992	0,19	2	47	0,827	Non Sig.	Var.
	UStTravelVAR , UStTravelVAR_Lag1Q , UStTravelVAR_Lag2Q	UStTravelVAR_Lag1Q	0,994	0,146	2	47	0,865	Non Sig.	Var.
		UStTravelVAR_Lag2Q	0,95	1243	2	47	0,298	Non Sig.	Var.
		UStTravelVAR_Lag1Q	0,993	0,169	2	46	0,845	Non Sig.	Var.
	UStTravelVAR_Lag1Q , UStTravelVAR_Lag2Q , UStTravelVAR_Lag3Q	UStTravelVAR_Lag2Q	0,944	1363	2	46	0,266	Non Sig.	Var.
		UStTravelVAR_Lag3Q	0,958	1.018	2	46	0,369	Non Sig.	Var.
		UStTravelVAR_Lag2Q	0,946	1276	2	45	0,289	Non Sig.	Var.
	UStTravelVAR_Lag2Q , UStTravelVAR_Lag3Q , UStTravelVAR_Lag4Q	UStTravelVAR_Lag3Q	0,956	1.045	2	45	0,360	Non Sig.	Var.
		UStTravelVAR_Lag4Q	0,892	2.730	2	45	0,076	Sig. Var.	
3Q	UStTravelVAR_Lag3Q , UStTravelVAR_Lag4Q , UStTravelVAR_Lag5Q	UStTravelVAR_Lag3Q	0,96	1	2	44	0,403	Non Sig.	Var.
		UStTravelVAR_Lag4Q	0,889	2.758	2	44	0,074	Sig. Var.	
		UStTravelVAR_Lag5Q	0,975	1	2	44	0,573	Non Sig.	Var.
		UStTravelVAR_Lag4Q	0,889	2.758	2	44	0,074	Sig. Var.	
	UStTravelVAR_Lag4Q , UStTravelVAR_Lag5Q , UStTravelVAR_Lag6Q	UStTravelVAR_Lag5Q	0,975	1	2	44	0,573	Non Sig.	Var.
		UStTravelVAR_Lag6Q	0,981	0	2	44	0,650	Non Sig.	Var.
		UStTravelVAR_Lag5Q	0,975	1	2	44	0,573	Non Sig.	Var.
	UStTravelVAR_Lag5Q , UStTravelVAR_Lag6Q , UStTravelVAR_Lag7Q	UStTravelVAR_Lag6Q	0,981	0	2	44	0,650	Non Sig.	Var.
		UStTravelVAR_Lag7Q	0,869	3303	2	44	0,046	Sig. Var.	
		UStTravelVAR_Lag6Q	0,974	1	2	43	0,572	Non Sig.	Var.
	UStTravelVAR_Lag6Q , UStTravelVAR_Lag7Q , UStTravelVAR_Lag8Q	UStTravelVAR_Lag7Q	0,861	3479	2	43	0,040	Sig. Var.	
		UStTravelVAR_Lag8Q	0,964	1	2	43	0,458	Non Sig.	Var.
4Q		UStTravelVAR	0,989	0,257	2	46	0,775	Non Sig.	Var.
	UStTravelVAR , UStTravelVAR_Lag1Q , UStTravelVAR_Lag2Q , UStTravelVAR_Lag3Q	UStTravelVAR_Lag1Q	0,993	0,169	2	46	0,845	Non Sig.	Var.
		UStTravelVAR_Lag2Q	0,944	1363	2	46	0,266	Non Sig.	Var.
		UStTravelVAR_Lag3Q	0,958	1.018	2	46	0,369	Non Sig.	Var.
	UStTravelVAR_Lag1Q , UStTravelVAR_Lag2Q , UStTravelVAR_Lag3Q , UStTravelVAR_Lag4Q	UStTravelVAR_Lag1Q	0,988	0,28	2	45	0,757	Non Sig.	Var.
		UStTravelVAR_Lag2Q	0,946	1276	2	45	0,289	Non Sig.	Var.
		UStTravelVAR_Lag3Q	0,956	1.045	2	45	0,360	Non Sig.	

USTravelVAR	1Q	SPX	USTravelVAR_Lag4Q	0,892	2.730	2	45	0,076	Var.
			USTravelVAR_Lag2Q	0,936	1512	2	44	0,232	Sig. Var.
			USTravelVAR_Lag2Q ,						Non Sig.
			USTravelVAR_Lag3Q ,						Var.
			USTravelVAR_Lag3Q	0,96	1	2	44	0,403	Non Sig.
			USTravelVAR_Lag4Q ,						Var.
			USTravelVAR_Lag4Q	0,889	2.758	2	44	0,074	Sig. Var.
			USTravelVAR_Lag5Q	0,975	1	2	44	0,573	Non Sig.
			USTravelVAR_Lag5Q						Var.
			USTravelVAR_Lag3Q	0,96	1	2	44	0,403	Non Sig.
			USTravelVAR_Lag3Q ,						Var.
			USTravelVAR_Lag4Q ,						Sig. Var.
			USTravelVAR_Lag4Q	0,889	2.758	2	44	0,074	Non Sig.
			USTravelVAR_Lag5Q ,						Var.
			USTravelVAR_Lag5Q	0,975	1	2	44	0,573	Non Sig.
			USTravelVAR_Lag6Q	0,981	0	2	44	0,650	Var.
			USTravelVAR_Lag4Q	0,889	2.758	2	44	0,074	Sig. Var.
			USTravelVAR_Lag5Q ,						Non Sig.
			USTravelVAR_Lag5Q	0,975	1	2	44	0,573	Var.
			USTravelVAR_Lag6Q ,						Non Sig.
			USTravelVAR_Lag6Q	0,981	0	2	44	0,650	Var.
			USTravelVAR_Lag7Q	0,869	3303	2	44	0,046	Sig. Var.
			USTravelVAR_Lag5Q	0,964	1	2	43	0,456	Non Sig.
			USTravelVAR_Lag5Q ,						Var.
			USTravelVAR_Lag6Q ,						Non Sig.
			USTravelVAR_Lag6Q	0,974	1	2	43	0,572	Var.
			USTravelVAR_Lag7Q ,						Sig. Var.
			USTravelVAR_Lag7Q	0,861	3479	2	43	0,040	Non Sig.
			USTravelVAR_Lag8Q	0,964	1	2	43	0,458	Var.
USTravelVAR	2Q	SPX	SPX	0,992	0	2	47	0,822	Non Sig.
			SPX_Lag1Q	0,99	0,23	2	46	0,795	Var.
			SPX_Lag1Q						Non Sig.
			SPX_Lag2Q	0,935	1534	2	44	0,227	Var.
			SPX_Lag2Q						Non Sig.
			SPX_Lag3Q	0,895	2.516	2	43	0,093	Sig. Var.
			SPX_Lag3Q						Non Sig.
			SPX_Lag4Q	0,958	1	2	42	0,407	Var.
			SPX_Lag4Q						Non Sig.
			SPX_Lag5Q	0,983	0	2	42	0,702	Var.
			SPX_Lag5Q						Non Sig.
			SPX_Lag6Q	0,941	1.308	2	42	0,281	Var.
			SPX_Lag6Q						Non Sig.
			SPX_Lag7Q	0,995	0,098	2	41	0,907	Var.
			SPX_Lag7Q						Non Sig.
			SPX_Lag8Q	0,997	0	2	41	0,947	Var.
			SPX_Lag8Q						Non Sig.
USTravelVAR	2Q	SPX , SPX_Lag1Q	SPX	0,986	0	2	44	0,726	Var.
			SPX_Lag1Q	0,968	1	2	44	0,488	Non Sig.
			SPX_Lag1Q ,						Non Sig.
			SPX_Lag2Q	0,982	0,392	2	42	0,678	Var.
			SPX_Lag2Q	0,881	2825	2	42	0,071	Sig. Var.
			SPX_Lag2Q ,						Non Sig.
			SPX_Lag3Q	0,935	1391	2	40	0,261	Var.
			SPX_Lag3Q	0,911	1.961	2	40	0,154	Non Sig.

3Q	SPX_Lag3Q , SPX_Lag4Q	SPX_Lag3Q	0,888	2.471	2	39	0,098	Sig. Var.
		SPX_Lag4Q	0,896	2.262	2	39	0,118	Non Sig. Var.
	SPX_Lag4Q , SPX_Lag5Q	SPX_Lag4Q	0,963	1	2	39	0,483	Non Sig. Var.
		SPX_Lag5Q	0,947	1.101	2	39	0,343	Non Sig. Var.
	SPX_Lag5Q , SPX_Lag6Q	SPX_Lag5Q	0,98	0	2	40	0,665	Non Sig. Var.
		SPX_Lag6Q	0,961	1	2	40	0,449	Non Sig. Var.
	SPX_Lag6Q , SPX_Lag7Q	SPX_Lag6Q	0,92	1.692	2	39	0,197	Non Sig. Var.
		SPX_Lag7Q	0,972	0,553	2	39	0,580	Non Sig. Var.
	SPX_Lag7Q , SPX_Lag8Q	SPX_Lag7Q	0,992	0,153	2	38	0,858	Non Sig. Var.
		SPX_Lag8Q	0,999	0	2	38	0,989	Non Sig. Var.
	SPX , SPX_Lag1Q , SPX_Lag2Q	SPX	0,991	0,18	2	40	0,836	Non Sig. Var.
		SPX_Lag1Q	0,95	1050	2	40	0,360	Non Sig. Var.
		SPX_Lag2Q	0,867	3074	2	40	0,057	Sig. Var.
	SPX_Lag1Q , SPX_Lag2Q , SPX_Lag3Q	SPX_Lag1Q	0,981	0,361	2	38	0,699	Non Sig. Var.
		SPX_Lag2Q	0,875	2725	2	38	0,078	Sig. Var.
		SPX_Lag3Q	0,95	1	2	38	0,381	Non Sig. Var.
	SPX_Lag2Q , SPX_Lag3Q , SPX_Lag4Q	SPX_Lag2Q	0,916	1645	2	36	0,207	Non Sig. Var.
		SPX_Lag3Q	0,903	1.940	2	36	0,158	Non Sig. Var.
		SPX_Lag4Q	0,822	3.888	2	36	0,030	Sig. Var.
		SPX_Lag3Q	0,851	3.162	2	36	0,054	Sig. Var.
	SPX_Lag3Q , SPX_Lag4Q , SPX_Lag5Q	SPX_Lag4Q	0,905	1.886	2	36	0,166	Non Sig. Var.
		SPX_Lag5Q	0,953	1	2	36	0,421	Non Sig. Var.
		SPX_Lag4Q	0,97	1	2	37	0,565	Non Sig. Var.
	SPX_Lag4Q , SPX_Lag5Q , SPX_Lag6Q	SPX_Lag5Q	0,934	1.305	2	37	0,283	Non Sig. Var.
		SPX_Lag6Q	0,946	1.061	2	37	0,356	Non Sig. Var.
		SPX_Lag5Q	0,978	0	2	37	0,668	Non Sig. Var.
	SPX_Lag5Q , SPX_Lag6Q , SPX_Lag7Q	SPX_Lag6Q	0,944	1.102	2	37	0,343	Non Sig. Var.
		SPX_Lag7Q	0,974	0,489	2	37	0,617	Non Sig. Var.
		SPX_Lag6Q	0,906	1.873	2	36	0,168	Non Sig. Var.
	SPX_Lag6Q , SPX_Lag7Q , SPX_Lag8Q	SPX_Lag7Q	0,963	0,699	2	36	0,504	Non Sig. Var.
		SPX_Lag8Q	0,98	0	2	36	0,689	Non Sig. Var.

4Q		SPX	0,98	0,368	2	36	0,695	Non Sig. Var.
	SPX , SPX_Lag1Q , SPX_Lag2Q , SPX_Lag3Q	SPX_Lag1Q	0,939	1177	2	36	0,320	Non Sig. Var.
		SPX_Lag2Q	0,857	3012	2	36	0,062	Sig. Var.
		SPX_Lag3Q	0,965	1	2	36	0,525	Non Sig. Var.
	SPX_Lag1Q , SPX_Lag2Q , SPX_Lag3Q , SPX_Lag4Q	SPX_Lag1Q	0,941	1061	2	34	0,357	Non Sig. Var.
		SPX_Lag2Q	0,851	2982	2	34	0,064	Sig. Var.
		SPX_Lag3Q	0,943	1.027	2	34	0,369	Non Sig. Var.
		SPX_Lag4Q	0,883	2.261	2	34	0,120	Non Sig. Var.
	SPX_Lag2Q , SPX_Lag3Q , SPX_Lag4Q , SPX_Lag5Q	SPX_Lag2Q	0,943	0,99	2	33	0,382	Non Sig. Var.
		SPX_Lag3Q	0,863	2.622	2	33	0,088	Sig. Var.
		SPX_Lag4Q	0,839	3.174	2	33	0,055	Sig. Var.
		SPX_Lag5Q	0,915	1.527	2	33	0,232	Non Sig. Var.
	SPX_Lag3Q , SPX_Lag4Q , SPX_Lag5Q , SPX_Lag6Q	SPX_Lag3Q	0,854	2.908	2	34	0,068	Sig. Var.
		SPX_Lag4Q	0,917	1.530	2	34	0,231	Non Sig. Var.
		SPX_Lag5Q	0,931	1.265	2	34	0,295	Non Sig. Var.
		SPX_Lag6Q	0,954	1	2	34	0,446	Non Sig. Var.
	SPX_Lag4Q , SPX_Lag5Q , SPX_Lag6Q , SPX_Lag7Q	SPX_Lag4Q	0,961	1	2	35	0,495	Non Sig. Var.
		SPX_Lag5Q	0,929	1.343	2	35	0,274	Non Sig. Var.
		SPX_Lag6Q	0,933	1.250	2	35	0,299	Non Sig. Var.
		SPX_Lag7Q	0,988	0,207	2	35	0,814	Non Sig. Var.
	SPX_Lag5Q , SPX_Lag6Q , SPX_Lag7Q , SPX_Lag8Q	SPX_Lag5Q	0,898	1.935	2	34	0,160	Non Sig. Var.
		SPX_Lag6Q	0,928	1.312	2	34	0,283	Non Sig. Var.
		SPX_Lag7Q	0,965	0,613	2	34	0,548	Non Sig. Var.
		SPX_Lag8Q	0,992	0	2	34	0,878	Non Sig. Var.

We will now present the results of our Wilk's Lambda tests performed on the 180 models generated. As we mentioned before, this test is used to verify if there are differences between the means of identified groups of subjects on a combination of dependent variables, therefore helping us to evaluate the statistical significance of our models.

Table D.2: Wilk's Lambda tests

		Wilks' Lambda Test				
		Test of Functions	Wilks' Lambda	Chi-square	df	Sig.
USAutoVAR	1Q	USAutoVAR	1	0,96	2,017	2 0,365
		USAutoVAR_Lag1Q	1	0,968	1,568	2 0,456
		USAutoVAR_Lag2Q	1	0,997	0,14	2 0,932
		USAutoVAR_Lag3Q	1	0,936	3,028	2 0,220
		USAutoVAR_Lag4Q	1	0,921	3,721	2 0,156
		USAutoVAR_Lag5Q	1	0,907	4,275	2 0,118
		USAutoVAR_Lag6Q	1	0,95	2,258	2 0,323
		USAutoVAR_Lag7Q	1	0,979	0,943	2 0,624
		USAutoVAR_Lag8Q	1	0,868	6,084	2 0,048
	2Q	USAutoVAR , USAutoVAR_Lag1Q	1	0,968	1,578	2 0,454
		USAutoVAR_Lag1Q , USAutoVAR_Lag2Q	1 through 2 2	0,972 0,999	1,335 0,057	4 0,855 1 0,811
		USAutoVAR_Lag2Q , USAutoVAR_Lag3Q	1 through 2 2	0,928 0,999	3,420 0,028	4 0,490 1 0,867
		USAutoVAR_Lag3Q , USAutoVAR_Lag4Q	1 through 2 2	0,808 0,997	9,482 0,13	4 0,050 1 0,718
		USAutoVAR_Lag4Q , USAutoVAR_Lag5Q	1 through 2 2	0,84 0,988	7,559 0,509	4 0,109 1 0,476
		USAutoVAR_Lag5Q , USAutoVAR_Lag6Q	1 through 2 2	0,862 0,951	6,476 2,169	4 0,166 1 0,141
		USAutoVAR_Lag6Q , USAutoVAR_Lag7Q	1 through 2 2	0,927 0,992	3,292 0,366	4 0,510 1 0,545
		USAutoVAR_Lag7Q , USAutoVAR_Lag8Q	1 through 2 2	0,831 0,98	7,875 0,853	4 0,096 1 0,356
	3Q	USAutoVAR , USAutoVAR_Lag1Q , USAutoVAR_Lag2Q	1 through 2 2	0,972 0,999	1,343 0,057	4 0,854 1 0,811
		USAutoVAR_Lag1Q , USAutoVAR_Lag2Q , USAutoVAR_Lag3Q	1 through 2 2	0,898 0,97	4,859 1,367	6 0,562 2 0,505
		USAutoVAR_Lag2Q , USAutoVAR_Lag3Q , USAutoVAR_Lag4Q	1 through 2 2	0,799 0,997	9,884 0,145	6 0,130 2 0,930
		USAutoVAR_Lag3Q , USAutoVAR_Lag4Q , USAutoVAR_Lag5Q	1 through 2 2	0,714 0,961	14,502 1,695	6 0,025 2 0,429
		USAutoVAR_Lag4Q , USAutoVAR_Lag5Q ,	1 through 2	0,804	9,391	6 0,153

		USAutoVAR_Lag6Q	2	0,949	2.264	2	0,322
		USAutoVAR_Lag5Q ,	1 through	0,844	7.314	6	0,293
		USAutoVAR_Lag6Q ,	2	0,936	2.864	2	0,239
		USAutoVAR_Lag7Q	2				
		USAutoVAR_Lag6Q ,	1 through	0,774	10.784	6	0,095
		USAutoVAR_Lag7Q ,	2	0,914	3.781	2	0,151
		USAutoVAR_Lag8Q	2				
		USAutoVAR , USAutoVAR_Lag1Q ,	1 through	0,897	4.868	6	0,561
		USAutoVAR_Lag2Q ,	2	0,97	1.376	2	0,503
		USAutoVAR_Lag3Q	2				
		USAutoVAR_Lag1Q ,	1 through	0,778	10.914	8	0,207
		USAutoVAR_Lag2Q ,	2	0,971	1.267	3	0,737
		USAutoVAR_Lag3Q ,	2				
		USAutoVAR_Lag4Q	2				
		USAutoVAR_Lag2Q ,	1 through	0,695	15.472	8	0,051
		USAutoVAR_Lag3Q ,	2	0,959	1.787	3	0,618
		USAutoVAR_Lag4Q ,	2				
		USAutoVAR_Lag5Q	2				
	4Q	USAutoVAR_Lag3Q ,	1 through	0,695	15.439	8	0,051
		USAutoVAR_Lag4Q ,	2	0,938	2.731	3	0,435
		USAutoVAR_Lag5Q ,	2				
		USAutoVAR_Lag6Q	2				
		USAutoVAR_Lag4Q ,	1 through	0,787	10.188	8	0,252
		USAutoVAR_Lag5Q ,	2	0,93	3.088	3	0,378
		USAutoVAR_Lag6Q ,	2				
		USAutoVAR_Lag7Q	2				
		USAutoVAR_Lag5Q ,	1 through	0,718	13.723	8	0,089
		USAutoVAR_Lag6Q ,	2	0,914	3.745	3	0,290
		USAutoVAR_Lag7Q ,	2				
		USAutoVAR_Lag8Q	2				
USBanksVAR	1Q	USBanksVAR	1	0,974	1.284	2	0,526
		USBanksVAR_Lag1Q	1	0,981	1	2	0,637
		USBanksVAR_Lag2Q	1	0,93	3403	2	0,182
		USBanksVAR_Lag3Q	1	0,909	4.405	2	0,111
		USBanksVAR_Lag4Q	1	0,902	4.662	2	0,097
		USBanksVAR_Lag5Q	1	0,944	2.514	2	0,285
		USBanksVAR_Lag6Q	1	0,957	1.950	2	0,377
		USBanksVAR_Lag7Q	1	0,628	20453	2	0,000
		USBanksVAR_Lag8Q	1	0,993	0	2	0,853
	2Q	USBanksVAR , USBanksVAR_Lag1Q	1 through	0,958	2.038	4	0,729
			2	1000	0	1	0,976
		USBanksVAR_Lag1Q ,	1 through	0,914	4.171	4	0,383
		USBanksVAR_Lag2Q	2				

		2	0,983	0,799	1	0,371
	USBanksVAR_Lag2Q ,	1 through				
	USBanksVAR_Lag3Q	2	0,837	8.096	4	0,088
		2	0,995	0,218	1	0,641
	USBanksVAR_Lag3Q ,	1 through				
	USBanksVAR_Lag4Q	2	0,821	8.776	4	0,067
		2	0,929	3256	1	0,071
	USBanksVAR_Lag4Q ,	1 through				
	USBanksVAR_Lag5Q	2	0,844	7.388	4	0,117
		2	0,949	2275	1	0,132
	USBanksVAR_Lag5Q ,	1 through				
	USBanksVAR_Lag6Q	2	0,901	4.537	4	0,338
		2	0,983	1	1	0,388
	USBanksVAR_Lag6Q ,	1 through				
	USBanksVAR_Lag7Q	2	0,596	22.505	4	0,000
		2	0,958	1872	1	0,171
	USBanksVAR_Lag7Q ,	1 through				
	USBanksVAR_Lag8Q	2	0,616	20.559	4	0,000
		2	0,993	0,303	1	0,582
	USBanksVAR , USBanksVAR_Lag1Q ,	1 through				
	USBanksVAR_Lag2Q	2	0,894	5.158	6	0,524
		2	0,962	1769	2	0,413
		1 through				
	USBanksVAR_Lag1Q ,	2	0,821	8.883	6	0,180
	USBanksVAR_Lag2Q ,	2	0,976	1.071	2	0,585
	USBanksVAR_Lag3Q					
		1 through				
	USBanksVAR_Lag2Q ,	2	0,755	12.386	6	0,054
	USBanksVAR_Lag3Q ,	2	0,9	4633	2	0,099
	USBanksVAR_Lag4Q					
		1 through				
3Q	USBanksVAR_Lag3Q ,	2	0,783	10.524	6	0,104
	USBanksVAR_Lag4Q ,	2	0,889	5.042	2	0,080
	USBanksVAR_Lag5Q					
		1 through				
	USBanksVAR_Lag4Q ,	2	0,811	9.019	6	0,173
	USBanksVAR_Lag5Q ,	2	0,918	3.674	2	0,159
	USBanksVAR_Lag6Q					
		1 through				
	USBanksVAR_Lag5Q ,	2	0,559	25.041	6	0,000
	USBanksVAR_Lag6Q ,	2	0,944	2.472	2	0,291
	USBanksVAR_Lag7Q					
		1 through				
	USBanksVAR_Lag6Q ,	2	0,575	23.266	6	0,001
	USBanksVAR_Lag7Q ,	2	0,939	2.645	2	0,266
	USBanksVAR_Lag8Q					
		1 through				
4Q	USBanksVAR , USBanksVAR_Lag1Q ,	2	0,788	10.594	8	0,226
	USBanksVAR_Lag2Q ,	2	0,953	2.165	3	0,539
	USBanksVAR_Lag3Q					
		1 through				
	USBanksVAR_Lag1Q ,	2	0,722	14.153	8	0,078
	USBanksVAR_Lag2Q ,	2	0,866	6.282	3	0,099
	USBanksVAR_Lag3Q ,					

		USBanksVAR_Lag4Q				
USConsMatVAR	1Q	USBanksVAR_Lag2Q ,	1 through	0,706	14.786	8 0,063
		USBanksVAR_Lag3Q ,	2	0,887	5.120	3 0,163
		USBanksVAR_Lag4Q ,	2			
		USBanksVAR_Lag5Q				
		USBanksVAR_Lag3Q ,	1 through	0,763	11.488	8 0,176
		USBanksVAR_Lag4Q ,	2	0,889	4.993	3 0,172
		USBanksVAR_Lag5Q ,	2			
		USBanksVAR_Lag6Q				
		USBanksVAR_Lag4Q ,	1 through	0,502	29.272	8 0,000
		USBanksVAR_Lag5Q ,	2	0,896	4.678	3 0,197
		USBanksVAR_Lag6Q ,	2			
		USBanksVAR_Lag7Q				
	2Q	USBanksVAR_Lag5Q ,	1 through	0,537	25.836	8 0,001
		USBanksVAR_Lag6Q ,	2	0,914	3.746	3 0,290
		USBanksVAR_Lag7Q ,	2			
		USBanksVAR_Lag8Q				
		USConsMatVAR	1	0,973	1.361	2 0,506
		USConsMatVAR_Lag1Q	1	0,996	0	2 0,903
		USConsMatVAR_Lag2Q	1	0,954	2198	2 0,333
		USConsMatVAR_Lag3Q	1	0,954	2.162	2 0,339
		USConsMatVAR_Lag4Q	1	0,878	5.873	2 0,053
		USConsMatVAR_Lag5Q	1	0,973	1.200	2 0,549
		USConsMatVAR_Lag6Q	1	0,996	0	2 0,911
		USConsMatVAR_Lag7Q	1	0,774	11287	2 0,004
		USConsMatVAR_Lag8Q	1	0,982	1	2 0,670
		USConsMatVAR ,	1 through	0,971	1.409	4 0,843
		USConsMatVAR_Lag1Q	2	0,997	0	1 0,719
		USConsMatVAR_Lag1Q ,	1 through	0,948	2.483	4 0,648
		USConsMatVAR_Lag2Q	2	0,996	0,202	1 0,653
		USConsMatVAR_Lag2Q ,	1 through	0,876	6.034	4 0,197
		USConsMatVAR_Lag3Q	2	0,995	0,233	1 0,629
		USConsMatVAR_Lag3Q ,	1 through	0,824	8.595	4 0,072
		USConsMatVAR_Lag4Q	2	0,958	1921	1 0,166
		USConsMatVAR_Lag4Q ,	1 through	0,86	6.568	4 0,161
		USConsMatVAR_Lag5Q	2	0,985	0,636	1 0,425
		USConsMatVAR_Lag5Q ,	1 through	0,969	1.351	4 0,853
		USConsMatVAR_Lag6Q	2	0,996	0	1 0,691
		USConsMatVAR_Lag6Q ,	1 through	0,731	13.656	4 0,008
		USConsMatVAR_Lag7Q	2	1000	0,003	1 0,960
		USConsMatVAR_Lag7Q ,	1 through	0,736	13.009	4 0,011
		USConsMatVAR_Lag8Q	2	0,982	0,791	1 0,374

3Q	USConsMatVAR ,	1 through	0,922	3.753	6	0,710
	USConsMatVAR_Lag1Q ,	2	0,989	0,513	2	0,774
	USConsMatVAR_Lag2Q ,	2				
	USConsMatVAR_Lag1Q ,	1 through	0,872	6.185	6	0,403
	USConsMatVAR_Lag2Q ,	2	0,992	0	2	0,842
	USConsMatVAR_Lag3Q ,	2				
	USConsMatVAR_Lag2Q ,	1 through	0,757	12.247	6	0,057
	USConsMatVAR_Lag3Q ,	2	0,883	5471	2	0,065
	USConsMatVAR_Lag4Q ,	2				
	USConsMatVAR_Lag3Q ,	1 through	0,805	9.322	6	0,156
	USConsMatVAR_Lag4Q ,	2	0,94	2.676	2	0,262
	USConsMatVAR_Lag5Q ,	2				
	USConsMatVAR_Lag4Q ,	1 through	0,858	6.602	6	0,359
	USConsMatVAR_Lag5Q ,	2	0,984	1	2	0,713
	USConsMatVAR_Lag6Q ,	2				
4Q	USConsMatVAR_Lag5Q ,	1 through	0,712	14.600	6	0,024
	USConsMatVAR_Lag6Q ,	2	0,975	1.100	2	0,577
	USConsMatVAR_Lag7Q ,	2				
	USConsMatVAR_Lag6Q ,	1 through	0,691	15.502	6	0,017
	USConsMatVAR_Lag7Q ,	2	0,982	1	2	0,676
	USConsMatVAR_Lag8Q ,	2				
	USConsMatVAR ,	1 through	0,842	7.668	8	0,467
	USConsMatVAR_Lag1Q ,	2	0,98	1	3	0,828
	USConsMatVAR_Lag2Q ,	2				
	USConsMatVAR_Lag3Q ,	2				
	USConsMatVAR_Lag1Q ,	1 through	0,753	12.316	8	0,138
	USConsMatVAR_Lag2Q ,	2	0,879	5.608	3	0,132
	USConsMatVAR_Lag3Q ,	2				
	USConsMatVAR_Lag4Q ,	2				
	USConsMatVAR_Lag2Q ,	1 through	0,728	13.490	8	0,096
	USConsMatVAR_Lag3Q ,	2	0,857	6.547	3	0,088
	USConsMatVAR_Lag4Q ,	2				
	USConsMatVAR_Lag5Q ,	2				
	USConsMatVAR_Lag3Q ,	1 through	0,796	9.676	8	0,289
	USConsMatVAR_Lag4Q ,	2	0,936	2.810	3	0,422
	USConsMatVAR_Lag5Q ,	2				
	USConsMatVAR_Lag6Q ,	2				
	USConsMatVAR_Lag4Q ,	1 through	0,596	21.961	8	0,005
	USConsMatVAR_Lag5Q ,	2	0,961	1.675	3	0,643
	USConsMatVAR_Lag6Q ,	2				
	USConsMatVAR_Lag7Q ,	2				
	USConsMatVAR_Lag5Q ,	1 through	0,675	16.323	8	0,038
	USConsMatVAR_Lag6Q ,	2				

USFinSerVAR	1Q	USConsMatVAR_Lag7Q , USConsMatVAR_Lag8Q	2	0,958	1.778	3	0,620
		USFinSerVAR	1	0,98	1	2	0,607
		USFinSerVAR_Lag1Q	1	0,994	0	2	0,861
		USFinSerVAR_Lag2Q	1	0,962	1843	2	0,398
		USFinSerVAR_Lag3Q	1	0,977	1.059	2	0,589
		USFinSerVAR_Lag4Q	1	0,87	6.285	2	0,043
		USFinSerVAR_Lag5Q	1	0,996	0	2	0,923
		USFinSerVAR_Lag6Q	1	0,904	4.425	2	0,109
		USFinSerVAR_Lag7Q	1	0,829	8245	2	0,016
		USFinSerVAR_Lag8Q	1	0,944	2.482	2	0,289
	2Q	USFinSerVAR , USFinSerVAR_Lag1Q	1 through 2	0,971	1.378	4	0,848
			2	0,994	0	1	0,591
		USFinSerVAR_Lag1Q , USFinSerVAR_Lag2Q	1 through 2	0,954	2.185	4	0,702
			2	1000	0	1	0,995
		USFinSerVAR_Lag2Q , USFinSerVAR_Lag3Q	1 through 2	0,927	3.439	4	0,487
			2	1000	0,004	1	0,948
		USFinSerVAR_Lag3Q , USFinSerVAR_Lag4Q	1 through 2	0,84	7.772	4	0,100
			2	0,982	0,806	1	0,369
		USFinSerVAR_Lag4Q , USFinSerVAR_Lag5Q	1 through 2	0,866	6.272	4	0,180
			2	0,997	0,129	1	0,719
	3Q	USFinSerVAR_Lag5Q , USFinSerVAR_Lag6Q	1 through 2	0,893	4.927	4	0,295
			2	1000	0	1	0,985
		USFinSerVAR_Lag6Q , USFinSerVAR_Lag7Q	1 through 2	0,751	12.457	4	0,014
			2	0,909	4144	1	0,042
		USFinSerVAR_Lag7Q , USFinSerVAR_Lag8Q	1 through 2	0,788	10.102	4	0,039
			2	0,968	1399	1	0,237
		USFinSerVAR , USFinSerVAR_Lag1Q , USFinSerVAR_Lag2Q	1 through 2	0,934	3.164	6	0,788
			2	0,978	1002	2	0,606
		USFinSerVAR_Lag1Q , USFinSerVAR_Lag2Q , USFinSerVAR_Lag3Q	1 through 2	0,923	3.628	6	0,727
			2	1000	0	2	0,998
		USFinSerVAR_Lag2Q , USFinSerVAR_Lag3Q , USFinSerVAR_Lag4Q	1 through 2	0,791	10.325	6	0,112
			2	0,947	2398	2	0,301
		USFinSerVAR_Lag3Q , USFinSerVAR_Lag4Q , USFinSerVAR_Lag5Q	1 through 2	0,839	7.526	6	0,275
			2	0,982	1	2	0,676
		USFinSerVAR_Lag4Q , USFinSerVAR_Lag5Q , USFinSerVAR_Lag6Q	1 through 2	0,781	10.622	6	0,101
			2	0,931	3.058	2	0,217

USRetailVAR	4Q	USFinSerVAR_Lag5Q ,	1 through	0,737	13.094	6	0,042
		USFinSerVAR_Lag6Q ,	2	0,901	4.467	2	0,107
		USFinSerVAR_Lag7Q	2				
		USFinSerVAR_Lag6Q ,	1 through	0,709	14.469	6	0,025
		USFinSerVAR_Lag7Q ,	2	0,876	5.575	2	0,062
		USFinSerVAR_Lag8Q	2				
		USFinSerVAR , USFinSerVAR_Lag1Q ,	1 through	0,893	5.037	8	0,754
		USFinSerVAR_Lag2Q ,	2	0,973	1.224	3	0,747
		USFinSerVAR_Lag3Q	2				
		USFinSerVAR_Lag1Q ,	1 through	0,777	10.950	8	0,205
		USFinSerVAR_Lag2Q ,	2	0,946	2.408	3	0,492
		USFinSerVAR_Lag3Q ,	2				
		USFinSerVAR_Lag4Q	2				
	1Q	USFinSerVAR_Lag2Q ,	1 through	0,774	10.890	8	0,208
		USFinSerVAR_Lag3Q ,	2	0,939	2.672	3	0,445
		USFinSerVAR_Lag4Q ,	2				
		USFinSerVAR_Lag5Q	2				
		USFinSerVAR_Lag3Q ,	1 through	0,755	11.922	8	0,155
		USFinSerVAR_Lag4Q ,	2	0,903	4.336	3	0,227
		USFinSerVAR_Lag5Q ,	2				
		USFinSerVAR_Lag6Q	2				
		USFinSerVAR_Lag4Q ,	1 through	0,672	16.902	8	0,031
		USFinSerVAR_Lag5Q ,	2	0,861	6.378	3	0,095
		USFinSerVAR_Lag6Q ,	2				
		USFinSerVAR_Lag7Q	2				
	2Q	USFinSerVAR_Lag5Q ,	1 through	0,688	15.508	8	0,050
		USFinSerVAR_Lag6Q ,	2	0,862	6.160	3	0,104
		USFinSerVAR_Lag7Q ,	2				
		USFinSerVAR_Lag8Q	2				
		USRetVAR	1	0,95	2.524	2	0,283
		USRetVAR_Lag1Q	1	1000	0	2	0,989
		USRetVAR_Lag2Q	1	0,944	2687	2	0,261
		USRetVAR_Lag3Q	1	0,889	5.424	2	0,066
		USRetVAR_Lag4Q	1	0,952	2.211	2	0,331
		USRetVAR_Lag5Q	1	0,957	1.919	2	0,383
		USRetVAR_Lag6Q	1	0,938	2.795	2	0,247
		USRetVAR_Lag7Q	1	0,887	5291	2	0,071
		USRetVAR_Lag8Q	1	0,933	2.975	2	0,226
		USRetVAR , USRetVAR_Lag1Q	1 through	0,937	3.101	4	0,541
			2	1000	0	1	0,889
		USRetVAR_Lag1Q , USRetVAR_Lag2Q	1 through	0,944	2.661	4	0,616
			2	1000	0,001	1	0,972
			2				

3Q	USRetVAR_Lag2Q , USRetVAR_Lag3Q	1 through 2	0,802	10.045	4	0,040
		2	0,993	0,312	1	0,577
	USRetVAR_Lag3Q , USRetVAR_Lag4Q	1 through 2	0,82	8.827	4	0,066
		2	0,995	0,231	1	0,631
	USRetVAR_Lag4Q , USRetVAR_Lag5Q	1 through 2	0,915	3.859	4	0,425
		2	0,974	1167	1	0,280
	USRetVAR_Lag5Q , USRetVAR_Lag6Q	1 through 2	0,876	5.739	4	0,219
		2	0,991	0	1	0,527
	USRetVAR_Lag6Q , USRetVAR_Lag7Q	1 through 2	0,831	8.073	4	0,089
		2	0,939	2715	1	0,099
	USRetVAR_Lag7Q , USRetVAR_Lag8Q	1 through 2	0,805	9.214	4	0,056
		2	0,948	2262	1	0,133
4Q	USRetVAR , USRetVAR_Lag1Q , USRetVAR_Lag2Q	1 through 2	0,863	6.792	6	0,341
		2	0,983	0,812	2	0,666
	USRetVAR_Lag1Q , USRetVAR_Lag2Q , USRetVAR_Lag3Q	1 through 2	0,795	10.323	6	0,112
		2	0,992	0	2	0,843
	USRetVAR_Lag2Q , USRetVAR_Lag3Q , USRetVAR_Lag4Q	1 through 2	0,713	14.905	6	0,021
		2	0,979	0,926	2	0,629
	USRetVAR_Lag3Q , USRetVAR_Lag4Q , USRetVAR_Lag5Q	1 through 2	0,765	11.542	6	0,073
		2	0,973	1.186	2	0,553
	USRetVAR_Lag4Q , USRetVAR_Lag5Q , USRetVAR_Lag6Q	1 through 2	0,831	7.952	6	0,242
		2	0,944	2.493	2	0,287
	USRetVAR_Lag5Q , USRetVAR_Lag6Q , USRetVAR_Lag7Q	1 through 2	0,75	12.354	6	0,055
		2	0,91	4.068	2	0,131
	USRetVAR_Lag6Q , USRetVAR_Lag7Q , USRetVAR_Lag8Q	1 through 2	0,757	11.715	6	0,069
		2	0,892	4.800	2	0,091
4Q	USRetVAR , USRetVAR_Lag1Q , USRetVAR_Lag2Q , USRetVAR_Lag3Q	1 through 2	0,747	12.957	8	0,113
		2	0,971	1.298	3	0,729
	USRetVAR_Lag1Q , USRetVAR_Lag2Q , USRetVAR_Lag3Q , USRetVAR_Lag4Q	1 through 2	0,709	14.987	8	0,059
		2	0,979	1	3	0,821

USTravelVAR	1Q	USRetVAR_Lag2Q , USRetVAR_Lag3Q , USRetVAR_Lag4Q , USRetVAR_Lag5Q	1 through 2	0,661	17.626	8	0,024
			2	0,969	1.339	3	0,720
			1 through 2	0,694	15.527	8	0,050
			2	0,887	5.083	3	0,166
		USRetVAR_Lag3Q , USRetVAR_Lag4Q , USRetVAR_Lag5Q , USRetVAR_Lag6Q	1 through 2	0,724	13.742	8	0,089
			2	0,886	5.135	3	0,162
		USRetVAR_Lag4Q , USRetVAR_Lag5Q , USRetVAR_Lag6Q , USRetVAR_Lag7Q	1 through 2	0,687	15.580	8	0,049
			2	0,882	5.216	3	0,157
		USTravelVAR_Lag1Q , USTravelVAR_Lag2Q , USTravelVAR_Lag3Q , USTravelVAR_Lag4Q , USTravelVAR_Lag5Q , USTravelVAR_Lag6Q , USTravelVAR_Lag7Q , USTravelVAR_Lag8Q	1	0,991	0	2	0,794
			1	0,995	0	2	0,876
			1	0,95	2423	2	0,298
			1	0,958	1.992	2	0,369
			1	0,892	5.154	2	0,076
			1	0,975	1.113	2	0,573
			1	0,981	1	2	0,650
			1	0,869	6155	2	0,046
			1	0,964	1.561	2	0,458
	2Q	USTravelVAR , USTravelVAR_Lag1Q	1 through 2	0,986	1	4	0,953
			2	0,995	0	1	0,617
		USTravelVAR_Lag1Q , USTravelVAR_Lag2Q	1 through 2	0,942	2.796	4	0,593
			2	0,996	0,203	1	0,653
		USTravelVAR_Lag2Q , USTravelVAR_Lag3Q	1 through 2	0,894	5.099	4	0,277
			2	0,986	0,664	1	0,415
		USTravelVAR_Lag3Q , USTravelVAR_Lag4Q	1 through 2	0,853	7.080	4	0,132
			2	0,998	0,105	1	0,746
		USTravelVAR_Lag4Q , USTravelVAR_Lag5Q	1 through 2	0,871	6.032	4	0,197
			2	0,989	0,502	1	0,478
		USTravelVAR_Lag5Q , USTravelVAR_Lag6Q	1 through 2	0,949	2.291	4	0,682
			2	1000	0	1	0,918
		USTravelVAR_Lag6Q , USTravelVAR_Lag7Q	1 through 2	0,848	7.193	4	0,126
			2	0,991	0,383	1	0,536
		USTravelVAR_Lag7Q , USTravelVAR_Lag8Q	1 through 2	0,831	7.885	4	0,096
			2	0,984	0,671	1	0,413
	3Q	USTravelVAR , USTravelVAR_Lag1Q ,	1 through	0,939	2.920	6	0,819

		2				
	UStTravelVAR_Lag2Q	2	0,992	0,351	2	0,839
	UStTravelVAR_Lag1Q ,	1 through	0,873	6.135	6	0,408
	UStTravelVAR_Lag2Q ,	2	0,982	1	2	0,670
	UStTravelVAR_Lag3Q					
	UStTravelVAR_Lag2Q ,	1 through	0,766	11.716	6	0,069
	UStTravelVAR_Lag3Q ,	2	0,968	1422	2	0,491
	UStTravelVAR_Lag4Q					
	UStTravelVAR_Lag3Q ,	1 through	0,838	7.611	6	0,268
	UStTravelVAR_Lag4Q ,	2	0,982	1	2	0,682
	UStTravelVAR_Lag5Q					
	UStTravelVAR_Lag4Q ,	1 through	0,844	7.282	6	0,296
	UStTravelVAR_Lag5Q ,	2	0,976	1.029	2	0,598
	UStTravelVAR_Lag6Q					
	UStTravelVAR_Lag5Q ,	1 through	0,836	7.704	6	0,261
	UStTravelVAR_Lag6Q ,	2	0,98	1	2	0,642
	UStTravelVAR_Lag7Q					
	UStTravelVAR_Lag6Q ,	1 through	0,801	9.320	6	0,156
	UStTravelVAR_Lag7Q ,	2	0,96	1.693	2	0,429
	UStTravelVAR_Lag8Q					
4Q	UStTravelVAR , UStTravelVAR_Lag1Q ,	1 through	0,871	6.147	8	0,631
	UStTravelVAR_Lag2Q ,	2	0,981	1	3	0,838
	UStTravelVAR_Lag3Q					
	UStTravelVAR_Lag1Q ,	1 through	0,736	13.334	8	0,101
	UStTravelVAR_Lag2Q ,	2	0,954	2.037	3	0,565
	UStTravelVAR_Lag3Q ,	2				
	UStTravelVAR_Lag4Q					
	UStTravelVAR_Lag2Q ,	1 through	0,734	13.124	8	0,108
	UStTravelVAR_Lag3Q ,	2	0,949	2.243	3	0,523
	UStTravelVAR_Lag4Q ,	2				
	UStTravelVAR_Lag5Q					
	UStTravelVAR_Lag3Q ,	1 through	0,798	9.575	8	0,296
	UStTravelVAR_Lag4Q ,	2	0,972	1.212	3	0,750
	UStTravelVAR_Lag5Q ,	2				
	UStTravelVAR_Lag6Q					
	UStTravelVAR_Lag4Q ,	1 through	0,698	15.278	8	0,054
	UStTravelVAR_Lag5Q ,	2	0,975	1.093	3	0,779
	UStTravelVAR_Lag6Q ,	2				
	UStTravelVAR_Lag7Q					
	UStTravelVAR_Lag5Q ,	1 through	0,786	9.986	8	0,266
	UStTravelVAR_Lag6Q ,	2	0,95	2.138	3	0,544
	UStTravelVAR_Lag7Q ,	2				

		UStavelVAR_Lag8Q				
1Q	UStavelVAR	SPX	1	0,992	0	2 0,822
		SPX_Lag1Q	1	0,99	0	2 0,795
		SPX_Lag2Q	1	0,935	2966	2 0,227
		SPX_Lag3Q	1	0,895	4.759	2 0,093
		SPX_Lag4Q	1	0,958	1.799	2 0,407
		SPX_Lag5Q	1	0,983	1	2 0,702
		SPX_Lag6Q	1	0,941	2.537	2 0,281
		SPX_Lag7Q	1	0,995	0,196	2 0,907
		SPX_Lag8Q	1	0,997	0	2 0,947
		SPX , SPX_Lag1Q	1 through 2	0,955	1.985	4 0,738
2Q	UStavelVAR		2	0,995	0	1 0,641
		SPX_Lag1Q , SPX_Lag2Q	1 through 2	0,867	5.903	4 0,207
			2	0,991	0,372	1 0,542
		SPX_Lag2Q , SPX_Lag3Q	1 through 2	0,821	7.791	4 0,100
			2	0,999	0,037	1 0,847
		SPX_Lag3Q , SPX_Lag4Q	1 through 2	0,79	9.083	4 0,059
			2	0,995	0,212	1 0,645
		SPX_Lag4Q , SPX_Lag5Q	1 through 2	0,915	3.414	4 0,491
			2	0,97	1163	1 0,281
		SPX_Lag5Q , SPX_Lag6Q	1 through 2	0,942	2.357	4 0,670
3Q	UStavelVAR		2	0,998	0	1 0,785
		SPX_Lag6Q , SPX_Lag7Q	1 through 2	0,898	4.156	4 0,385
			2	0,999	0,049	1 0,825
		SPX_Lag7Q , SPX_Lag8Q	1 through 2	0,992	0	4 0,989
			2	1000	0,006	1 0,936
		SPX , SPX_Lag1Q , SPX_Lag2Q	1 through 2	0,815	7.999	6 0,238
			2	0,984	0,624	2 0,732
		SPX_Lag1Q , SPX_Lag2Q , SPX_Lag3Q	1 through 2	0,79	8.739	6 0,189
			2	0,995	0	2 0,912
		SPX_Lag2Q , SPX_Lag3Q , SPX_Lag4Q	1 through 2	0,658	14.654	6 0,023
	UStavelVAR		2	0,981	0,686	2 0,710
		SPX_Lag3Q , SPX_Lag4Q , SPX_Lag5Q	1 through 2	0,736	10.726	6 0,097
			2	0,981	1	2 0,716
		SPX_Lag4Q , SPX_Lag5Q , SPX_Lag6Q	1 through 2	0,86	5.441	6 0,489
			2	0,972	1.039	2 0,595

4Q	SPX_Lag5Q , SPX_Lag6Q , SPX_Lag7Q	1 through	0,911	3.360	6	0,763
		2	0,997	0	2	0,955
	SPX_Lag6Q , SPX_Lag7Q , SPX_Lag8Q	1 through	0,854	5.508	6	0,480
		2	0,984	1	2	0,759
	SPX , SPX_Lag1Q , SPX_Lag2Q , SPX_Lag3Q	1 through	0,768	9.116	8	0,333
		2	0,996	0	3	0,986
	SPX_Lag1Q , SPX_Lag2Q , SPX_Lag3Q , SPX_Lag4Q	1 through	0,683	12.402	8	0,134
		2	0,968	1.046	3	0,790
	SPX_Lag2Q , SPX_Lag3Q , SPX_Lag4Q , SPX_Lag5Q	1 through	0,642	13.947	8	0,083
		2	0,957	1.393	3	0,707
	SPX_Lag3Q , SPX_Lag4Q , SPX_Lag5Q , SPX_Lag6Q	1 through	0,736	9.974	8	0,267
		2	0,979	1	3	0,879
	SPX_Lag4Q , SPX_Lag5Q , SPX_Lag6Q , SPX_Lag7Q	1 through	0,837	5.974	8	0,650
		2	0,959	1.388	3	0,708
	SPX_Lag5Q , SPX_Lag6Q , SPX_Lag7Q , SPX_Lag8Q	1 through	0,806	6.991	8	0,538
		2	0,989	0	3	0,947

Annex E: Results of the estimation of the models described in section “4.1.3. Models estimated in Section C: Achieving high quality information”

For our final model estimated, we now present the Structure Matrix. As indicated above, this will indicate the simple correlation between our variables and the Standardized Discriminant Function.

Table E.1: Structure Matrix of the best model

	Function	
	1	2
USBanksVAR_Lag7Q	,284(*)	,001
USConsMatVAR_Lag7Q	,206(*)	,033
USFinSerVAR_Lag7Q	,172(*)	,027
USRetVAR_Lag3Q	,168(*)	,008
USTravelVAR_Lag7Q	,147(*)	,048
USRetVAR_Lag7Q	,143(*)	,047
USAutoVAR_Lag8Q	,134(*)	,104
USAutoVAR_Lag3Q	,115(*)	-,084
USAutoVAR_Lag5Q	,095(*)	,093
USAutoVAR_Lag4Q	,091(*)	-,019
USRetVAR_Lag4Q	,072(*)	,060
USConsMatVAR_Lag6Q	,025(*)	,011

USFinSerVAR_Lag6Q	-,027	,226(*)
USFinSerVAR_Lag4Q	,104	,184(*)
USBanksVAR_Lag4Q	,067	,177(*)
USBanksVAR_Lag6Q	-,008	,170(*)
USRetVAR_Lag6Q	-,010	,169(*)
USRetVAR_Lag8Q	-,050	,158(*)
USConsMatVAR_Lag5Q	-,021	-,134(*)
USRetVAR_Lag5Q	,046	-,128(*)
USConsMatVAR_Lag4Q	,115	,124(*)
USFinSerVAR_Lag8Q	-,064	,118(*)
USRetVAR_Lag2Q	,098	-,111(*)
USBanksVAR_Lag5Q	,073	-,096(*)
USConsMatVAR_Lag8Q	-,006	,093(*)
USFinSerVAR_Lag5Q	-,002	-,060(*)
USBanksVAR_Lag8Q	-,007	,058(*)
Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions Variables ordered by absolute size of correlation within function.		
*. Largest absolute correlation between each variable and any discriminant function		