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Sector Correlation as a U.S Recession Predictor

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Preface

This thesis is the completion of our Master of Science in Financial Economics at the Norwegian University of Science and Technology (NTNU). After countless, frustrating and tiresome hours in group rooms at campus, we have finished this master thesis.

We wanted to write about contexts in financial markets, and was therefore very excited when we were allowed to write about low sector correlations as a predictor for recessions.

We would like to thank Snorre Lindset for being our supervisor and guiding us through the process of writing the thesis. Also, we would like to direct our gratitude to Costanza Biavaschi for econometric guidance and help.

Finally, we wish to thank each other for a good partnership throughout this semester.

Abstract

Based on a notion proposed in Dagens Næringsliv 15th of May 2017 we test if low correlations between sector returns can predict an upcoming recession. Using sector returns from the S&P 500, with weekly and monthly observations from 1989 to 2018, we calculate average sector correlation through time.

The explanatory variable, average sector correlation, is tested for significant marginal effects and the models are tested for predictive powers. We use three different model structures. First, a simple probit model with one explanatory variable. The second structure adds a lagged dependent variable. The third and final structure adds the yield spread as an explanatory variable, which is a proven recession predictor. Model selection for all structures are based on the highest $pseduo - R^2$. We find that low average sector correlation, even though it has a negative and significant marginal effect, is not a reliable recession predictor. Adding a lagged dependent variable result in unrealistic high goodness-of-fit and makes the average sector correlation insignificant. Adding the yield spread improves the goodness-of-fit and slightly improves the predictive power of the model. Still, the predictive powers are unreliable.

Simulating investment strategies using average sector correlation as a buy or sell indicator results in little or no gain relative to a buy & hold strategy.

Abstrakt

Med utgangspunkt i Dagens Næringslivs artikkel, publisert 15. mai 2017, tester vi om lav sektorkorrelasjon kan predikere resesjoner. For å teste hypotesen, bruker vi avkastningen til sektorene på S&P 500. Datasettet består av ukentlige og månedlige observasjoner fra 1989 til 2018. Forklaringsvariabelen vi bruker, gjennomsnittlig sektorkorrelasjon, er spesifisert med ulike prognosehorisonter og ulike korrelasjonsintervaller.

Vi tester for signifikante marginaleffekter til forklaringsvariabelen og prediktive egenskaper til modellene. Den første modelstrukturen er en enkel probit model med én forklaringsvariabel. I den andre modellen legger vi til en lagget avhengig variabel. I den tredje og siste modelstrukturen legger vi til avkastningsforskjellene mellom 10-årig og 3-månedlig statsobligasjoner. For å velge de beste modelspesifikasjonene, måler vi forklaringskraft med $pseduo - R^2$. Vi finner at lav gjennomsnittlig sektorkorrelasjon, selv om den har negativ og signifikant marginaleffekt, ikke er en god prediktor for resesjoner. Når vi legger til en lagget avhenig variabel, får vi urealistisk høy forklaringskraft og insignifikant marginal effekt. Avkastningsforskjellene mellom statsobligasjonene forbedrer forklarings- og prediksjonskraften til modellen. Prediksjonskraften er likevell ikke til å stole på.

Simulerte investeringsstrategier viser at gjennomsnittlig sektorkorrelasjon ikke gir noen nevneverdig meravkastning enn en "buy & hold" strategi.

Contents

1. Introduction

During downturns, sector correlations have a tendency to be high, everything falls at the same time. In Dagens Næringsliv 15th of May 2017, Harper claims that low correlation between sector returns, increases the probability of a subsequent fall in the market (Havnes 2017). Figure 1 illustrates the notion of low average sector correlation before a recession (Harper 2018).

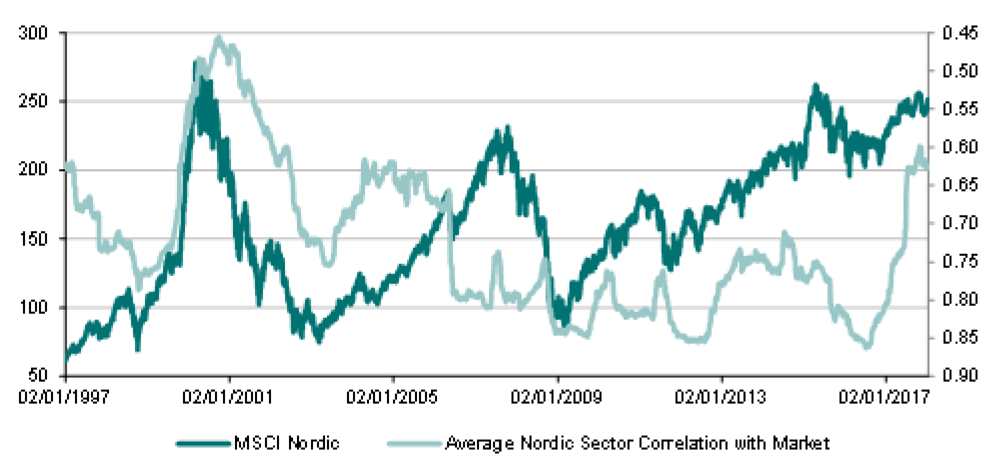

Figure 1.1: MSCI Nordic Countries Index and average Nordic sector correlation with the MSCI Nordic index. The y-axis on the right side, specify the correlation level at a descending order, while the y-axis on the left specify the value of the MSCI Nordic index. (Harper 2018)

The last time sector correlations in the Nordic countries was observed as low as in 2017 and early 2018, was prior to the global financial crisis of 2007-2008. A possible explanation presented in the article, argues that this is caused by investors' interpretations of the market. When correlations are low, investors tend to consider firm-specific news rather than macroeconomic events. (Havnes 2017)

This speculation drives the stock price. There are several possible macroeconomic events that can affect Nordic and worldwide stock markets. A possible war between the U.S and North Korea, a hard "landing" in China or a black swan, are some examples of plausible recession drivers. Nielsen (Havnes 2017) rejects that low correlation between sectors are a concern. He claims that correlations are stochastic and have no predictive power for the return of the stock market.

Low correlations between sectors have also drawn attention in the US stock market. In an interview with CNBC, Xu (2017) reports that average correlation between sectors on the S&P 500 is at its lowest since the onset of the tech bubble. Changes in physical policies is the main factor that effect sector correlation, which becomes evident with the fall in correlation after the 2016 presidential election. After this election, where the Republicans took over both the White House and Congress, possibilities for significant changes in physical policies are anticipated. It becomes increasingly more important to evaluate policies to pick winners and losers. For example, at the start of 2017, there was a demand-increase in the financial and industrial sector. At the same time there was a decrease in energy and IT, where energy and IT are "non-Trump" related sectors. Average sector correlation during 2017 and early 2018 was at a similar level as prior to the tech bubble. However, the difference is that during the tech bubble there was one sector that stood out, whereas in 2017 and early 2018 there are several. (Xu 2017)

Both Harper (Havnes 2017) and Xu (2017) agrees that when sector correlations are high, the stock market is driven by macroeconomic conditions. When sector correlations are low, they both agree that the stock market is driven by firm-specific speculations. Like Nielsen(Havnes 2017), Xu(2017) disagrees with Harper(Havnes 2017) that low sector correlations are a concern.

Based on Dagens Næringsliv's article and CNBC news report, the aim of our master thesis is to examine if average sector correlation can be a recession predictor. Our paper consider the average correlation between sector indices on the S&P 500. We choose to examine the U.S stock market because the data is easily accessible and complete for a long period. Econometric modelling and testing, inspired by earlier literature, are done with probit models. We investigate several model specifications to search for any predictive power. This include adding an autoregressive variable, using different correlation lengths and in combination with another explanatory variable. We investigate our models using both weekly and monthly observations. Further we will simulate and test investment strategies, where average sector correlation is used as a buy or sell signal. If average sector correlation is able to foresee big movements in the stock market, it should be a useful tool to utilize.

2. Earlier literature

Econometric work on predicting recessions have attracted a lot of attention. Fornari and Lemke (2010) see this as no surprise. Expected future economic activity is important information for both public and private organizations. Fornari and Lemke (2010) mention central banks, financial system surveillance authorities, banks and investments funds as organization that have great interest in such information.

There are several studies where the objective is to identify a predictor that can forecast business cycles. Estrella and Mishkin (1998) finds that the yield spread between 10-year and 3-month Treasury bonds is the superior predictor. The yield spread predicts best 4 quarters before a recession starts. Their results shows that good prediction models with the yield spread can also be done with forecast horizons between 2 and 6 quarters.

Their approach to find the superior predictor is to estimate simple probit models. In total they estimate 27 models. To decide on the best model, Estrella and Mishkin (1998) compare goodness-of-fit for their models. Goodness-of-fit is measured with $pseudo - R^2$ developed in Estrella (1998). Further, they find that combining yield spread with another variable, like NYSE index, improves the goodness of fit for forecast horizons shorter than 4 quarters. They use quarterly data from 1959 to 1995 for the U.S.

Dueker (1997) adds a lagged dependent variable to Estrella and Mishkins (1998) model and confirms their conclusion that the yield spread is the superior predictor. His addition eliminates the possibility of autocorrelation and adds dynamic structure to the prediction model. Dueker (1997) writes that many time-series applications violate the assumption of the error term being *i.i.d.* His opinion is that it is implausible for the mean of the error term to be zero if there is no reference in the model to whether the economy is in a recession or not. He use the same data as Estrella and Mishkin (1998), but with monthly observations.

Moneta (2003) finds that the superior predictor in the Euro area is also the yield spread between 10-year and 3-month Treasury bonds, four quarters ahead of a recession. Predicting the probabilities with the in-sample results, Moneta (2003) follows Stock and Watson (1990) method of false positive and false negative rate and finds that the yield spread rarely predict recessions that does not occur. However, the yield spread fails to predict 70% of recessions. He is using quarterly data from 1970 to 2003 in the euro area.

Wang (2017) investigates if low sector correlation can be used as an investment strategy to trade the S&P 500. Wang (2017) forms a correlation strategy where she invests in a S&P 500 tracker if correlations are increasing and sells if correlations are decreasing. Wang(2017) finds that the correlation strategy yields an average annual return of 11.9 %, from the period 2003 to 2016. In comparison, a buy & hold for the same period yields an average annual return of 8.7 %.

3. Data

3.1 Raw Data

Raw data is obtained from Thomson Reuters Eikon, the National Bureau of economic research and the Federal Reserve Bank of ST. Louise. The data set includes monthly and weekly observations of the S&P 500 index, S&P 500 sector indices, the 10 year and 3 months yield spread and recession dates. The data set ranges from September 1989 to May 2018.

To calculate average correlation, we need to obtain sector returns. S&P 500 are divided into 11 sectors by the *Global Industry Classification Standard* (GICS). Companies that compose these sectors are categorized according to their main business profile (S&PGlobal 2016). These 11 S&P 500 sectors are reported with their relative weightings in Table 3.1.

Table 3.1: The Global Industry Classification Standard sectors and their S&P500-weights. ("S&P 500 sector weightings 1979-2018." 2018)

Sector	**Weights**
Consumer Discretionary	12.21%
Consumer Staples	8.20%
Energy	6.08%
Finance	14.79%
Health Care	13.78%
Industry	10.27%
Information Technology	23.78%
Materials	2.99%
Real Estate	2.89%
Telecommunication Services	2.06%
Utilities	2.94%

To estimate average correlation together with another explanatory variable, we collect the yield spread. This data is obtained from the Federal Reserve Bank of St. Louise. The yield spread is calculated as the difference in return between a 10 year Treasury bond and a 3 months Treasury bill, both with constant maturity.

To determine whether sector correlations can predict recessions we need to define the periods of recessions. We use the *National Bureau of Economic Research* (NBER) standard start and through dates (NBER 2012). For periods of U.S recessions within the time span of our data set, see Table 3.2. There are several methods to determine recessions, but the NBER method is considered to be the top historical performer (Boldin 1994). A drawback with the NBER methodology is that the start and through dates are not confirmed quickly. They are determined by a committee in hindsight, thus it takes time for an ongoing recession to be defined.

Table 3.2: National Bureau of Economic Research standard start and end dates of U.S recessions from 1989.

Start date	**Through date**
July 1990	March 1991
March 2001	November 2001
December 2007	June 2009

3.2 Processed Data

The sector indices of Materials, Real Estate, Telecommunication Services and Utilities are omitted. This is to make the estimation of correlation coefficients more manageable. The remaining sectors comprise roughly 90% of the value of the S&P500 index, which should be sufficient for correlation estimations. By omitting the four smallest sectors, we reduce correlation coefficients from 55 pairs to 28 pairs. A drawback with studies using correlation is that it is easy for statisticians to compute many correlations coefficients and only include those that are significant (Boldin 1994). Note that we have not computed any significant tests prior to cutting the four sectors.

For the seven sectors we estimate weekly and monthly logarithmic returns. The logarithmic returns are estimated as

$$R = ln(\frac{V_t}{V_{t-1}}), \tag{3.1}$$

where V_t is the sector index value at time t and V_{t-1} is the value of the sector index in the previous period. Logarithmic returns are chosen over arithmetic returns, because logarithmic returns are closer to normal distribution. Normality tests on weekly data shows that only the arithmetic returns for the energy sector is closer to normal distribution than the logarithmic returns. For the six remaining sectors, logarithmic returns are closer to normal distribution.

We calculate *Pearson's r*, also called the *product-moment* correlation coefficient. The correlation coefficient between two sector index returns, denoted r, is given by

$$r = \frac{\sum(x_t - \bar{x})(y_t - \bar{y})}{\sqrt{\sum(x_t - \bar{x})^2 \sum(y_t - \bar{y})^2}}, \tag{3.2}$$

where x_t and y_t are the logarithmic returns for sector x and sector y at time t. (Altman 1991, p.293). To estimate Pearseons correlation coefficients, Altman (1991) writes that is preferable that both variables in a correlation pair are approximately normally distributed. Figure 7.1 and 7.2 in the Appendix shows that all logarithmic sector returns are approximately normally distributed. All distributions are more pointed (leptokurtic) than normal distribution. Some tend to have negative skewness. Hypothesis testing shows that all correlation coefficients between sectors are significant.

For weekly logarithmic returns we estimate correlation coefficients with rolling windows of 12, 24 and 36 weeks. Monthly logarithmic return correlation coefficients are estimated with rolling windows of 3, 6 and 9 months. In total, 28 different correlation coefficients are calculated for each correlation interval. The average sector correlations, which we are testing as a predictor, are estimated at each time t. Average correlations are calculated arithmetically,

$$avgcorr_t = \frac{1}{28} \sum_{x,y=1}^{28} r_{xy,t}. \tag{3.3}$$

Where $avgcorr_t$ is the average correlation at time t and r, x and y are defined as in Equation 3.2. Note that correlation coefficients are only estimated when $x \neq y$. Names of the variables and descriptive data statistics are found in Table 3.3.

3.3 Descriptive data

Table 3.3: Summarize of the data set variables. Includes total observations (N), mean, standard deviation, min and max values.

Variable	Obs	Mean	Std. Dev.	Min	Max
$avgCorr12w$	1,486	0.570	0.216	-0.037	0.968
$avgCorr24w$	1,474	0.582	0.198	0.043	0.952
$avgCorr36w$	1,462	0.589	0.189	0.078	0.935
$recessionWeekly$	1,497	0.098	0.298	0	1
$spreadWeekly$	1.49	1.78	1.12	-0.78	3.87
$avgCorr3m$	342	0.548	0.198	-0.058	0.878
$avgCorr6m$	339	0.522	0.251	-0.056	0.932
$avgCorr9m$	336	0.542	0.216	-0.044	0.894
$recessionMonthly$	345	0.107	0.310	0	1
$spreadMonthly$	345	1.77	1.12	-0.77	3.82

The first five variables in Table 3.3 are calculated with weekly data. $avgCorr12w$, $avgCorr24w$ and $avgCorr36w$ refers to the average correlation over the past 12, 24 and 36 weeks, respectively. $recesionWeekly$ is a dummy variable taking on a value of 1 if there is a NBER defined recession that week, 0 otherwise (see Table 3.2 for recession dates). The variable $spreadWeekly$ is the yield spread that week, expressed in percentage points.

The latter five variables are calculated with monthly data. $avgCorr3m$, $avgCorr6m$ and $avgCorr9m$ refers to the average correlation over the past 3, 6 and 9 month, respectively. $recessionMonthly$ is a dummy variable taking on a value of 1 if there is a NBER defined recession that week, 0 otherwise. $spreadMonthly$ is the yield spread that month, expressed in percentage points.

Weekly data are reported every Monday. If Monday is a holiday, values are reported on Tuesday. Monthly data are reported on the 11th day of each month. From the *mean* in Table 3.3 we can see that 9.8% of weekly observations are weeks in a recession while 10.7% of monthly observations are months in a recession. For weekly data, the first observation in a recession is the 43rd. For monthly data, it is the 10th. Therefore, observations omitted by increasing correlation intervals are non-recession periods, resulting in a higher proportion of recessions. For longer correlation windows, the number of usable observations decreases.

avgCorr6m is the most volatile variable with the highest standard deviation, while *avgCorr36w* is the least volatile. All average correlation variables have a minimum value close to 0, which means that at times there are no linear association between the sectors. Maximum values are close to 1 for all variables, meaning that at times sectors vary almost perfectly together. The minimum value for *spreadWeekly* and *spreadMonthly* are -0.78 and -0.77, respectively. This implies that at times, short term interest rates, yields higher returns than long term interest rates and the yield curve is inverted.

Figure 3.1: Average weekly sector correlation through time. Correlation estimated with 12, 24 and 36 weeks rolling window. Grey bars are U.S recession periods.

Correlations with weekly observations are volatile, see Figure 3.1. Fluctuations for 12, 24 and 36 weeks correlation follow a similar pattern. As Xu (2017) point out, there is a period of low correlation prior to the recessions in 2001 and 2007-2009. Also, we see that the correlation was low at the time Dagens Næringsliv's article (Havnes 2017) were published. Current correlation (May 2018) is higher. There are no periods of abnormal low correlation prior to the recessions in 1990-1991. There are two spikes of low correlation in 1994 and 1996, but no recessions.

Figure 3.2: Average monthly sector correlation through time. Grey bars are U.S recession periods.

Monthly average correlations looks to follow similar patterns as well. Average correlation over six months, the green line in Figure 3.2, is clearly more volatile with larger spikes than three and nine month average correlations. The six month average correlation graph contradicts Harper (Havnes 2017) and Xu(2017) assertion that average correlations are at its lowest since before the 2001 and 2007-2009 recessions. Average correlations have been at the same and lower level several times after 2001 and 2007-2009 recessions.

4. Methodology

4.1 Model specification

We are using a probit model to predict recessions in the U.S economy. Earlier studies, such as Estrella and Mishkin (1998), Dueker (1997) and Moneta (2003), use a probit model. The probit model defines the dependent variable as a binary outcome, where

$$recession_t = \begin{cases} 1, \text{if there is a recession at time } t \\ 0, \text{if there is not a recession at time } t. \end{cases} \tag{4.1}$$

By formulating the dependent variable as a dummy, we achieve a more accurate date and length of the recessions. If the dependent variable was defined as the return of the S&P 500 index, corrections in the stock market could be interpreted as a start or an end of a recession. (Dueker 1997)

Specifying the dependent variable as a binary outcome allows us to explore how each explanatory variable affects the probability for a recession to occur (Long and Freese 2006).

To understand the logic behind the probit model, we follow Long and Freese (2006, p.132-135) derivation of binary models.

Assume that there is a latent variable $recession_t^*$ which is unobserved. The latent variable can be expressed with one independent variable and form the structural model,

$$recession_t^* = \beta_0 + \beta_1 * avgCorr_{t-k} + \epsilon_t, \tag{4.2}$$

which is identical to a linear regression except that the dependent variable is not observed. We can however observe $recession_t$, which is the positive (1) or the negative (0) outcome. The link between $recession_t$ and $recession_t^*$ can be expressed as

$$recession_t = \begin{cases} 1, \text{ if } recession_t^* > 0 \\ 0, \text{ if } recession_t^* \leq 0 \end{cases} \tag{4.3}$$

, where unobserved $recession_t^*$ greater than 0 will result in observed value of $recession_t = 1$.

The relation between the probability for $recession_t = 1$ given an explanatory variable, $avgCorr_{t-k}$, can be written

$$Pr(recession_t = 1|avgCorr_{t-k}) = Pr(recession_t^* > 0|avgCorr_{t-k}), \tag{4.4}$$

and inserting (4.2) and rearranging terms gives us

$$Pr(recession_t = 1|avgCorr_{t-k}) = Pr(\epsilon > -[\beta_0 + \beta_1 avgCorr_{t-k}]|avgCorr_{t-k}). \tag{4.5}$$

We see that the probability for recession depends on the value of ϵ. For probit models, ϵ is assumed to have standard normal distribution with $mean = \mu = 0$ and a variance fixed at 1 ($Var(\epsilon) = 1$).

This leads to the probit model (4.5) to become

$$Pr(recession_t = 1|avgCorr_{t-k}) = \int_{-\inf}^{\beta_0+\beta_1*avgCorr_{t-k}} \frac{1}{\sqrt{2\pi}} * e^{-\frac{t^2}{2}} dt, \tag{4.6}$$

and is be expressed graphically in Figure 4.1.

Shaded areas in Figure 4.1 accumulate into the cumulative density function;

$$Pr(recession_t = 1|avgCorr_{t-k}) = G(\beta_0 + \beta_1 avgCorr_{t-k}), \tag{4.7}$$

where G is the normal cumulative distribution function.

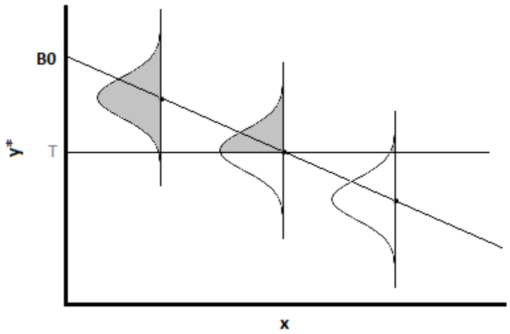

Figure 4.1: Linear regression (Equation 4.2) graph for the unobserved $recession_t^*$ as $y*$ and x is the independent variable. $E(\beta_1) < 0$. Graphed is the normal distribution of ϵ at three different values of x. The shaded area over T is when $y^* > 0$ and corresponds to $Pr(recession_t = 1|avgCorr_{t-k})$.

4.2 Marginal effects

Because the model is non-linear, the magnitude of $avgCorr_{t-k}$'s coefficient (β_1), is not very useful (Wooldridge 2008, p.582). However, the sign tells us if it has a positive or negative effect. To interpret the magnitude of $avgCorr_{t-k}$'s coefficient on the probability of a recession, we need to consider the marginal effect of $avgCorr_{t-k}$. A consequence of the non-linearity is that the marginal effect is not constant. The magnitude is determined by the initial value of average sector correlation and on the values of other included explanatory variables. Marginal effects can therefore be reported at several levels, often reported on average or at means. Because the differences are small between the two, we choose to only report marginal effects on average. When we look at the change in probability given a change in average sector correlation, we consider a unit decrease of one standard deviation which is reported in Table 3.3.

4.3 Maximum Likelihood Estimations

Another consequence of the probit model being non-linear, is that it cannot be estimated with OLS. Instead it is estimated with maximum likelihood (MLE). This estimation process utilizes the distribution of the dependent variable $recession_t$ given the explanatory variable $avgCorr_{t-k}$, which automatically accounts for the heteroscedastic variance. For our sample size n, we express the density of $recession_t$ given $avgCorr_{t-k}$ as

$$f(recession_t|avgCorr_{t-k};\beta_1) = [G(avgCorr_{t-k}\beta_1)]^{recession_t}[1-G(avgCorr_{t-k}\beta_1)]^{1-recession_t}, \tag{4.8}$$

where $recession_t = 0$ or 1. For $recession_t = 1$ we get

$$f(recession_t|avgCorr_{t-k}\beta_1) = [G(avgCorr_{t-k}\beta_1)] \tag{4.9}$$

and for $recession = 0$ we get

$$f(recession_t|avgCorr_{t-k}\beta_1) = [1 - G(avgCorr_{t-k}\beta_1)]. \tag{4.10}$$

We then obtain the log-likelihood estimation by taking the log of the density-function

$$\ell_t(\beta_1) = recession_t log[G(avgCorr_{t-k}\beta_1)]+(1-recession_t)log[1-[G(avgCorr_{t-k}\beta_1)]. \tag{4.11}$$

$G(avgCorr_{t-k}\beta_1)$ takes on values between 0 and 1 in a probit model, which makes $\ell_t(\beta_1)$ defined given the value of β_1. For our sample size n, the log-likelihood is obtained by summing up $\ell_t(\beta_1)$ for all observations

$$\mathcal{L}(\beta_1) = \sum_{t=1}^{n} \ell_t(\beta_1). \tag{4.12}$$

The MLE of β_1 is obtained by maximizing this log-likelihood. (Wooldridge 2008, p.578-579)

4.4 Autoregressive model

A simple probit model with no lagged dependent variable lacks dynamic structure (Dueker 1997). We estimate models where we add a lagged dependent variable with the same forecast horizon, k, $avgCor_{t-k}$. The model is written

$$P(recession_t = 1 | avgCorr_{t-k}, recession_{t-k}) = G(\beta_0 + \beta_1 avgCorr_{t-k} + \beta_2 recession_{t-k}), \tag{4.13}$$

where β_2 is the coefficient for the lagged dependent variable. t and k is the same as before.

4.5 Multiple regression model

Estimating with lagged dependent variables are not useful in practice (Boldin 1994), because recession dates are only available with very long lags. Following Estrella and Mishkin (1998), we estimate models with two explanatory variables. We look at the predictive power of average sector correlation combined with the yield spread. The yield spread is associated with the steepness and direction of the yield curve, which is considered as an accurate predictor of real activity in the economy, especially between 2 and 6 quarters ahead (Estrella and Mishkin 1998). Including an additional relevant explanatory variable should increase the predictive power of the model and may help against autocorrelation and omitted variable bias.

The multiple response probability model is specified ass

$$P(recession_t = 1 | avgCorr_{t-k}, yieldSpread_{t-k}) = G(\beta_0 + \beta_1 avgCorr_{t-k} + \beta_2 yieldSpread_{t-k}), \tag{4.14}$$

4.6 Alternative model specification

In the process of selecting a probability model, both the linear probability model (LPM) and the logit model are prominent alternatives. Because the linear probability model is linear, we can estimate it with OLS. This makes the estimation simpler and the model becomes easier to work with. The drawback with the LPM, is that because it is linear, the fitted probabilities can be less than 0 or greater than 1. This was also the case when we used this model for our data set. For this reason, a probit or logit model is a better choice.

The logit model is very similar to the probit model and estimating our data set with a logit model yield similar probabilities. However, economists tend to favor the probit model because the error term has a standard normal distribution, while the logit model has a standard logistic distribution. Considering previous studies on U.S recessions have favored the probit model, it is the obvious choice between the two. (Wooldridge 2008, p.577)

4.7 Stationarity

One of the criteria for a well-estimated model is that variables are stationary (Enders 2015, p.112). With a Dickey-Fuller test, we find that all variables except $avgCorr36w$ are stationary. Using first difference, $avgCorr36w$ becomes stationary, which mean that the variable is integrated by order 1. Therefore, our models are estimated with $avgCorr12w$, $avgCorr24w$, $avgCorr3m$, $avgCorr6m$ and $avgCorr9m$ and the first difference of $avgCorr36w$.

We find that $spreadWeekly$ and $spreadMonthly$ are non-stationary. By taking first-differences, they become stationary and are integrated by order 1.

Because $recession$ is a dummy-variable, there is no need to test for stationarity. By definition, $E(dummy) = p$ and $Var(dummy) = p(1-p)$, where p is the probability, same as the mean, for the dummy to be true. This implies that a dummy variable cannot be a random walk.

4.8 Testing the probit model

To test the significance of our explanatory variable, average sector correlation, we conduct likelihood ratio (LR) tests. This test exploits the difference in the log-likelihood functions for the restricted and unrestricted model. Where the unrestricted model includes average sector correlation and the restricted omits average sector correlation as an explanatory variable. In the same way that R^2 decreases when we drop a variable, the log-likelihood also decreases. Therefore, the LR test checks if the decrease in log-likelihood is large enough to conclude that the effect of the variable is significant. The LR statistic is given by

$$LR = 2(L_{ur} - L_r), \tag{4.15}$$

where L_{ur} is the log-likelihood function for the unrestricted model and L_r is for the restricted model. Note that the log-likelihood function is always a negative value, but because the unrestricted model is always greater or equal to the restricted model, the LR statistic is always greater or equal to zero. Under H_0, LR is approximately chi-squared distributed. Thus, we use the table for the chi-square distribution to determine the critical value.

To determine the goodness-of-fit and compare our estimated models, we can use various $pseudo - R^2$ measures. The most popular, which is also reported in programs such as Stata, is the McFadden's (1974) $pseudo - R^2$, given by

$$pseudo - R^2 = 1 - L_{ur}/L_r. \tag{4.16}$$

Where L_{ur} is the log-likelihood function for the estimated model and L_r is the log-likelihood function for a model with only a constant. Given no explanatory power, the term $L_{ur}/L_r = 1$ and thus $R^2 = 0$.

In the earlier literature, $pseudo - R^2$ was measured by the one developed by Estrella (1998). Because Estrellas (1998) $pseudo - R^2$ is defined

$$pseudo - R^2 = 1 - \frac{L_{ur}}{L_r}^{\frac{-2}{n} * L_r}, \tag{4.17}$$

where n is the number of observations, will the values differ from the Statas reported McFadden $pseudo - R^2$. For simplicity, we only use the McFadden $pseudo - R^2$ to choose between our model specifications. We expect to get lower $pseudo - R^2$ with Mcfaddens specification than with Estrellas (Walker and Smith 2016).

4.9 Testing for predictive power

To test the predictive power of the models, we run predictions in Stata. Values predicted are the probabilities for a positive outcome, $P(recession_t = 1)$. Probabilities are calculated from 1989 to 2018. Stata use the selected model and iterate through time using observed values of the explanatory variables. The predicted probabilities are obtained as the probability for a recession at time $t + k$. The forecast formulas are

$$P(recession_{t+k} = 1|avgCorr_t) = G(\beta_0 + \beta_1 avgCorr_t), \tag{4.18}$$

$$P(recession_{t+k} = 1|avgCorr_t) = G(\beta_0 + \beta_1 avgCorr_t + \beta_2(recession_t) \tag{4.19}$$

and

$$P(recession_{t+k} = 1|avgCorr_t) = G(\beta_0 + \beta_1 avgCorr_t + \beta_2 yieldSpread_t), \tag{4.20}$$

where $avgCorr_t$, $recession_t$ and $yieldSpread_t$ are actual observations of each variable at time t.

The predicted probabilities are measured on how often they become true. Following Stock and Watson (1990) we estimate the false positive and false negative rate. False positive rate is the average fraction of times when a recession is forecasted and no recession happens. False negative rate measures the average fraction of times a recession is not forecasted, but a recession occurs. By default, Stata uses a prediction threshold of 0.5. This indicate that whenever the predicted probability values goes over 0.5, a recession is forecasted.

Altman (1991) divides binary results into true positive, false positive, false negative and true negative. Table 4.1 illustrates how these are defined.

Table 4.1: Defining true positive, false positive, false negative and true negative for model estimations.

Estimated Recession Status	Actual Recession Status	Name
1	1	True positive
1	0	False positive
0	1	False negative
0	0	True negative

The rates are calculated as

$$Falsepositiverate = \frac{Falsepositive}{FalsePositive + TruePositive} \tag{4.21}$$

and

$$Falsenegativerate = \frac{FalseNegative}{FalseNegative + TrueNegative}, \tag{4.22}$$

where $falsepositive + truepositive$ are total $recession = 1$ predictions and $falsenegative + truenegative$ are total $recession = 0$ predictions.

Wooldridge (2008, p.581) defines a similar prediction measure called "percent correctly predicted". This is calculated by dividing correct recession prediction and correct non recession prediction on total observations. Some have criticized this measurement for using a threshold value of 0.5. Threshold values for testing predictive powers are called cut-off values. Often one of the outcomes is much less likely than the other. As for this thesis. Only 9.8% of weekly data and 10.7% of monthly data are observations made in recessions ($recession = 1$). It could happen that with a cut-off value of 0.5, prediction of recessions never occur in our models. One alternative is to use the percentage of success in the data set (Wooldridge 2008, p.581). Thresholds for testing our models predictive power are therefore 9.8% for weekly data and 10.7% for monthly data.

Percentage correctly predicted is a useful measure of predictive power. It can however be misleading (Wooldridge 2008, p.581). A high percentage of correctly predicted values can be found when the least likely outcome is very poorly predicted. If one of our models never predicts a recession, it will still predict correct 90.2% for weekly data and 89.3% for monthly data. This is because 90.2% and 89.3% of the observations in the data set are not recessions ($recession = 0$). These percentages are not the same for all models predicted. This is because of the omitted observations caused by the increasing of forecast horizons and correlation intervals. They do not change more than 1 percentage point.

4.10 Heteroscedasticity

Heteroscedasticity in probit models are largely discussed. A problem with measuring and accounting for heteroscedasticity is that the variance of the error term (ϵ) must be assumed rather than measured. Thus, a model is undefined unless we make an assumption about the variance of the error term. For probit models, the assumption is $Var(\epsilon) = 1$. (Long and Freese 2006, p.134, Williams 2009)

The assumption of $Var(\epsilon) = 1$ implies homoscedasticity. Under this restrictive assumption, MLE is consistent and asymptotically efficient. However, if this assumption is violated, then the MLE will not be consistent. Ginker and Lieberman (2017) shows that coefficients, in the presence of heteroscedasticity, will be misspecified. Predictions will be unaffected by heteroscedastic misspecification.

Several methods to cope for heteroscedasticity have been proposed. One of which is the heteroskedastic probit model recommended by Wooldridge (2015). This methodology is a suggestion on how to cope and check for heteroscedasticity in probit models (Stata-Press 2013). This methodology is not acknowledged as a solution to the problem, but will provide useful information under the presence of heteroscedasticity.

Unlike the regular probit model, the variance of the error term is not fixed at 1. The variance vary as a function of the independent variables,

$$var(\epsilon_i) = \sigma_i^2 = e^{(x_i * g)^2} \tag{4.23}$$

where $x_i = (avgCorr12w_{t-k}, avgCorr24w_{t-k}, avgCorr36w_{t-k}, avgCorr3m_{t-k}, avgCorr6m_{t-k}, avgCorr9m_{t-k}, recession_{t-k}, yieldSpread_{t-k})$ and i represent each variable included in the model.

In the Stata code they also have included a LR-test for the presence of heteroscedasticity, where under the null hypothesis the variance of the error is homosedastic. Full derivation of the model is found in Stata-Press 2013.

4.11 Investment strategy

Predicting recessions have practical possibilities. We conduct back-testing to examine if average sector correlation can be used as an indicator to trade the S&P 500. We use two different strategies.

Similarly to Wang (2017), the first strategy uses change in average sector correlation as a buy or sell signal. If average sector correlation increase, we buy a position (or hold if we already have invested) in the S&P500 and if correlation decrease, we sell (or hold if we have no investment in the S&P 500) the position. We impose a threshold value on the change in average sector correlation to make the strategy less susceptible to small changes in correlation, which might not correspond to a subsequent fall in the market. We measure the change in average sector correlation for different time intervals, where we look at the change between two dates.

The second strategy, sells the position in the S&P 500 when average sector correlation decrease below a threshold. If correlation increase above the threshold, we buy a position in S&P 500. We simulate with several threshold values, all of which are below one standard deviation from the mean.

For both strategies, selling a position is the equivalent of investing in a risk free asset. For simplicity we assume a 0% interest rate and all investments are done with a 100 % of the capital. The simulation of the investment strategies are done for the entire period of our data set. We assume an initial investment sum of a 100,000, which is invested in the first period and automatically sold in the last. We compare both our strategies with a simple buy & hold strategy, where we invest in the first period and sell in the last.

5. Empirical results

5.1 Probit model with one explanatory variable

Table 5.1: Measures of fit, $pseudo - R^2$, for the probit models.

$P(recession_t = 1 \mid x_{t-k}) = G(\beta_0 + \beta_1 x_{t-k})$					
k = weeks/months ahead					
x_{t-k} *variables*	k=1	k=3	k=6	k=9	k=12
$avgCorr12w_{t-k}$	0.0051	0.0039	0.0022	0.0012	0.0003
$avgCorr24w_{t-k}$	0.0001	0.0003	0.000	0.0001	0.0006
$avgCorr36w_{t-k}$	0.0022	0.0012	0.0005	0.0002	0.000
$avgCorr3m_{t-k}$	0.0081	0.0321	0.0651	0.0700	0.0591
$avgCorr6m_{t-k}$	0.0059	0.0003	0.0210	0.0276	0.0253
$avgCorr9m_{t-k}$	0.000	0.0058	0.032	0.0492	0.0464

Table 5.2: Marginal effects for probit model variables by themselves. The LR statistics are reported in the parenthesis.

$P(recession_t = 1 \mid x_{t-k}) = G(\beta_0 + \beta_1 x_{t-k})$					
k = weeks/months ahead					
x_{t-k} *variables*	k=1	k=3	k=6	k=9	k=12
$avgCorr12w_{t-k}$	0.081 (7.48**)	0.070 (6.62*)	0.052 (5.66*)	0.038 (5.28*)	0.020 (5.1*)
$avgCorr24w_{t-k}$	0.034 (5.76*)	0.020 (5.68*)	0.002 (6.06*)	-0.011 (6.76**)	-0.030 (7.92**)
$avgCorr36w_{t-k}$	0.494 (9.8**)	0.364 (9.28**)	0.231 (9.24**)	0.158 (22.82**)	0.053 (36.56**)
$avgCorr3m_{t-k}$	-0.112 (2.82)	-0.219 (8.88**)	-0.310 (17.24**)	-0.313 (30.9**)	-0.275 (41.6**)
$avgCorr6m_{t-k}$	0.079 (2.96)	-0.016 (2.12)	-0.136 (20,14**)	-0.149 (35.14**)	-0.134 (48.76**)
$avgCorr9m_{t-k}$	0.001 (6.5*)	-0.083 (16.78**)	-0183 (36.24**)	-0.212 (53.32**)	-0.211 (53.32**)

(*) notes significant at the 5 % level and (**) at the 1 % level.

Based on $pseudo - R^2$ reported in Table 5.1, we find that a model including the variable $avgCorr3m_{t-9}$ is the best predictor. This model has a $pseudo - R^2$ of 0.070, which means that it explains 7.0 % of the variation in *recession*.

The marginal effects are reported in Table 5.2. We find that the marginal effect of $avgCorr3m_{t-9}$ is -31,3 %, which means that a decrease of one standard deviation, 0.198, in average sector correlation will increase the probability of a recession in 9 months by 6.20 percentage points. This result supports the notion of low correlation as a predictor of recessions. The LR-test shows that the effect of $avgCorr3m_{t-9}$ is significant at the 1%-level.

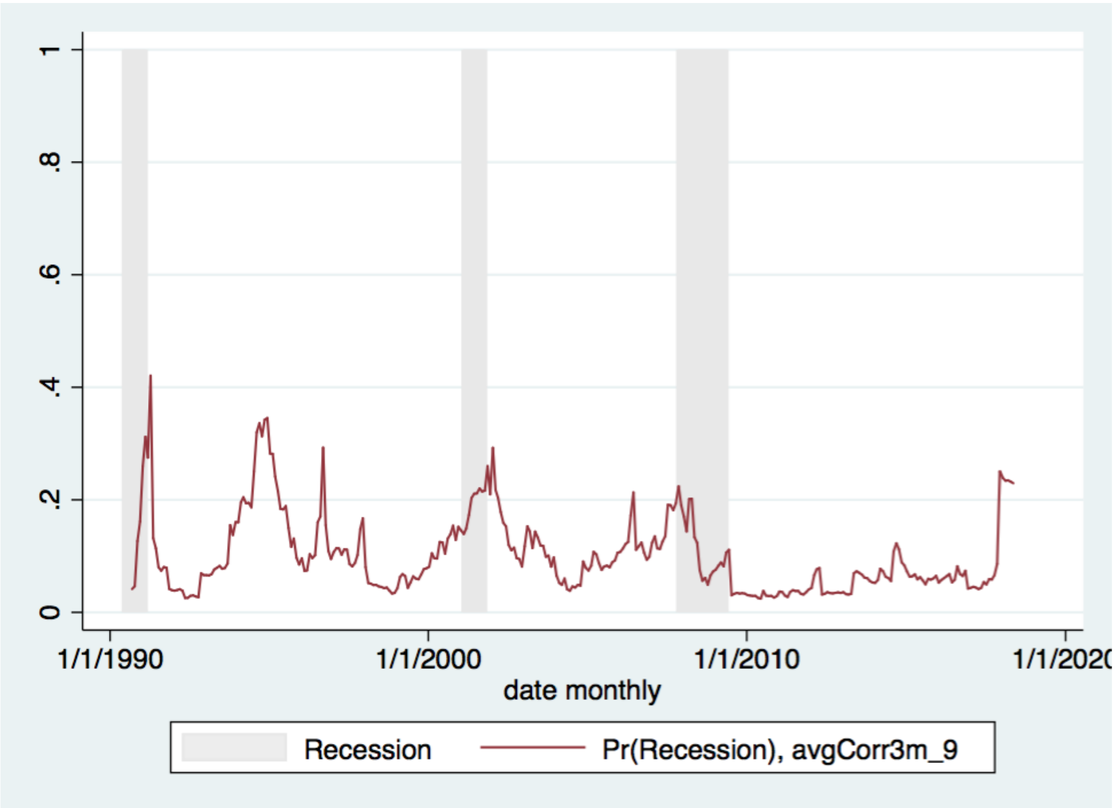

Figure 5.1: Blue line is the predicted probability when using $avgCorr3m_{t-9}$ as a predictor for recession. Recessions are grey areas in the graph.

The graph in Figure 5.1 shows the predicted probabilities through time of the data set. Optimally, the graph should go towards 1 when there is a recession. Predicted probabilities have several spikes that peaks between 0.3 and 0.4. Just after the 1990 recession the probability is at its highest, reaching its peak at 0.421 (see Table 7.1 in Appendix). This peak occurs just after the recession is through, which means that the recession is predicted too late. The same pattern can be seen for the 2001 recession, where probability peaks just after. For the 2007-2009 recession, there are two peaks close together. The first peak is premature and the second occurs at the start of the recession, suggesting that the second predicts the recession.

From 1989 to 2007 predicted probabilities have bigger fluctuations than in the period after 2007. In the latter period, predicted probabilities are low with much smaller fluctuations. The predicted probability suddenly rises at the end of our data set, suggesting that the probability for a recession in the near future is increasing.

We follow Wooldridge's (2008, p.581) suggestion and set the prediction threshold to 10.7%. The results are reported in Table 5.3 and 5.4. False positive and false negative rate reveals that 32.78% of the recessions predicted are not recessions and 38.24 % of recession periods are not predicted. The model fails to predict 12 recession months that occurs and 98 of the recession months it predicts are incorrect (see table 5.2). This model correctly predicts 66.67% of the observations. Compared to a model that never predicts recessions, which will predict 89.3% of the observations, this is low.

The LR-test for the heteroskedastic probit model keeps the null hypothesis of homoscedasticity (see Appendix 7.2).

Table 5.3: Predictions of recession using $avgCorr3m_{t-9}$ as a predictor vs true recessions.

	recession = 1	recession = 0	Total
Pr(recession = 1)	21	98	119
Pr(recession = 0)	13	201	214
Total	34	299	333

Table 5.4: False positive rate and false negative rate for $avgCorr3m_{t-9}$ prediction of recessions. Threshold 10.7%.

False Positive Rate	32.78%
False Negative Rate	38.24%
Correctly Classified	66.67%

5.2 Probit model including an autoregressive term

Table 5.5: Measures of fit, $pseudo-R^2$, for the probit models

$P(recession_t = 1 \mid x_{t-k}, recession_{t-k}) = G(\beta_0 + \beta_1 x_{1t-k} + \delta recession_{t-k})$ k = weeks/months ahead					
x_{1t-k} *variables*	k=1	k=3	k=6	k=9	k=12
$avgCorr12w_{t-k}$	0.9252	0.8173	0.6881	0.5799	0.4867
$avgCorr24w_{t-k}$	0.9254	0.8181	0.5812	0.5817	0.4883
$avgCorr36w_{t-k}$	0.9248	0.8174	0.6880	0.5980	0.5172
$avgCorr3m_{t-k}$	0.7912	0.5367	0.2735	0.1199	0.0791
$avgCorr6m_{t-k}$	0.7791	0.5044	0.2819	0.0984	0.0596
$avgCorr9m_{t-k}$	0.8184	0.5791	0.3270	0.1350	0.0793

Table 5.6: Marginal effects of probit model variables by themselves. The LR statistics are reported in the parenthesis.

$P(recession_t = 1 \mid x_{t-k}, recession_{t-k}) = G(\beta_0 + \beta_1 x_{1t-k} + \delta recession_{t-k})$ k = weeks/months ahead					
x_{t-k} *variables*	k=1	k=3	k=6	k=9	k=12
$avgCorr12w_{t-k}$	-0.003 (0.24)	-0.009 (0.68)	-0.019 (1.58)	-0.029 (3.80)	-0.043 (4.00*)
$avgCorr24w_{t-k}$	-0.005 (0.60)	-0.017 (1.92)	-0.031 (3.44)	-0.43 (6.04*)	-0.59 (6.76**)
$avgCorr36w_{t-k}$	-0.02 (0.22)	-0.154 (1.80)	-0.281 (3.08)	-0.340 (28.56**)	-0.420 (48.52**)
$avgCorr3m_{t-k}$	-0.078 (5.66*)	-0.199 (14.14**)	-0.292 (18.40**)	-0.305 (31.28**)	-0.272 (27.30**)
$avgCorr6m_{t-k}$	-0.046 (3.00)	-0.114 (6.72**)	-0.1963 (30.02**)	-0.181 (39.10**)	-0.158 (36.88**)
$avgCorr9m_{t-k}$	-0.050 (13.06**)	-0.125 (29.78**)	-0.2144 (49.30**)	-0.231 (59,14**)	-0.226 (41.14**)

(*) notes significant at the 5 % level and (**) at the 1 % level.

Adding a lagged dependent variable removes the potential problem of autocorrelation (Dueker 1997). The best fitted model is obtained with $avgCorr24w_{t-1}$, which has a $pseudo-R^2$ of 0.9254. From Table 5.6, we can see that all marginal effects have negative signs, which supports the notion of low correlation as a predictor of a recession. The marginal effect of $avgCorr24w_{t-1}$ is -0.5 %, which means that a standard deviation decrease, 0.198, in $avgCorr24w_{t-1}$, increases the chance of recession with -0.1 percentage points. The LR-test shows that the effect is not significant at any conventional level.

From the graph in Figure 5.2, we can clearly see that this model yields high $pseudo-R^2$. The graph follows the three recessions almost perfectly. Table 5.8 shows that the false positive rate, false negative rate and percentage correctly classified are close to perfect as well. Six times throughout the data set does the model predict wrong. All three recessions are predicted one week too late and one week to long. This is because the model only forecast a recession in one week if current week is in a recession.

Most of the models report in Table 5.5 have relatively high $pseudo - R^2$. Such high goodness-of-fit values indicate that the lagged dependent variable explains almost all the variation of the dependent variable, $recession_t$. Further, it indicate that the values are decaying when the forecast horizon increases. From Table 5.7 we see that the false positive rate is 0.23%, the false negative rate is 2.04 % and the percentage correctly classified is 99.57 %. These predictions are unrealistically accurate, which derives from the high explanatory power of the autoregressive variable.

The high goodness-of-fit values are not a surprise. Only six times in the data set does an observation of the dependent variable change from 0 to 1 and from 1 to 0 in the next observation. These changes occurs at the start and the end of the three recessions.

Opinions on adding a lagged dependent variable to a prediction model differs. Estrella and Mishkin(1998) combined predictors in a model rather than adding a lagged dependent variable. They argue that recessions are defined long after the economy starts declining, thus making this information unavailable when predicting in the future.

As well as in the last model, according to the heteroskedastic probit model, there is not a problem with heteroscedasticity(see Table 7.2 in Appendix).

Table 5.7: Predictions of recession using $avgCorr24w_{t-1}$ and $recession_{t-1}$ as a predictor vs true recessions.

	recession = 1	recession = 0	Total
Pr(recession = 1)	144	3	147
Pr(recession = 0)	3	1324	1327
Total	147	1327	1474

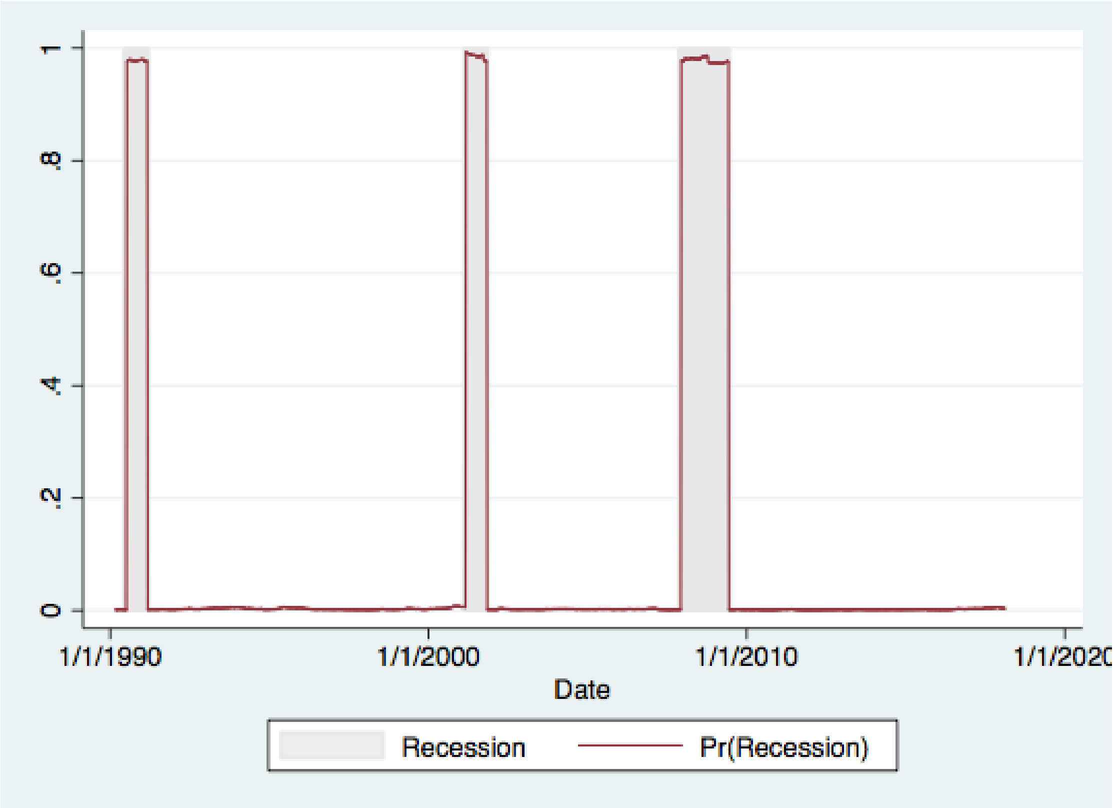

Figure 5.2: Blue line is the predicted probability when using $avgCorr24w$ and a lagged dependent variable, $Recession_{t-1}$, as a prediction model for $Recession$. Recessions are grey areas in the graph.

Table 5.8: False positive rate and false negative rate for $avgCorr24w_{t-1}$ and $recession_{t-1}$ prediction of recessions. Threshold 9.8%.

False Positive Rate	0.23%
False Negative Rate	2.04%
Correctly Classified	99.57%

5.3 Probit model including yield spread

Table 5.9: Measures of fit, $pseudo - R^2$, for the probit models.

$P(recession_t = 1 \| x_{t-k}, yieldSpread_{t-k}) = G(\beta_0 + \beta_1 x_{t-k} + \beta_2 yieldSpread_{t-k})$. k = weeks/months ahead					
x_{t-k} *variables*	k=1	k=3	k=6	k=9	k=12
$avgCorr12w_{t-k}$	0.0155	0.0126	0.0093	0.0057	0.0067
$avgCorr24w_{t-k}$	0.0112	0.0091	0.0071	0.0046	0.007
$avgCorr36w_{t-k}$	0.0125	0.01	0.0076	0.0056	0.0066
$avgCorr3m_{t-k}$	0.0509	0.0701	0.1150	0.0840	0.0647
$avgCorr6m_{t-k}$	0.0532	0.0407	0.0669	0.0376	0.0284
$avgCorr9m_{t-k}$	0.0537	0.0482	0.0821	0.0596	0.0494

Table 5.10: Marginal effects of probit model variables by themselves. The LR statistics are reported in the parenthesis.

$P(recession_t = 1 \| x_{t-k}, yieldSpread_{t-k}) = G(\beta_0 + \beta_1 x_{t-k} + \beta_2 yieldSpread_{t-k})$. k = weeks/months ahead					
x_{t-k} *variables*	k=1	k=3	k=6	k=9	k=12
$avgCorr12w_{t-k}$	0.083 (7.18**)	0.070 (5.80*)	0.054 (4.26*)	0.040 (3.28)	0.021 (2.38)
$avgCorr24w_{t-k}$	0.037 (5.52*)	0.022 (4.96*)	0.005 (4.64*)	-0.008 (4.70*)	-0.027 (5.18*)
$avgCorr36w_{t-k}$	0.486 (9.48**)	0.360 (8.58**)	0.231 (7.90**)	0.154 (21.52*)	0.044 (33.86**)
$avgCorr3m_{t-k}$	-0.103 (2.06)	-0.209 (7.44**)	-0.304 (15.96**)	-0.313 (25.22**)	-0.276 (21.98**)
$avgCorr6m_{t-k}$	0.095 (3.24)	-0.005 (1.24)	-0.132 (17.30**)	-0.150 (28.44**)	-0.135 (28.54**)
$avgCorr9m_{t-k}$	0.020 (8.00**)	-0.067 (15.82**)	-0.173 (33.44**)	-0.211 (46.58**)	-0.211 (33.08**)

(*) notes significant at the 5 % level and (**) at the 1 % level.

By adding the explanatory variable $yieldSpread_{t-k}$ to the original model, we achieve a model with higher explanatory power. The best fitted model is found with the variable $avgCorr3m_{t-6}$ and $yieldSpread_{t-6}$. This result is similar to the findings of Estrella and Mishkin (1998), Dueker (1997) and Moneta (2003), which finds that a forecast horizon between 6 and 18 months, yields the highest $pseudo - R^2$ for a model with the yield spread. The $pseudo - R^2$ is 0.1150, which means that it explain 11.5 % of the variation in $recession_t$. We achieve considerably lower $pseudo - R^2$ than the studies mentioned, even though we have one additional explanatory variable. This could be a result of differing data sets.

The marginal effect is -0.304, which means that on average a decrease in average correlation of one standard deviation, 0.198, will increase the probability of a recession by 6.02 percentage points.

The graph in Figure 5.3 shows that the predicted recessions are more timely now than the probit model with just $avgCorr3m_{t-9}$ as the predictor. Still the same pattern emerges. Predicted probabilities have more and greater spikes before the 2007-2009 recession than after. The highest peak is in the 2001 recession. As in Figure 5.1, the predicted probabilities rises at the end of this data set.

The model fails to predict 11 recession months that occurs and 92 of the recession months it predicts are incorrect. False positive rate is 30.77% and false negative rate is 29.73%. Percentage correctly classified is 69.35 %, which means that it increase slightly when we include yield Spread in the model. It is still much lower than a model which never predict recessions.

A LR-test reveals that this model suffers from heteroscedasticity(see Table 7.2 in Appendix). Running a heteroskedastic probit model shows that the marginal effect of $avgCorr3m_{t-6}$ is now -0.282. A decrease by one standard deviation will increase the probability by 5.58 percentage points. We see that the original estimates of the marginal effect changes slightly as a consequence of the heteroscedasticity. Predictions are unchanged.

Table 5.11: Predictions of recession using $avgCorr3m_{t-6}$ and yield spread as a predictor vs true recessions.

	recession = 1	recession = 0	Total
Pr(recession = 1)	26	92	118
Pr(recession = 0)	11	207	218
Total	37	299	336

Table 5.12: False positive rate and false negative rate for $avgCorr3m_{t-6}$ and $spread_{t-6}$ prediction of recessions. Threshold 10.7%.

False Positive Rate	30.77%
False Negative Rate	29.73%
Correctly Classified	69.35%

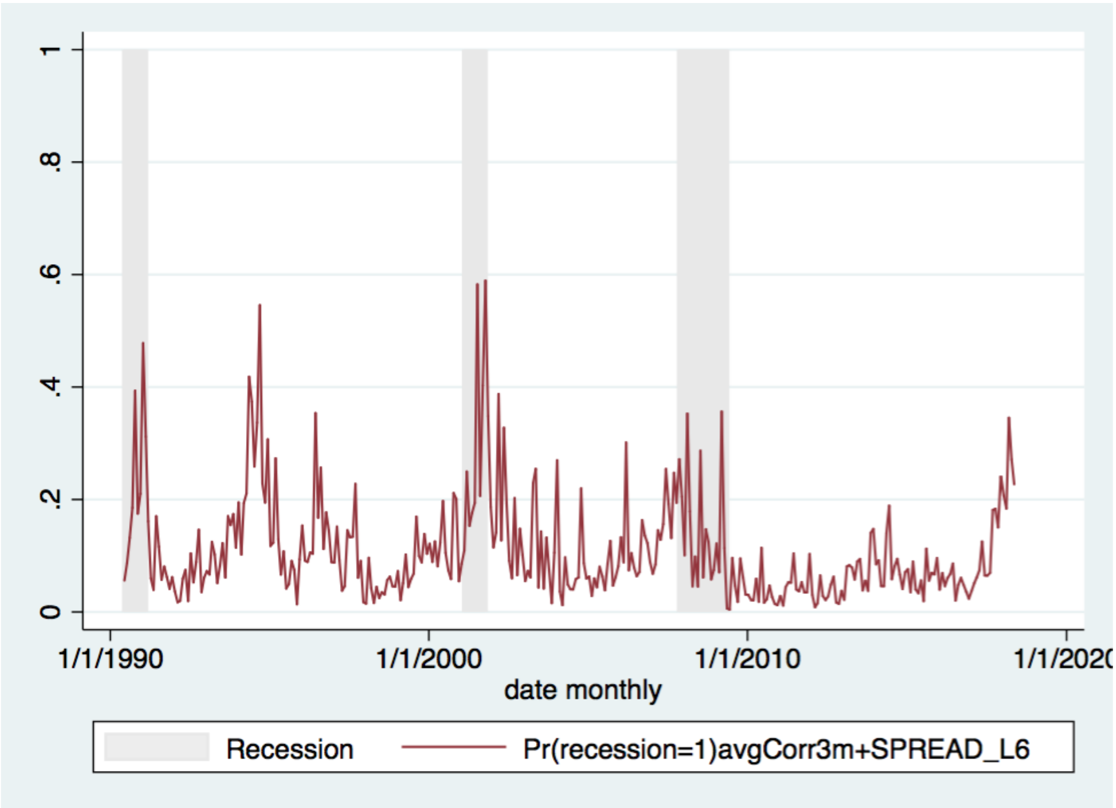

Figure 5.3: Predicted probabilities combining $avgCorr3m_{t-6}$ and $yieldSpread_{t-6}$ for recessions.

5.4 Investment strategy

Table 5.13: Annual returns using the change in average sector correlation as a buy or sell signal. All investments are in the S&P 500 for the entire period of our data set, with monthly data. The top axis specify the threshold value on the change in correlation required for a buy or sell to be executed. The left vertical axis specify the time interval, which is the number of weeks back in time, the change in correlation is measured against. All returns are reported in percentage.

	0.2	**0.4**	**0.6**	**0.8**
1 month	5.88	6.07	6.30	6.78
2 months	6.26	7.09	7.11	7.62
3 months	5.92	7.07	6.93	7.67
6 months	5.21	7.17	7.31	7.62

Table 5.13 reports the results of an investment strategy using the change in correlation as buy or sell signal. The highest annual return is 7.67 %, obtained with a threshold of 0.8 and a time interval of 3 months. This is marginally better than a buy & hold strategy, which yield an annual return of 7.62 %. The similarity is no surprise, considering a change in correlation of 0.8 is rare, resulting in only 4 transactions. Using a 0.8 threshold value with a time interval of 2 and 6 months, results in no transactions. All results obtained with a threshold value lower than 0.8, underperform relative to the buy & hold strategy. There seems to be little to gain from this strategy and in most circumstances we achieve a lower return than the buy & hold strategy.

Table 5.14: Annual returns using the change in average sector correlation as a buy or sell signal. All investments are in the S&P 500 for the entire period of our data set, with weekly data. The top axis specify the threshold value on the change in correlation required for a buy or sell to be executed. The left vertical axis specify the time interval, which is the number of weeks back in time, the change in correlation is measured against. All returns are reported in percentage.

	0.2	**0.4**	**0.6**	**0.8**
1 week	5.64	6.64	7.43	7.65
4 weeks	5.81	7.04	7.99	7.67
8 weeks	6.63	6.53	8.78	7.64
12 weeks	4.32	7.60	6.96	7.56
24 weeks	6.49	6.19	6.39	7.66

Using the same strategy with weekly data allows us to execute transactions more frequently. From Table 5.14 we see that the highest annual return was 8.78 %. This return was achieved with a threshold of 0.6 and a time interval of 8 weeks. Relative to a buy & hold strategy with a return of 7.66 %, it achieves 33.52 % higher return for the period. 12 transactions were executed during the period, all during the 2001 recession and in 2017 and 2018. We see that for a threshold value of 0.8, returns are very similar to a buy & hold strategy. This is because a change in correlation of 0.8 occurs very rarely, resulting in few transactions. None of the returns produced with a threshold value of 0.2 and 0.4 managed to beat the buy & hold strategy. Even though some combinations of threshold values and time intervals beat the buy & hold strategy, there is little consistency and the results appears to be random.

Table 5.15: Annual returns using the level of average sector correlation as a buy or sell signal. All investments are in the S&P 500 for the entire period of our data set, with monthly data. The top axis specify the threshold value. If correlation decrease below this value, the position in the S&P 500 is sold and placed in a risk free asset. When correlation increase above this threshold, a position in the S&P 500 is bought. All returns are reported in percentage.

Threshold	Return
0.34	8.01
0.32	8.20
0.30	8.25
0.28	8.70
0.26	7.82
0.24	7.62
0.22	7.47
0.20	7.43
0.1	7.91
0.05	8.05

Table 5.15 report the results of an investment strategy using the level of average sector correlation as a buy or sell signal. The highest annual return is 8.70 % and is achieved with a threshold value of 0.28. Compared to the return of a buy & hold strategy with a return of 7.62 %, this strategy achieve 32.26 % higher return for the period. 20 transactions were executed during the period. We see that subtle differences in threshold values yields different results. Both the highest and the lowest threshold value outperformed the buy & hold strategy, while several

of the values in between, did not. This volatility in the returns makes it difficult to determine whether the correlation level actually has any significance on return from the S&P 500.

Table 5.16: Annual returns using the level of average sector correlation as a buy or sell signal. All investments are in the S&P 500 for the entire period of our data set, with monthly data. The top axis specify the threshold value. If correlation decrease below this value, the position in the S&P 500 is sold and placed in a risk free asset. When correlation increase above this threshold, a position in the S&P 500 is bought. All returns are reported in percentage.

Threshold	**Return**
0.34	6.67
0.32	6.96
0.30	6.98
0.28	7.53
0.26	7.67
0.24	7.37
0.22	7.71
0.20	7.70
0.1	8.21
0.05	7.74

Table 5.16 report the same strategy using weekly data. The highest annual return is 8.21 %, achieved with a threshold value of 0.1. This results outperform the buy & hold strategy with 15.25 % for the period. Using weekly data, there seem to be a tendency of lower threshold values yielding higher returns, with a peak at 0.1. The returns are still quite sensitive to small changes in the threshold value. As we see when the threshold value decreases from 0.1 to 0.05. Because the returns are still sensitive to small changes in the threshold value and are quite similar to the yield of the buy & hold strategy, we cannot draw any conclusions.

6. Conclusion

This paper examines low average sector correlation as a recession predictor. As Estrella and Mishkin (1998), Dueker (1997) and Moneta (2003) we use a probit model. We find that for two of our model structures, a decrease in average sector correlation will increase the probability for a recession. Based on low explanatory- and predictive powers of these two model structures, we conclude that low average sector correlation cannot be used as a recession predictor.

The first model we explore is the simple probit model with only average sector correlation as the independent variable. Estimating with different forecast horizons and correlation lengths, we find that the superior model has a forecast horizon of 9 months and a correlation length over the previous 3 months. A decrease in average sector correlation by one standard deviation will increase the probability for a recession in 9 months by 6.20 percentage points. Using this specification as a predictor, we predict correctly 66.67 % of the binary outcomes.

Following Dueker (1997), we add a lagged dependent variable to remove potential autocorrelation. The model with highest goodness-of-fit is estimated with a forecast horizon of 1 week and a correlation length of 24 weeks. The autoregressive variable renders the marginal effect of average sector correlation insignificant. Another issue to consider is that the performance of this model is not realistic. This is because it takes time for an economy to realize and determine that a recession has started.

By adding another explanatory variable, the yield spread, we achieve a better fitting model with slightly better predictive properties. We find that the best fitting model is estimated with a forecast horizon of 6 months and correlation over the previous 3 months. A decrease in average sector correlation by one standard deviation, increases the probability of a recession by 6.02 percentage points.

Diagnostic testing reveals that this model suffers from heteroscedasticity. Running a heteroscedastic probit model produce a different marginal effect. A decrease by one standard deviation will now affect the probability for a recession by 5.58 percentage points. The model predicts 69.35 % of the binary outcomes.

We simulate investment strategies using average sector correlation as a buy or sell indicator for the S&P 500. Results show that there are little or no gain to these strategies, relative to a buy & hold strategy.

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7. Appendix

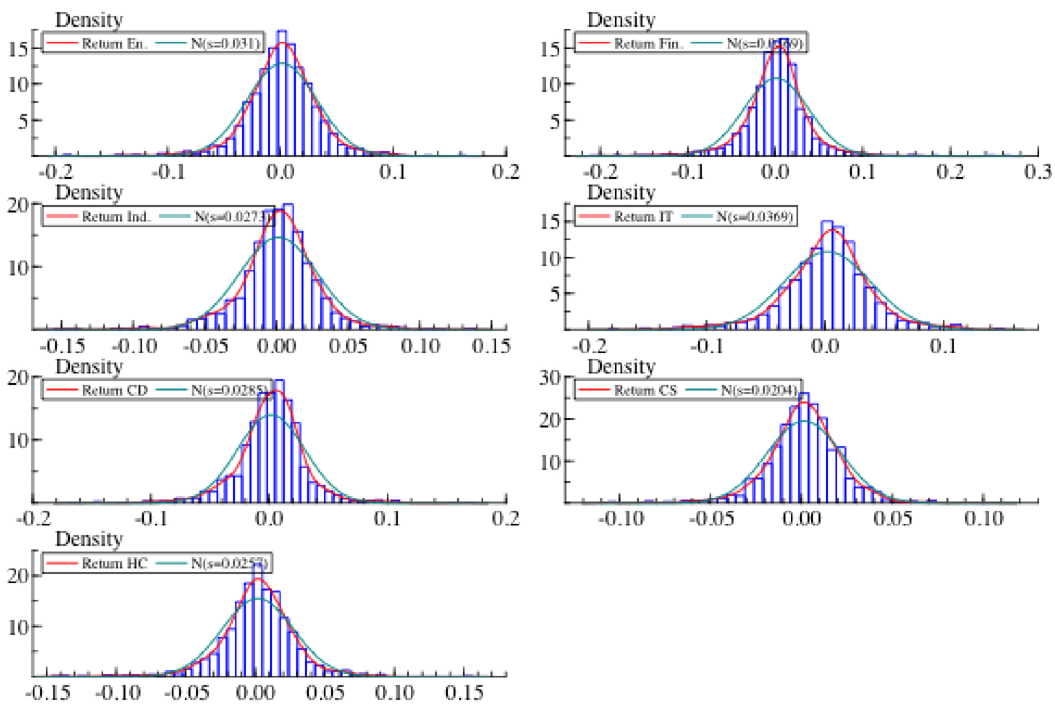

Figure 7.1: Sectors distribution of weekly logarithmic returns vs normal distribution.

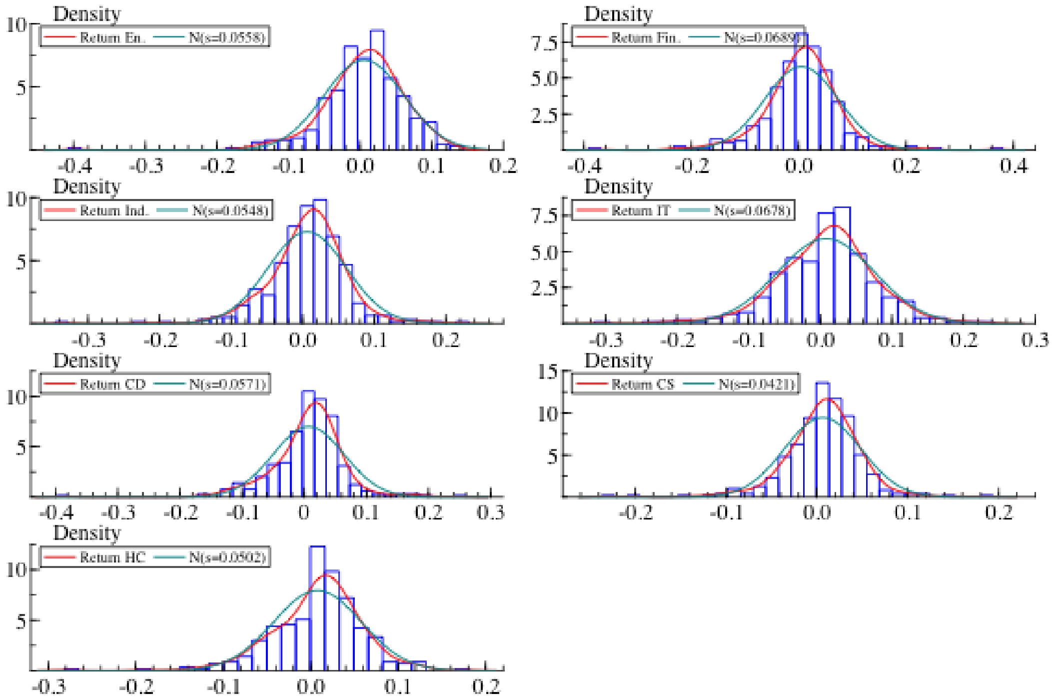

Figure 7.2: Sectors distribution of monthly logarithmic returns vs normal distribution.

Table 7.1: Summarize of predicted probabilities. 3Months.

Variable	Obs	Mean	Std. Dev.	Min	Max
$\text{pr}_a vgCo\ mL1$	342	0.109	0.023	0.074	0.191
$\text{pr}_a vgCo\ mL3$	342	0.109	0.047	0.048	0.297
$\text{pr}_a vgCo\ mL6$	342	0.111	0.070	0.030	0.409
$\text{pr}_a vgCo\ mL9$	342	0.104	0.072	0.024	0.421
$\text{pr}_a vgC\ mL12$	342	0.097	0.064	0.025	0.375

Table 7.2: LR-tests for heteroscedasticity.

One explanatory variable	1.47
Lagged dependent variable	0.57
Yield spread	6.57*

(*) notes significant at the 5 % level.