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Stock Market Data as a Leading Indicator of the Real Economy – A Horse Race on the Norwegian Market with a Special Focus on Liquidity

Navn: Hanna Cecilie Boehlke Reinertsen, Karianne Lydersen Hollerud

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Oslo, August 2017

Cecilie Reinertsen.

Hanna Cecilie Boehlke Reinertsen

MSc in Business, Major in Finance

Karianne Hollerud

Karianne Lydersen Hollerud

MSc in Business, Major in Finance

ii. Abstract[1]

The aim of this thesis is to investigate whether stock market data, with a special focus on liquidity, can aid in the forecast of GDP for the Norwegian market. Included in stock market data, are asset prices and three illiquidity measures; the Amihud illiquidity ratio, relative quoted spread and Roll implicit spread estimator. Furthermore, the predictive power of these variables are compared by performing a horse race. Contributing to this field of research, in-sample and pseudo out-of-sample analyses of the past 20 years are performed. In-sample, both the superior illiquidity measure, namely *Roll*, and asset prices improve the prediction of GDP. Additionally, we find indications of out-of-sample improvements of GDP forecasts by including *Roll*. However, we do not find sufficient evidence to confirm our hypothesis that stock market data indeed may aid in improvement of forecasting GDP.

[1] Hanna Cecilie Boehlke Reinertsen, e-mail: hceciliebr@gmail.com, Karianne Lydersen Hollerud, e-mail: Karianne.hollerud@outlook.com. If in need of the data set or computations, please e-mail us.

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1. Introduction

A vast amount of literature has tried to investigate the relationship between asset prices and the real economy. Over the past 15 years, there have been several contributions using asset prices to forecast economic activity and inflation (Stock & Watson, 2003). The forward-looking features of asset prices give reason to trust such a relationship. Asset prices are defined as the discounted expected future cash flows of a company. Hence, they incorporate investors' expectations regarding the future state of the company and their beliefs regarding the overall state of the economy. In a seminar paper, Stock and Watson (2003) present an extensive overview of the historical development with different angles on this matter, arguing ambiguous results in the predictive power of asset prices. Despite their findings, they still express support of a predictive relationship between asset prices and the real economy. Other researchers advocating the predictive relationship, amongst those Aastveit and Trovik (2012), are able to find strong predictive power in asset prices for the Norwegian market.

Discussing the many elements making up asset prices in light of predicting the real economy, many researchers raise concerns regarding the incorporation of too much noise and non-relevant information with respect to future economic expectations. Furthermore, the results presented by Stock and Watson, amongst others, contributed to a shift in focus. Newer research aimed attention toward one particular aspect of asset prices, namely their liquidity, arguably containing valuable information influencing the overall economy. The relationship has become more prominent in the literature during the last years, and is the primarily focus in our paper.

When referring to stock market liquidity we borrow the definition used by Pastor and Stambaugh (2003) arguing that liquidity is "a broad and elusive concept that generally denotes the ability to trade large quantities quickly, at low cost, and without moving the price" (p. 644). Given the numerous definitions and aspects of liquidity, liquidity measures are divided in two categories: "spread based measures", and "price impact measures", discussed more extensively in *Section 4 Methodology*.

Our contribution is to perform a horse race between several illiquidity measures and asset prices to find the best performing stock market data (SMD) variable. Asset prices and three illiquidity measures; the Amihud illiquidity ratio (ILR), the relative quoted spread (RS) and the Roll implicit spread estimator (Roll), constitute the SMD variables. This enables us to compare the more recent literature with focus on liquidity, against the well-established relationship between asset prices and the real economy. Thereby, we test the existence of these relationships for the Norwegian market and which is considered the most informative. Due to the lack of the research within this field for the Norwegian market, we investigate the following research question:

"Is stock market data, with a primary focus on illiquidity measures, a good leading indicator of the Norwegian real economy, and which variables, making up stock market data, are superior in forecasting GDP?"

Our research question mainly focuses on improving the prediction of gross domestic product (GDP).[2] In answering our research question, we conduct an in- and out-of-sample horse race. In the former horse race, the predictive power of all the SMD variables are compared. The out-of-sample horse race is on the other hand conducted by comparing the superior illiquidity measure with asset prices in the pseudo out-of-sample (POOS) analysis. The evaluation is done through several metrics, including adjusted R^2, mean squared error (MSE), root mean squared forecasting error (RMSFE) and Theil's U_{II} (U_{II}).

The research on the predictive power of stock market liquidity is somewhat divided with respect to focus and empirical findings. While some find stock market liquidity to be a good leading indicator of the real economy, others provide results with more instability. Nonetheless, research on using stock market liquidity to forecast economic growth is still not extensively covered, particularly in the Norwegian market. According to our literature review, Næs, Skjeltorp and Ødegaard (2011) are the only ones studying this relationship

[2] We use GDP as our main proxy for the state of the economy, while private consumption (CONS) and investment (INV) are used to confirm our results for robustness purposes. Hence, the regressions using GDP as macro variable are considered our main regressions. Furthermore, all macro variables are adjusted for inflation. For simplicity, we have chosen to write "growth in GDP", while meaning "growth in real GDP". This is the same for all macro variables.

for the Norwegian market. However, their focus is primarily on the US market. Næs et al.´s article provided us with great inspiration as they are some of the few researchers studying general SMD in relation to the Norwegian business cycle. We will partly follow their article and see if their results hold after incorporating new data.
Forecasting economic growth is highly desirable. It can be beneficial for society due to its policy implications (Shi 2015) and the ability to aid governments in regulating and attenuating the business cycle. The Central Bank is also dependent on valuable predictions of economic growth in their appointed assignment to set the key policy interest rate. Along those lines, the forward-looking characteristic of SMD could aid in this manner. This gives rise to our main motivation behind the thesis.

Our thesis is structured in the following way: *Section 2 Literature Review* explores existing literature on using SMD to predict the business cycle. *Section 3 Hypotheses* highlights the hypotheses we have developed in line with our research question. In *Section 4 Methodology,* we provide a thorough description of each of the SMD variables used and the time series adjustments made. *Section 5 Data* outlines how and where the variables are retrieved. In *Section 6 Analysis,* we performed our horse race by first doing an in-sample analysis and thereafter a POOS forecasting. For the former, we ran regressions using all the SMD variables with the various dependent variables to obtain the superior. For the latter, we proceed with the illiquidity measure performing superior in-sample and asset prices. This is also where we investigate the main part of our research question. Lastly, *Section 7 Conclusion* provides a conclusion regarding our findings on the research question we examine.

2. Literature Review

2.1 Link between Asset Prices and the Business Cycle

Due to the forward-looking features of asset prices, extensive research has been conducted to evaluate whether asset prices could potentially contribute to improve economic forecasts. In their review article, Stock and Watson (2003) presented an overview of results from 93 articles on the subject, a study conducted over 15 years. Overall, they found mixed evidence in the predictive power of asset prices, as their results indicated that a successful prediction one period is no guarantee for later successful predictions. As the use of solely one predictor may cause inconsistencies, the authors tested various combinations of predictors. However, the results were still unclear. Regardless of the gloomy results presented in their article, the authors ultimately offered comforting thoughts as they reassured that the predictive relationship between asset prices and the business cycle is likely to be prominent. Their adverse findings may origin from the vast limitations of existing models.

In contrast to Stock and Watson (2003), other researchers such as Aastveit and Trovik (2012) have found asset prices to significantly improve the estimates for the real economy, measured with GDP. Aastveit and Trovik's study was solely conducted for the Norwegian market, using panel data with 148 monthly observations. The relatively small size of the companies listed on Oslo Stock Exchange, accompanied by the open and small features characterizing the Norwegian market, could give rise to particularly informative asset prices, supporting their hypothesis.

Due to the features of the Norwegian market, one would expect outside shocks to influence the economy quite fast and the overall impact to be of greater magnitude than for larger economies. The Norwegian economy is also expected to be less diversified than these economies. The authors argue that equities listed on multiple exchanges in different countries are strongly correlated. As expected, Norway is no exception. However, another important factor is that the equities listed on the Oslo Stock Exchange exhibit a profoundly positive correlation with the oil price, as the Norwegian economy highly depends on the developments in the oil market. This is one feature distinguishing Norway from other countries. Furthermore, Aastveit and Trovik argue that as the average Norwegian company is considerably smaller compared to those of the American market, the informativeness of asset prices for the Norwegian market is greater. Thereby, the predictions of Norwegian GDP are more accurate compared to the US. Most research on this matter is performed on the US market, with Aastveit and Trovik (2010) being one of few exceptions. This opens up the need for a thorough study on the Norwegian market.

Panopoulou (2007) performed an extensive study on how financial variables, deemed forward-looking, could contain future economic expectations to predict GDP.[3] The 12 European countries in the study differ largely with respect to economic developments and country characteristics.[4] The data employed in the study ranged from 1988 to 2005 available at a monthly frequency. Her results suggested that the most important financial determinant of the real economy is stock market returns, followed by money supply growth. The choice of financial determinants was based on well-established variables prominent in the existing literature. Other non-financial variables included were oil prices and US growth.

For forecasting, Panopoulou used linear models including various combinations of the financial variables mentioned, with the aim of improving GDP forecasts. The models were assessed using a simple autoregressive (AR) model. Arguably, linear models have shown to outperform both nonlinear and multivariate models providing support to her choice of forecasting models (Panopoulou, 2007).[5] The metric used to assess the models was mean squared forecast errors, where stock market returns provided the best overall forecasting improvement among the financial variables.[6] However, the results suggested that on a country-specific level, none of the financial variables systematically outperformed the benchmark. Aggregating the European countries for this study, the forecasting improved significantly for all the financial variables over multiple forecast horizons, except when including exchange rates.

2.2 Link between Stock Market Liquidity and the Business Cycle

As mentioned above asset prices as a predictor of the real economy have traditionally been the most frequently used explanatory variable. Despite the

[3] The financial variables examined are; term spread, real stock market returns, real money supply growth, exchange rate returns, short-term interest rates.
[4] The countries being Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal and Spain.
[5] Banerjee and Marcellino (2006) and Marcellino, Stock and Watson (2003) cited Panopoulou (2007).
[6] Yielding a success rate of 75%.

ambiguous results of asset prices, there is a common consensus amongst many researchers that SMD contain information valuable for predictions of GDP.

In the attempt to improve the performance of SMD as a predictor of the real economy, a natural step is to employ stock market liquidity. This was a reasonable development as the link between asset prices and liquidity has theoretical and empirical support through considerable research in the 21st century. For instance, the traditional CAPM has been augmented with a newly added liquidity risk factor. These models have proven to be valuable in explaining the channels that affect asset prices, as well as providing some support to the "flight to liquidity" concept. Acharya and Pedersen (2005) provided such an asset pricing model with liquidity risk, which they found to outperform the traditional CAPM. Their evidence suggested that liquidity explains approximately 1.1% of the total return. The motivation behind exploring stock market liquidity as an explanatory variable of the real economy could have originated from the mixed results presented in previous research and the evident link between asset prices and liquidity. Numerous researchers try to explain the relationship between stock market liquidity and the business cycle. The explanations provide different causes as to why stock market liquidity may be a good leading indicator of the real economy.

Brunnermeier and Pedersen (2009) provided an alternative explanation between the linkage of stock market liquidity and the business cycle to that of Næs et al. (2011). They created a model establishing a relationship between stock market liquidity and traders funding liquidity. According to their view, traders provide the market with liquidity. However, in order to trade they need funding, which is naturally limited by capital and margin requirements. Following this logic, one of their findings was that market liquidity is positively correlated with the economy, as funding depends on the latter. Their model provides a linkage between a security's illiquidity and risk premium to its margin requirements, as well as the general costs of funding. This link suggests usefulness for policy implications, by aiding in the mitigation of liquidity problems through managing the funding liquidity. The researchers also suggest a reinforced mechanism between market and funding liquidity that could potentially lead to liquidity spirals.

Both Eisfeldt (2004) and Shi (2015) provide other explanations to the link between stock market liquidity and the real economy. According to Eisfeldt, market liquidity is assumed to be varying with the state of the economy, documented by the presence of liquidity crisis in economic downturns. Her findings suggest a link between productivity in industries and economies to the liquidity level of asset markets, where increased productivity leads to growth in liquidity. Her research providing evidence of a prominent relationship is highly valuable to us.

> A sudden drop in asset market liquidity, which may not necessarily be related to changes in economic fundamentals, causes the equity price to fall. The lower equity price reduces the funds for investment that a firm can raise by issuing equity and/or using equity as collateral on borrowing. Thus, investment falls, output falls and an economic recession starts (Shi, 2015, p.116).

In accordance with this quote, Shi (2015) examined the liquidity shock hypothesis to evaluate the importance of frictions in the financial market and how this affects the real economy. In the recent financial crisis liquidity evaporated from the money markets caused by, amongst other things, changes in economic fundamentals. This led investors to flee to safer assets, known as the concept of "flight to quality". In the aftermath of the crisis, questions regarding the role of liquidity and shocks to it in relation to the business cycle were raised. Consequently, the relationship has retrieved plenty of focus from researchers in the recent years and Shi provided empirical support for his hypothesis. Another finding was the quantification of the lead-lag relationship between stock prices and investments, where the former leads by one to two quarters to the other. This suggests that liquidity shocks are likely to affect the business cycle through asset prices. The implications of such a relationship are vast and in times when closing into a recession, governments might inject liquidity to the stock market to support the asset prices. Hence, they will - hopefully - prevent deterioration of the investments and business cycle as a whole, with the aim of stabilizing the real economy. Overall, negative financial shocks to an asset's liquidity or a firm's collateral constraint may cause investment, employment and consumption to fall, in addition to the fall in output, GDP.

During periods of financial distress, the stock market has been observed drying up. This phenomenon can be observed back to at least the Second World War, whereas it was more lately evident during the financial crisis of 2007 to 2009 (Næs et al., 2011). These observations formed part of the basis for the linkage between stock market liquidity and the business cycle, inspiring researchers towards testing this empirically.

One paper to examine this link closely was Næs et al. (2011). In doing so, they focused mainly on the US market and testing the Norwegian market primarily to confirm the external validity of their results. The data used spanned from 1947 to 2008 for the US and 1980 to 2008 for Norway. To measure the liquidity in the US stock market they used several measures: Amihud´s illiquidity measure, Lesmond, Ogden and Trzcinka (1999) measure (LOT) and the Roll measure. However, for the Norwegian market, only the Amihud measure and the relative spread were applied. Their main focus for the Norwegian study was to test for the existence of the "flight to quality" concept.[7] The idea is that during economic downturns, investors want to hold more liquid and safer stocks, which would be reflected in a shift of their portfolio composition. Their study contributed with two empirical observations. Firstly, they provided evidence that useful information can be extracted from stock market liquidity in estimating current and future states of the economy. Secondly, they observed behaviour consistent with the concept of "flight to quality", where the participation in the stock market, especially concerning the smallest firms, decreases when liquidity worsens. Thirdly, the informativeness of stock market liquidity as a predictor of the real economy differs across stocks, and the most informative are those for smaller firms.[8]

[7] This concept is used interchangeably with "flight to liquidity".
[8] Smaller firms may generally have less liquid stocks

Inspired by the research of Næs et al. (2011), Galariotis and Giouvris (2015) performed additional tests incorporating six G7 countries.[9] In their findings, they discovered that different markets do not behave similarly, i.e. the results are country dependent. Solely, Canada had liquidity variables that were able to consistently predict a recession, whereas the results for the other economies were more inconclusive. Their country specific results highly coincide with those of Panopoulou, disregarding the use of a different independent SMD variable. However, due to their findings the researchers questioned those of Næs et al., as they were unable to confirm the relationship as implied. Acknowledging that their results are country specific, the findings are not necessarily contradictory to the ones of Næs et al. as their study did not include neither the US nor Norway. As a proxy for stock market liquidity, the liquidity measures of Roll and Amihud were used. For the comparison of results to those of Næs et al. (2011), these researchers also excluded "penny shares" meaning those trading below one unit of local currency.[10] Their choice of illiquidity measures and shaving of data gave inspiration to our research.

Lastly, we have chosen to include the article by Goyenko, Holden and Trzcinka (2009). Conducting a horse race between different illiquidity measures with low- and high frequency data, they evaluated the performance of different measures. The measures were calculated based on daily and intraday data respectively, where the latter has been the most commonly used in literature.[11] In order to study liquidity in stock markets for a longer period and across countries, their choice of data was restricted due to the availability of microstructure data. They performed the horse race by evaluating annual and monthly estimates of the measures against a predefined liquidity benchmark. This benchmark is based on known liquidity measures widely acknowledged in the literature.

[9] Countries included were Canada, France, Germany, Italy, Japan and the UK.
[10] Supposedly comparable to the exclusion done by Næs et al. for shares trading below NOK 10.
[11] The measures were computed on an annually and monthly basis, comparing the use of daily and intraday data.

Their findings suggest that the effective and realized spreads outperform the other measures with the correlations and mean squared prediction errors, while the commonly known Amihud measure also performed well. Overall, they find support for their hypothesis that it is useful to apply low frequency liquidity measures to investigate liquidity in markets over a longer period. They argued that the estimation of liquidity from intraday data is unnecessarily time consuming and not worth the hassle. As opposed to their horse race, our horse race is set between liquidity and asset prices where the ultimate goal is the improved prediction of GDP. Nevertheless, their research is highly valuable to us as it substantiates our choice of liquidity measures and frequency of data.

3. Hypotheses

As shown above, there is a vast amount of literature on the subject of using financial variables as predictors for the real economy. Our main contribution to this line of research is a horse race comparing asset prices and several illiquidity measures. For our horse race, we find inspiration from the article of Næs et al. (2011), as they are one of the few researchers examining Norwegian SMD in association with the business cycle.

To differentiate ourselves from them, we add extensions and modifications to their research. Using data from 1996Q4 to 2016Q4, Næs et al.'s (2011) analysis is updated by including newer data from 2009. The different timeframe enables us to test whether the results presented by Næs et al. (2011) are still valid for more recent data. Another extension is the employment of the Roll measure, in addition to the ones already applied for the Norwegian market by Næs et al. (2011), namely ILR and RS. When including another measure of illiquidity we hope to improve the validity of our findings by avoiding dependency on solely two measures. Moreover, a couple of modifications are made to the analysis. These modifications include analysis through a separation of the sample into a training and test period. We use the training period to conduct our in-sample analysis and the test period for the POOS analysis. Furthermore, the use of a recursive estimation scheme instead of a rolling window distinguishes us from Næs et al.. Lastly, our POOS predictions are assessed by other means of evaluations.

Based on existing literature, with a special focus on the results presented by Næs et al. (2011), we expect to find a negative relationship between illiquidity and GDP, and the opposite for asset prices. We also expect each of the financial variables to be significant predictors of the business cycle, hence presenting a lead-lag relationship with GDP. Based on existing research we believe that the Amihud measure will explain the most variance in GDP as opposed to the other measures of illiquidity.

Based on our research question we have formed the following two hypotheses, for the in- and out-of-sample horse race:

Hypothesis 1: In-Sample

H_0: The coefficient of SMD is zero
H_A: SMD has non-zero coefficient

With this hypothesis, we will see if any of the SMD variables are significant in the prediction of GDP. If we find support for this hypothesis, we will inspect the reported adjusted R^2 and RMSE and look for improvements when incorporating *SMD* in the regression. If we find evidence to confirm this hypothesis for multiple illiquidity measures, we continue with the superior. Given that we also confirm this hypothesis using asset prices, we further proceed to the second hypothesis, and the POOS horse race. The horse race is between the superior illiquidity measure and asset prices, using a simple AR model for each of the dependent variables as a benchmark.

Hypothesis 2: Pseudo Out-of-Sample

H_0: The inclusion of SMD does not improve the out-of-sample prediction of GDP
H_A: SMD contributes to an improved out-of-sample prediction of GDP

Given present in-sample evidence, the second hypothesis tests whether either of the SMD variables contributes to forecast GDP out-of-sample in excess of a model excluding SMD. If the regression including *SMD* does well out-of-sample, these forecasts are highly valuable, due to the real life similarities. The forecasts are tested on data for which the model is not developed from and assessed by multiple measures of evaluation.

4. Methodology

To address our hypotheses, we use data on stock market returns and construct several illiquidity measures. For the computations of these independent variables, we use equally weighted (EW) averages both across firms and across time.[12] The reason for choosing EW as opposed to value weighting (VW) is to allow smaller firms to have a stronger influence on the measures of illiquidity. Aastveit and Trovik (2012), for instance, argue that, smaller firms have SMD with higher informational content and could therefore improve the ability of illiquidity measures to predict GDP as opposed to larger firms. Næs et al. (2011) also used EW illiquidity measures in their article based on a similar argument. In light of those studies, we consider it valuable to empower the smaller firms through EW averages.

4.1 Asset Prices

One of the variables we test as a predictor to the business cycle are asset prices. As asset prices exhibit a unit root, we work with the log difference of the variable, *dP*. The closing prices of each company is EW over the market, obtaining a daily market closing price. Thereafter the price per quarter is attained by averaging over time. Following, the log difference is taken to obtain stationarity, which is essentially the same as the stock market return.

[12] On a practical note all SMD variables are computed in excel from daily data, before aggregating them to a quarterly frequency. Thereby, completing our analysis on the quarterly data using Stata.

4.2 Liquidity

Theoretical research provides various definitions of liquidity. Using these definitions, empirical studies have developed different methods capturing liquidity in the data. To capture different aspects of the liquidity definition chosen, we employ the following measures: (i) ILR, (ii) RS and (iii) Roll. Each of the liquidity measures are calculated from daily data to a quarterly basis for the individual firms, before EW across the market.

Due to the length of our sample, daily input is collected as opposed to intraday data. The use of intraday data could potentially lead to spurious results, inducing a vast amount of noise. Hence, computing each measure quarterly, using daily data, SMD variables enable us to examine trends in the liquidity of stock markets and for asset prices. Thereby the illiquidity measures have to be adaptable to a low frequency, i.e. daily data, limiting the choice of measures.[13] As previously mentioned there are two types of illiquidity measures, spread based and price impact measures. These measures can, in accordance with the discussion above, further be separated according to the frequency of the data used to calculate the measures, intraday and daily input. Specified in *Section 2 Literature Review*, Goyenko et al. (2009) performed a horse race between various intraday- and daily input based measures of illiquidity. Even though most empirical measures require intraday information, their study supports the use of low frequency measures.

4.2.1 Price Impact Measure

The Amihud (2002) Illiquidity Ratio

Amihud´s illiquidity ratio, ILR, based on Kyle’s 1985 concept of illiquidity, measures how much prices move in response to the trading volume of that specific security. The rationale behind the measure is that more illiquid stocks are

[13] All the measures used are “illiquidity measures” meaning that when they produce high values this coincides with a higher degree of illiquidity in the stock market. According to the research field of liquidity, daily data is considered to be of a low frequency (Goyenko et al. 2009). Furthermore, Handbook of research methods and applications in empirical finance: Edward Elgar Publishing (Bell, Brooks and Prokopczuk, 2013) is diligently used in understanding the measures.

often associated with substantial price changes in response to the execution of a trade. ILR gives the absolute price change, which can be interpreted as the daily price response associated with the trading volume expressed in one unit of local currency, namely NOK.

$$ILR_{iyq} = \frac{1}{D_q} \sum_{q=1}^{D_q} \frac{|R_{iyqd}|}{VOL_{iyqd}}$$

D_q is the number of trading days within a quarter q. $|R_{iyqd}|$ is the absolute return of company i, in year y, in quarter q and on day d. VOL_{iyqd} is the respective trading volume on day d in NOK.

Even though there are finer measures of illiquidity, this is in our experience one of the most frequently used. Possible reasons for the widespread use of this measure are the minor requirements of microstructure data and the fact that the measure is both intuitive and simple to employ. One of the main disadvantages of the measure is related to the explanation of price changes. Such changes may simply be a result of the market incorporating new information in the prices, and not necessarily a consequence of the stock being illiquid. Thus, as the model does not distinguish between the underlying causes of the price change, it may yield erroneous results. Some researchers, including Acharya and Pedersen (2005), state that ILR may not be stationary. Thus, we perform stationarity tests to all measures to ensure stationarity, where we find unit root solely in the RS measure.

4.2.2 Spread Based Measures

An intuitive measure of liquidity is the bid-ask spread, which is the difference between the best bid and ask price. This captures the magnitude of disagreement on the security's price, risk associated with the security and the trader's potential profit. Rather than using the bid-ask spread we construct two alternative measures, the relative quoted spread and the Roll implicit spread estimator.

The Relative Quoted Spread

The relative spread, RS, captures the relative difference between the lowest ask and the highest bid, as a fraction of the quoted midpoint.[14] RS enables comparison of shares with different price levels. The spread is considered a well-known and highly recognized measure of illiquidity.

$$RS_{iyq} = \frac{1}{D_q}\sum_{q=1}^{D_q} \frac{A_{iyqd} - B_{iyqd}}{M}$$

$$where\ M = \frac{A_{iyqd} + B_{iyqd}}{2}$$

D_q is the number of trading days within a quarter q. A_{iyqd} and B_{iyqd} is the ask and bid, respectively, of company i, in year y, in quarter q and on day d.

As we use data in a daily frequency, RS is calculated based on daily closing bid and ask prices, instead of the lowest ask and highest bid, which is intraday data. Thereby our computations are not completely in accordance with the specification of the formula. Other researchers using daily frequency data and the RS measure have performed the computation in the same manner.

In order to apply the measure, two requirements must be met; (i) the volume available exceeds the transaction size and (ii) other prices more favourable than the best bid and ask viz. price improvement, may not occur. If one of the assumptions is violated, alternative models are preferred. A spread using a volume-weighted average of the prices is a potential solution if assumption (i) is violated. Furthermore, an effective bid-ask spread is desirable to solve price improvement, which does not comply with assumption (ii). In our analysis, we presume that the above restrictions are compassed. Due to RS's requirements of microstructure data, several alternative measures have been developed to deal

[14] The quoted midpoint is the average between the two.

with this obstacle. One of them is the Roll measure, which we include to substantiate the analysis and underpin our results further.

The Roll (1984) Implicit Spread Estimator

The Roll measure captures the implicit spread, estimated as the effective bid-ask spread calculated from data on daily returns. We calculate the measure by taking the square root of the negative Scov, which is the first-order serial covariance of successive price changes. The covariance is computed quarterly for each company. The reason for choosing this measure is that bid and ask prices rarely are obtainable for all markets. A high spread reflects illiquidity through high costs of trading.

$$Roll_{iyq} = \sqrt{-Cov(\Delta p_t, \Delta p_{t-1})_{iyq}}$$

$$\widehat{Roll_{iyq}} = \sqrt{-Scov_{iyq}}$$

Roll is only defined for Scov < 0 (i.e. first-order serial covariance of successive price changes smaller than zero). $Roll_{iyq}$ *is the Roll measure for company i, in year y, in quarter q.*

The bid-ask spread is the market maker´s gross revenue and is a source of transaction costs for investors. The market maker needs to be compensated for several costs. Thereby, the bid-ask spread is constituted by the following components; (i) costs of doing business (including e.g. fixed and variable costs, and the opportunity cost of time), (ii) compensations related to the risk of holding inventory, and (iii) compensation tied to the risk of trading with more informed counterparties (the adverse selection component).

One shortcoming of Roll is that it does not incorporate the last two components. Furthermore, an underlying assumption of the measure is market efficiency, where all relevant information is immediately reflected in prices. Thereby price changes are only a result of new information to the market participants. This gives rise to a second potential shortcoming, as full market efficiency does not necessarily hold. Another shortcoming of Roll is that the covariance is only defined when Scov is below zero. This has been thoroughly discussed and in 1990, Harris presented a new "version" incorporating positive Scovs. However, this model allowed for negative transaction costs in equity trading, which is not economically reasonable to assume. Thereby we choose to use the original Roll measure, only defined when Scov is negative. Despite these shortcomings, Roll is a recognized measure and we thereby see no obstacles using it.

4.3 Adjustments of Time Series Data

As mentioned, we test for stationarity and the absence of structural breaks before we proceed with our analysis. This is done by testing for unit root with an Augmented Dickey-Fuller test (ADF) and the complementary Kwiatkowski–Phillips–Schmidt–Shin test (KPSS). The former tests the null hypothesis stating that the variable contains at least one unit root against the alternative hypothesis that the variables are stationary, whereas the latter tests the opposite. Time series data need to be stationary, with a probability distribution that is time invariant, to be able to draw statistical inferences. We find no evidence of structural breaks testing with a standard Chow test.

All the macro variables contain unit root as well as the RS measure and asset prices, indicated by both the ADF and the KPSS test. There are several methods to deal with the problem of unit roots. To transform the variables we try two acknowledged methods, namely log differencing and applying the Hodrick-Prescott filter on the variables (Eurostat, 2017). For the macro variables and asset prices, we log difference the variables as this is considered equivalent to the growth in the macro variables and returns, respectively.[15] For RS, we continue with the HP filtered and log differenced version.[16]

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[15] Yielding the following variables: dGDP, dCONS, dINV, returns.
[16] HP filtered and log differenced RS is hpRS and dRS, respectively.

5. Data

5.1 Stock Market Data

To calculate stock market liquidity and returns, we use data from the Oslo Stock Exchange (OSE) available at Datastream.[17] The sample length is a trade-off between collecting enough data to obtain results of statistical inference and working with a long and detailed sample. Furthermore, as discussed under *Section 3 Hypotheses*, expanding the research by Næs et al. (2011), as well as including recent data affect our decision regarding the sample length. Based on the arguments above, 20 years of daily data is chosen, yielding a sample from 1996Q4 to 2016Q3.

We download all listed companies on the OSE during this period, corresponding to 818 companies. The sample includes companies listed, dead, merged, and delisted during the period, where they are only accounted for when present on the exchange. For the exclusion of outliers, we remove all observations for equities that within a year have less than 20 trading days in that year or trade below NOK 10. The omission of highly illiquid stocks and penny shares is in alignment with the research by Næs et al. (2011). We winsorize the data at the 1st and 99th percentile to further drop outliers. After removing outliers and securities with inadequate data, 422 companies are included in the calculation of the illiquidity measures and the use of asset prices.[18] For asset prices the data requirements are lower, however, we choose to use the same companies for comparability reasons.

Table 1: Summary Descriptive Statistics

This table shows the descriptive statistics of the SMD variables used in the regressions for our analysis. Return represents asset prices and is the quarterly average return for the market. Included are both the transformations of the RS

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[17] Appendix 1 includes an overview of the variables retrieved from Datastream with information and the datastream codes for each of the variables

[18] Several of the initial 818 companies retrieved from Datastream have missing data figures for the variables we need. Hence, these companies are removed. This, in combination to the exclusion of outliers as described above contribute to the drastically decline in number of companies we proceed with for our analysis.

variable, dRS and hpRS, as well as the variable itself. The other variables included are Roll and ILR. The descriptives are calculated for the entire sample.

	No.obs	Mean	Median	St.dev	Min	Max
RS	7 238	0.045	0.0363	0.0241	0.0171	0.1142
dRS	7 238	-0.0001	-0.0009	0.011	-0.0361	0.0412
hpRS	7 238	7.82e-12	-0.0026	0.0141	-0.0224	0.0435
Roll	7 717	0.0172	0.0167	0.0031	0.0108	0.0276
ILR	11 207	0.5883	0.5305	0.3415	0.1430	2.0059
Return	726 032	-0.0265	0.0008	0.2448	-0.7440	0.9137

The mean for the different liquidity measures are 0, 0.045, 0, 0.02 and 0.59 for *hpRS, dRS, RS, Roll* and *ILR*, respectively. When comparing the mean of the SMD variables to their median they seem quite close, hence no outliers are assumed. The number of observations used to compute these measures vary due to the different data requirements and computational frequency.[19] For asset prices, the total average market price was 932.25, while for returns we obtain a negative mean of -0.03.

5.2 Macro Data and Control Variables

As prediction of the state of the economy is a main focus of our research question, GDP struck us as the most prevalent to investigate. Data on mainland GDP is downloaded from SSB.[20] However, for robustness of our results, private consumption (CONS) and investment (INV) are also investigated and retrieved from SSB. Furthermore, data for the control variables is obtained from Norges Bank and Datastream. The control variables we choose are similar to those used

[19] The number of observations is the sum of all computations made for each individual stock when present at OSE. As returns are calculated on a daily basis for each stock, this number deviates highly from the others. The other measures are calculated once each quarter for each stock, when data required is available.
[20] The use of mainland GDP is due to Norway being a large oil exporter and having considerable income related to oil, which gives a skewed picture of the economy. The data on GDP, CONS and INV are all expressed in market value with current years prices, and are unadjusted.

by other researchers within this field and are commonly known to contain valuable information regarding economic growth.

As stock market control variables, we use *excess market return (ER)* and *stock market volatility (VOLA)*. *ER* is obtained by taking the difference between the market return, proxied by the return on the main index, OSEBX, and the 3-month Norwegian government bond.[21] *VOLA* is attained by calculating the standard deviation for each stock in our sample over a quarter. The bond market control variable chosen is the *term spread (TERM)*, which is the difference between 10-year and 3-month Norwegian government bonds. We include this variable due to the argued explanatory power of the yield curve in the association of GDP (Harvey, 1989). All the macro variables and data for the computation of *TERM* are downloaded in a quarterly manner. However, *ER* and *VOLA* are converted to this frequency by EW daily data.

Table 2: Correlations

The table below presents the correlation matrix of the different variables. All the SMD and control variables are lagged. The correlations are calculated for the entire sample period. lILR, lRS, ldRS, lhpRS, lRoll and ldP are the lagged SMD variables. The bond market control variable included is lTERM representing the lagged term spread. Whereas, the stock market controls are lVOLA and lER representing lagged stock market volatility and excess market return, respectively. lVOLA is the standard deviation of the stocks in our sample. lER is the market return, proxied by the OSEBX, in excess of the risk free rate, proxied by the 3-month Norwegian government bond. For the dependent variables, dGDP represents real GDP growth. Accordingly, dCONS and dINV are growth in real consumptions and investments, respectively.

[21] OSEBX is used to capture as accurate proxy of the state of the economy as possible. OBX was considered used, however, we thought this might yield a bias by setting the market return to the 25 most liquid stocks on the Oslo Børs.

	dGDP	***dCONS***	***dINV***	***lILR***	***lRS***	***ldRS***	***lhpRS***	***lRoll***	***ldP***	***lVOLA***	***lTERM***
dGDP	1										
dCONS	0.6236	1									
dINV	0.6746	0.6088	1								
lILR	-0.0238	-0.0559	-0.1267	1							
lRS	-0.0445	-0.0549	-0.1341	0.5895	1						
ldRS	0.0925	-0.0178	0.0205	0.2472	0.2379	1					
lhpRS	-0.0913	-0.0978	-0.1794	0.7542	0.7449	0.3732	1				
lRoll	-0.2788	-0.3466	-0.2702	0.5804	0.4768	0.2406	0.5632	1			
ldP	0.2285	0.2377	0.2106	-0.5739	-0.3678	-0.3853	-0.5571	-0.4308	1		
lVOLA	-0.2267	-0.266	-0.2913	0.4761	0.6703	0.2767	0.6052	0.7639	-0.3575	1	
lTERM	0.0827	0.0656	0.1275	-0.2934	-0.459	-0.3841	-0.3942	-0.2801	0.4175	-0.4341	1
lER	0.0039	0.122	0.1454	-0.3255	-0.3606	-0.7301	-0.4106	-0.3845	0.5481	-0.3943	0.5018

As expected the correlation between the illiquidity measures are positive. This indicates that they capture the same phenomenon expressed by the percentage correlation. When comparing the correlations of *dRS*, *RS* and *hpRS* with growth in GDP and the other SMD variables, a considerable change in the correlations is observed using *dRS* compared to *RS*. This change is less extensive for hpRS. Based on the correlation with the other variables, the characteristics of the *RS* variable seem to be better preserved using *hpRS*. Thus, we will proceed with a focus on *hpRS*, despite also running the analysis for *dRS*.

Additionally, we wish to emphasise the correlation between *hpRS* and *Roll*. As these measures are both proxies of the bid-ask spread we expect a particularly high association between these variables. Even though a high correlation is observed, we find it peculiar that an even higher correlation is detected between *ILR* and the two. The correlation between *ILR*, *hpRS* and GDP is low, which may lead to a struggle of obtaining significant results with respect to these measures. Finally, the Roll measure and returns exhibit a highly significant correlation with GDP, being negative and positive, respectively.

The macro variables are also highly positively correlated with each other and arguably being suitable measures capturing the state of the economy. We expect the relationship between the macro variables and the illiquidity measures to be negative, as lower market liquidity is associated with lower economic wealth. Furthermore, the opposite should be true for returns. The illiquidity measures (return) yield a negative (positive) association with *TERM* and *ER*. The term spread captures the relationship between the long-and short-term interest rate on government bonds. A positive yield-spread suggests that long-term borrowing is compensated relative to short-term. This would imply that the economy is doing well and that investors are positive towards future economic outlook. The opposite is true for negative term-spreads or spreads closing into zero. For stock market volatility, we exhibit the expected countercyclical feature where higher volatility in the stock market is often associated with lower economic wealth. Thus, VOLA is positively associated with the illiquidity measures while the relationship is inverse for returns.

6. Analysis

We start testing our first hypothesis, by performing an in-sample analysis of illiquidity measures and asset prices. Thereafter, we run a pseudo out-of-sample (POOS) analysis with the superior illiquidity measure, retrieved from our in-sample horse race, and asset prices to test our second hypothesis. Thus, our sample is split in two. Firstly, by using 75% of the data for the in-sample predictions i.e. the training period, we estimate the model. Secondly, the model is evaluated using POOS, i.e. in a test period, including the last 25% of the data. The separation of a training and test period creates a fictitious setting resembling the real world, where models based on historical data are used to predict the present. The training sample is set to 60 quarters, or 15 years, spanning from 1996Q3 to 2011Q3. The test sample is consequently 20 quarters, or 5 years, including the remainder of our data. This split is set in line with what we find to be commonly used in econometrics. This way of performing out of sample predictions is another distinction from Næs et al. (2011).

6.1 In-sample Analysis

The model we employ tests whether asset prices or either of the illiquidity measures contribute to GDP forecasts in the following way:

$$Macro_{t+1} = \alpha_0 + \beta_{SMD} SMD_t + \gamma_{CTRL} \underline{CTRL}_t$$

The general regression contains one lag of a *SMD* variable and a vector of first lagged control variables, CTRL. As previously stated other variables have proven to contain economic informativeness. Thus, based on literature we include different combinations of the following control variables *TERM, ER, VOLA* and lags of the dependent variable.[22] The reason for the time lag between the dependent and the independent variables is that we are curious to discover whether current *SMD* might be able to predict future GDP forecasts one quarter ahead. The model is evaluated through the significance level, root mean squared error (RMSE) and adjusted R^2. The specific regressions run are presented in appendix 2.

The Schwarz information criterion suggests an optimal lag selection of four lags for each of the macro variables used as control variables. However, when running several AR models with up to four lags and examining the correlogram for all the macro variables, rather high adjusted R^2s are obtained. Concerned about an overfitted and biased model, we examine the partial autocorrelation and autocorrelation. The first lag for all the macro variables is one of the most informative, further confirmed by the highly significant first lag of the AR models. Therefore, all the regressions are run including one lag of the dependent macro variable and the control variables in multiple combinations.[23] Our general regression is computed with Newey West standard errors with four lags of autocorrelation.[24]

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[22] The lagged SMD variable includes either lILR, lRoll, lhpRS or ldP. The lagged control variables included are: lTERM, lER, lVOLA and one lag of the dependent variable, namely ldGDP, ldCONS or ldINV.

[23] The six different regressions are presented in appendix 2. Regressions with other combinations are also run. However, these did not yield any new results and are therefore not reported.

[24] Newey West was chosen to cope with the possible problem of autocorrelation in the error terms and heteroscedasticity. Four lags of autocorrelation was included as a combination between that

We choose to run six regressions in order to evaluate how well each of the SMD variables explain the variation in GDP. Regression I is run for each of the SMD variables, with solely one lag of the dependent variable. The essence is to isolate the effect of the SMD variable. This is the starting point for all the other regressions run. As discussed in *Section 5 Data* we include one bond market variable, namely the term spread, and two stock market variables, being stock market volatility and excess market return. These variables have proven to contain valuable information regarding the future state of the economy. To isolate the effect each of the control variables have on GDP we extend regression I by running three separate regressions including ER, TERM and VOLA one at a time. Thereafter we incorporate the stock- and bond market control variables separately. As we only have one bond market variable, this is equivalent to the regression solely including TERM. Finally, we include all the control variables to see if even more variation in the dependent variable is explained. The reason for doing this separation of the different regressions are to find out if the SMD variables are useful when predicting the real economy, even when incorporating other well acknowledged variables.

6.1.1 In-sample Evidence

Due to the idea of a horse race, the first regression essential to run, regression I*, includes all the three liquidity variables, ILR, hpRS and Roll, and one lag of the dependent variable.[25] This regression forms the basis for the further analysis that later incorporates the six regressions, mentioned above. Regression I* is an augmented version of regression I, as all the illiquidity measures are incorporated at the same time as opposed to one at a time. Based on this regression we are able to disclose which of the measures have the most explanatory power in relation to the dependent variables.

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being the optimal lag selection for each of the macro variables and that this was the same number of lags included by Næs et al. (2011).

[25] For the RS measure, we use the Hodrick-Prescott filter on the variable to ensure stationarity. This is discussed under Section 5 Data, correlation matrix, and further below in Section 6 Analysis, end of 6.1.1 In-sample Evidence.

Table 3: All illiquidity measures

In this table the results from running the augmented regression I, namely regression I, where all the three illiquidity measures are incorporated simultaneously are presented. The model run is as follows:*

$$Macro_{t+1} = \alpha_0 + \beta_{ILR} ILR_t + \beta_{hpRS} hpRS_t + \beta_{Roll} Roll_t + \gamma_{Macro} Macro_t$$

The dependent variable used is growth in GDP (dGDP). The coefficients are reported with associated p-values below.

Macro (t+1)		$\hat{\alpha}_0$	$\hat{\beta}^{ILR}$	$\hat{\beta}^{hpRS}$	$\hat{\beta}^{Roll}$	$\hat{\gamma}^{Macro}$	$\bar{R}^2$	$\bar{R}^2_{Ex.SMD}$	$RMSE$	$RMSE_{Ex.SMD}$
	dGDP	0.0912	0.0163	-0.0471	-4.56***	-0.4064	0.2665	0.2009	0.0312	0.0326
		(5.69)	(0.97)	(-0.18)	(-4.30)	(-4.19)				
*I**	*dCONS*	0.1463	0.0533***	-0.212	-9.0148***	-0.3162	0.2601	0.1234	0.0472	0.0514
		(3.53)	(2.80)	(-0.52)	(-3.46)	(-6.63)				
	dINV	0.1451	0.0242	-0.8607	-7.8165***	-0.5208	0.3371	0.2424	0.0644	0.0689
		(4.12)	(0.70)	(-1.04)	(-3.41)	(-7.32)				

Examining the results from *Table 3: All illiquidity measures* in light of GDP, *Roll* deems highly significant at a 1% significance level, while the others are not significant at all. Both *Roll* and *hpRS* have a negative sign, in contrast to *ILR*. We do not emphasize this due to the variable's insignificance. The negative sign implies that a more illiquid market is associated with lower growth in GDP. Our results are in line with what we expect from the correlations between the illiquidity measures and GDP growth, where Roll had the highest correlation with this dependent variable. By comparing the adjusted R^2 for regression I* with an AR(1) model we observe an improvement, confirming our initial hypothesis. Anyhow, we still want to test each of the measures including the control variables in different regressions, in the manner mentioned above.

Table 4: Panels A, B, C & D - In-sample evidence

The tables below present the results from our in-sample analysis with data from the period of 1996Q4 to 2011Q3. The results are obtained running the following regression:

$$Macro_{t+1} = \alpha_0 + \beta_{SMD} SMD_t + \gamma_{CTRL} \underline{CTRL}_t$$

Here we estimate growth in real GDP (dGDP), consumption (dCONS) and investments (dINV) one quarter a head by including different SMD and control variables. The SMD variables (reported with coefficient beta) included are; Amihud Illiquidity ratio (Panel A, ILR), Relative Quoted Spread (Panel B - hpRS), Roll Implicit Spread Estimator (Panel C - Roll) and Asset Prices (Panel D - Return). The Hodrick-Prescott filter is employed on the relative spread, to induce stationarity. Furthermore, asset prices are log differenced, obtaining returns, for the same reason. None of the other SMD or control variables is non-stationary, with the exception of the lagged dependent variable. Included in the regressions are the following lagged control variables (CTRL, expressed with coefficient gamma): the term spread (TERM), stock market volatility (VOLA), excess market return (ER) and one lag of the dependent variable.

*The coefficients are reported with the associated p-value below to assess the significance level of the SMD variable. Furthermore, the adjusted R^2 and the RMSE are reported for the regressions both with and without the SMD variable. This is to see if SMD improves GDP forecasts. We run all the regressions with and without the SMD variables. This is to evaluate whether the model including SMD variables contribute with enhanced GDP forecast accuracy. The first regression in each panel, namely regression I, excluding the SMD variable, equates an AR(1) model for the dependent macro variable. The significance level is further marked using *, ** and *** for the p-values within a 10%, 5% and 1% significance level, respectively. The extended panels are presented in* appendix 3.

Panel A: Amihud Illiquidity Ratio – ILR

Macro (t+1)		$\hat{\alpha}_0$	$\hat{\beta}^{SMD}$	$\hat{\beta}^{MD}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{ER}$	$\hat{\gamma}^{VOLA}$	$\bar{R}^2$	$\bar{R}^2_{Ex.SMD}$	$RMSE$	$RMSE_{Ex.SMD}$
I	*dGDP*	0.0275	-0.0097	-0.4582				0.1956	0.2044	0.0327	0.0306
		(3.59)	(-0.74)	(-4.96)							
	dCONS	0.0201	-0.002	-0.352				0.1076	0.1234	0.0519	0.0514
		(3.16)	(-0.19)	(-7.43)							
	dINV	0.0507	-0.049*	-0.5368				0.278	0.2424	0.0672	0.0689
		(3.41)	(-1.99)	(-7.10)							
VI	*dGDP*	0.0757	0.0071	-0.4311	0.0425	-0.0316	-1.9473	0.2374	0.2485	0.0319	0.0316
		(4.28)	(0.57)	(-4.65)	(0.16)	(-1.14)	(-3.22)				
	dCONS	0.1137	0.0366***	-0.3633	-0.3948	0.025	-3.7131	0.2	0.1752	0.0491	0.0499
		(3.65)	(2.70)	(-6.00)	(-0.86)	(0.60)	(-3.51)				
	dINV	0.1671	-0.0005	-0.5518	0.4047	-0.0502	-4.8704	0.3642	0.3762	0.0631	0.0625
		(4.05)	(-0.02)	(-9.80)	(0.67)	(-0.66)	(-3.14)				

Panel B: Relative Quoted Spread – hpRS

Macro (t+1)		$\hat{\alpha}_0$	$\hat{\beta}^{SMD}$	$\hat{\beta}^{MD}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{ER}$	$\hat{\gamma}^{VOLA}$	$\bar{R}^2$	$\bar{R}^2_{Ex.SMD}$	$RMSE$	$RMSE_{Ex.SMD}$
I	*dGDP*	0.022	-0.261	-0.4521				0.2006	0.2009	0.0326	0.0326
		(7.98)	(-1.27)	(-4.92)							
	dCONS	0.019	-0.2598	-0.3504				0.1136	0.1234	0.0517	0.0514
		(6.23)	(-0.84)	(-7.17)							
	dINV	0.0236	-1.2955**	-0.5341				0.3021	0.2424	0.0661	0.0689
		(3.32)	(-2.50)	(-6.72)							
VI	*dGDP*	0.0798	0.1457	-0.4359	0.0492	-0.0314	-1.9517	0.2366	0.2485	0.0319	0.0316
		mar.76	(0.57)	(-4.78)	(0.18)	(-1.14)	(-2.83)				
	dCONS	0.1318	0.6778*	-0.3737	-0.3686	0.025	-3.6442	0.1839	0.1752	0.0496	0.0499
		apr.44	(1.99)	(-6.07)	(-0.79)	(0.62)	(-3.97)				
	dINV	0.1602	-0.1758	-0.5548	0.3963	-0.0536	-4.645	0.365	0.3762	0.0631	0.0625
		apr.27	(-0.43)	(-9.56)	(0.67)	(-0.66)	(-3.54)				

Panel C: Roll Implicit Spread Estimator – Roll

Macro (t+1)		$\hat{\alpha}_0$	$\hat{\beta}^{SMD}$	$\hat{\beta}^{MD}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{ER}$	$\hat{\gamma}^{VOLA}$	$\bar{R}^2$	$\bar{R}^2_{Ex.SMD}$	$RMSE$	$RMSE_{Ex.SMD}$
I	*dGDP*	0.0831	-3.5532***	-0.4272				0.2797	0.2009	0.031	0.0326
		(5.59)	(-4.16)	(-4.76)							
	dCONS	0.1229	-6.0217***	-0.3323				0.226	0.1234	0.0483	0.0514
		(3.57)	(-3.12)	(-6.82)							
	dINV	0.1751	-8.775***	-0.5185				0.3501	0.2424	0.0638	0.0689
		(6.16)	(-5.12)	(-7.84)							
VI	*dGDP*	0.0939	-3.5117**	-0.4362	0.172	-0.0463	-0.4355	0.2665	0.2485	0.0312	0.0316
		(5.42)	(-2.07)	(-4.95)	(0.63)	(-1.84)	(-0.45)				
	dCONS	0.1308	-4.8649	-0.3402	-0.2291	-0.0033	-0.8718	0.1862	0.1752	0.0495	0.0499
		(2.89)	(-1.36)	(-6.73)	(-0.60)	(-0.08)	(-0.65)				
	dINV	0.1836	-2.8426	-0.5529	0.5131	-0.0601	-3.8201	0.3687	0.3762	0.0629	0.0625
		(4.79)	(-0.67)	(-10.26)	(0.90)	(-0.88)	(-1.56)				

Panel D: Asset Prices – dP

Macro (t+1)		$\hat{\alpha}_0$	$\hat{\beta}^{SMD}$	$\hat{\beta}^{MD}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{ER}$	$\hat{\gamma}^{VOLA}$	$\bar{R}^2$	$\bar{R}^2_{Ex.SMD}$	$RMSE$	$RMSE_{Ex.SMD}$
I	*dGDP*	0.02165	0.0328***	-0.4194				0.2414	0.2009	0.0318	0.0326
		(8.77)	(3.12)	(-4.68)							
	dCONS	0.019	0.0418**	-0.3435				0.1476	0.1234	0.0507	0.0514
		(6.04)	(2.02)	(-7.27)							
	dINV	0.0233	0.0723***	-0.5114				0.2865	0.2424	0.0668	0.0689
		(3.25)	(3.17)	(-5.84)							
VI	*dGDP*	0.0665	0.0398***	-0.4169	-0.1225	-0.0611	-1.4845	0.2858	0.2485	0.0308	0.0316
		(3.86)	(2.85)	(-4.87)	(-0.46)	(-2.22)	(-2.74)				
	dCONS	0.0981	0.0297	-0.3568	-0.5316	-0.0072	-2.4992	0.1722	0.1752	0.0499	0.0499
		(3.14)	(1.37)	(-6.58)	(-1.13)	(-0.16)	(-2.53)				
	dINV	0.1596	0.0437*	-0.5588	0.2362	-0.0811	-4.5935	0.3776	0.3762	0.0624	0.0625
		(4.03)	(1.74)	(-9.45)	(0.41)	(-1.04)	(-3.36)				

Presented in each of the panels above, the first regression, regression I, consists solely of the SMD variable and one lag of the dependent variable, whereas the last incorporates all the control variables, regression VI. We evaluate whether SMD is able to contribute to the improved forecasts of GDP by examining the adjusted R^2 and RMSE with and without the incorporation of the SMD variables, measuring the explanatory power and the error of the model, respectively. These means of evaluation are reported to the far right of the panels in *Table 4: In-sample evidence.* When *SMD* is statistically significant, the explanatory power of the regression increases, compared to a regression excluding the variables. As expected, *SMD* appears to become less significant when control variables are included, as these variables deem to explain something earlier captured in *SMD*. By including more relevant variables, i.e. with significance, a higher adjusted R^2 is obtained.

In alignment with previous literature, our results reveal a strong positive association between asset prices and the dependent macro variables. This indicates that when stock prices increase, the economy as a whole is doing better, which is reflected in an increased growth in GDP, investments and private consumption. The results also suggest the existence of a strong relationship between stock market liquidity and the business cycle for the Norwegian market, based on the highly significant Roll. The association is negative indicating that when the market becomes less liquid, this is reflected in lower GDP growth, a weaker investment rate and decreased private consumption. The associations are evident through the significant coefficients of these SMD variables. Our main focus will be on the results retrieved from regression I and VI. Examining both the SMD variables from regression I, the betas we attain are significant at a 1% level. We also observe regression VI to yield highly significant results when using dGDP, with coefficients significant at a 5% level for both SMD variables.

Reviewing our first hypothesis, the strong positive association Roll and asset prices exhibit towards the dependent variables, expressed in the highly significant coefficients, enables us to reject the null hypothesis for these two independent variables. Therefore, we proceed with examination of the adjusted R^2 and RMSE.

Based on this, we explore whether the prediction of the real economy, measured by GDP, CONS and INV, is improved by the inclusion of SMD variables. Examining regression I, using Roll and growth in GDP, we see an enhancement in the adjusted R^2 of 7.88 p.p.. The AR(1) model, including solely one lag of the dependent variable, yields an adjusted R^2 of 20.09%, whereas when including Roll the adjusted R^2 increases to 27.97%.[26] Similarly, the inclusion of asset prices improves the adjusted R^2 by 4.05 p.p., as the reported adjusted R^2 for asset prices is 24.14%. Improvements to the RMSE are also observed.[27] Examining regression VI, the incorporation of Roll and asset prices improves the adjusted R^2 with 1.8 p.p. and 3.73 p.p., respectively. Therefore, no clear indication is present regarding which *SMD* variable is superior. However, both variables give support to the first hypothesis from *Section 3 Hypotheses*, as neither of the coefficients are significantly non-zero, and both the variables improve the in-sample prediction of the real economy.

Furthermore, we interpret the coefficients of Roll and asset prices from regression I, due to their proven upgrade of forecasting GDP in excess of the AR(1) model. As the exact same calculations may be performed for regression VI, we choose to only interpret the coefficients for regression I. By examining *dGDP* in relation to *Roll*, an increase of the Roll measure by one standard deviation is observed to yield a decline in GDP growth by 0.0113 p.p. We calculate this by multiplying the estimated coefficient of *lRoll* with its standard deviation for the training period.[28] Comparing this to the mean of *dGDP* during the training period, 0.0144%, the change in *dGDP* followed by the shock would represent over three quarters of the quarterly average growth. Furthermore, the same computation shows that a one standard deviation increase in Roll yields a decline in the growth of private consumption and investments by 0.0191 p.p. and 0.0279 p.p., respectively. Similarly, if asset prices increase by one standard deviation, growth in GDP would rise by approximately 0.0085 p.p., about half of the quarterly average

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[26] By excluding the SMD variable in regression I we obtain an AR(1) model.
[27] RMSE for the AR(1) model is 0.0326. Including Roll to the AR(1) model the RMSE is 0.031, while including asset prices to the AR(1) model the RMSE is 0.0318.
[28] The standard deviation of lRoll is 0.0032.

during the period.[29] Growth in private consumption and investments will both increase by 0.0108 p.p. and 0.0187 p.p., respectively, based on a one standard deviation increase in asset prices. Based on these findings, changes to SMD of one standard deviation affects the real economy extensively, expressed by growth in GDP, investments and private consumption.

Examining the results obtained from regression I with *dRS*, *SMD* has proven statistically insignificant with contradictory signs of what economic intuition suggests.[30] Further, when reviewing the correlation for *dRS* with respect to the macro variables, a positive correlation of no significance is uncovered. Considering the latter, the results are somewhat expected. Nonetheless, the significant results from the other regressions are unsettling and not in line with our expectations. The results indicate that an increase in the change of illiquidity, measured by *dRS*, would increase growth in GDP. Further, an increase in growth of investments and private consumption would also occur, i.e. the opposite of what economic intuition and most other literature suggests. Contemplating, we consider the possibility of computational or transformational error. Anyhow, when examining the descriptive of the non-differenced *RS*, its mean is highly comparable with that of Næs et al. (2011).[31] It is worth mentioning that this variable, *RS*, also performs better in light of economic intuition. However, due to the existence of a unit root in the variable, we are prevented from using this interpretation.

Due to the unit root in the RS variable being difficult to detect by examining its plots, choosing the right transformation of the variable could be challenging. Using the Hodrick-Prescott filter on the RS measure, most of the regressions yield coefficients in line with economic intuition, despite a general lack of significance. This supports the use of the Hodrick-Prescott filter additional to the argument presented by the correlation matrix. Thereby, using *hpRS* and *ILR*, both the variables yield results in line with economic intuition. The results indicate that an

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[29] The standard deviation of ldP is 0.2591.
[30] See Appendix 3 – Tables 4 Panel E
[31] The non-differenced RS is reported under Methodology Section 4. The mean of Næs et al. (2011) for the non-differenced RS is 0.042.

increase in illiquidity would decrease the growth in GDP, as well as the growth in private consumption and investments. However, only the association between *dINV* and the respective *ILR and hpRS* measures deems to be significant, hence, no statistical inferences can be drawn from the other regressions. Furthermore, the economic intuition is breached for regressions incorporating consumption, as *CONS* in combination with *VOLA* yield positive and significant coefficients for *hpRS* and *ILR*, respectively.

The first lag of the macro variables in all regressions run are highly significant and negatively associated with the dependent variable. For the control variables in regression VI, we find ER and TERM to vary with respect to both significance and sign. VOLA on the other hand, is in most cases both negative and highly significant, indicating that the intuition is as expected. Increased stock market volatility is associated with better economic outlooks, reflected in increased GDP growth.

6.1.2 Causality

Our thesis primarily focuses on the relationship between *SMD* and the business cycle, with the growth in GDP as the main dependent variable.[32] However, the connection is not necessarily a one-way relationship. To disclose whether the relationship indeed goes in this direction, we perform a Granger causality test on *SMD* and all the dependent variables. The test also works as a robustness check of our results.

Firstly, we ran vector autoregressions with one lag for each of the *SMD* variables and growth in the macro variables, and thereafter performing the Granger causality test where the null hypothesis states "no Granger causality present".[33] Following is a table presenting our results, where the first hypothesis is that growth in a macro variable *does not* Granger cause stock market illiquidity or returns. The second hypothesis explores whether stock market illiquidity or returns *do not* Granger cause growth in either of the macro variables.

Table 5: Granger Causality test
*The table below reports the chi-squared (X2) and the associated p-values (p). A low chi-squared and high p-value indicates no Granger causality, while the opposite is the case when the chi-squared is high and the p-value low. The Granger causality tests are run between all the macro variables and the SMD variables; Amihud illiquidity measure (ILR), Hodrick-Prescott filtered relative quoted spread (hpRS), the Roll implicit spread estimator (Roll) and asset prices (Return). To reject the null hypothesis we use the standard critical level for the p-values within a 10%, 5% and 1% significance level for the test which is marked with *, ** and ***, respectively.*

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[32] Granger causality test on the other macro variables have been performed and confirms the results obtained from dGDP.
[33] We have chosen to use solely one lag of the dependent variables and not the optimal lag selection of the variables to avoid overfitting the regression. Accordingly, one lag of the SMD variables was used. Furthermore, we wanted to perform the causality test on the chosen regression from our in-sample evidence.

		dGDP	dCONS	dINV
ILR				
H_0: MD $\nrightarrow$ ILR	X^2	0.1920	0.8323	0.0696
	p	(0.661)	(0.362)	(0.792)
H_0: ILR $\nrightarrow$ MD	X^2	0.6716	0.0110	3.9732**
	p	(0.413)	(0.916)	(0.046)
hpRS				
H_0: MD $\nrightarrow$ hpRS	X^2	1.1033	0.0654	0.1004
	p	(0.294)	(0.798)	(0.751)
H_0: hpRS $\nrightarrow$ MD	X^2	1.0322	0.40674	6.1085**
	p	(0.310)	(0.524)	(0.013)
Roll				
H_0: MD $\nrightarrow$ Roll	X^2	0.0753	1.8351	0.8905
	p	(0.784)	(0.176)	(0.345)
H_0: Roll $\nrightarrow$ MD	X^2	7.5194***	8.8871***	10.843***
	p	(0.006)	(0.003)	(0.001)
Return				
H_0: MD $\nrightarrow$ Return	X^2	1.1632	0.0791	0.0045
	p	(0.281)	(0.778)	(0.947)
H_0: Retrun $\nrightarrow$ MD	X^2	4.2136**	2.7365*	4.7105**
	p	(0.040)	(0.098)	(0.030)

The test returned an insignificant relationship between *dGDP* and *dCONS* with respect to both *hpRS* and *ILR*, by finding no Granger causality between the variables in either direction. However, we observe *ILR* and *hpRS* to Granger cause *dINV*. This complies with the results we obtain from the previously run regressions. Moreover, we find *Roll* and *returns* to Granger cause *dGDP*, where we reject the null hypothesis at a 1% and 5% significance level respectively. Additionally, we discover that *Roll* and *returns* Granger cause both dCONS and dINV. For the opposite relationship, we find no indication that any of the macro variables Granger cause either *Roll* or *returns*. Based on the in-sample evidence and the results of the causality tests, we conclude that *Roll* and *returns* are the finest SMD variables, where *Roll* is the superior of the two. For the POOS forecasting part, the two variables are used and the model´s accuracies evaluated.

6.2 Pseudo Out-of-sample Analysis

The last part of our analysis, namely POOS, is performed to answer our second hypothesis. With the second hypothesis, our aim is to examine whether SMD variables have any predictive improvement on GDP based on our in-sample evidence.[34] Thereby we run a horse race testing the superior illiquidity measure, namely Roll, against asset prices, due to their superior in-sample performance. However, we also run the POOS analysis for the regressions without the respective SMD variables in order to isolate the effect attainable to the SMD variables. For regression I this implies an AR(1) model where only one lag of the dependent variable is included to forecast the dependent variable itself, i.e. a univariate model. This is to find out whether either of these SMD variables are able to enhance GDP forecasts. We continue with our two main regressions, namely regression I and VI.

However, forecasting out-of-sample may often be more demanding, as the results obtained are usually inferior to those in-sample in terms of adjusted R^2 and significance. This is because for in-sample predictions the model is estimated and evaluated using the same data. When including parameters that are more relevant the model will fit the data better and a higher adjusted R^2 and significance are attained. However, when this model is used on data from a separate period, the out-of-sample period, an equally satisfying fit becomes more difficult to obtain. Despite this, the information retrieved from the POOS analysis contains more valuable information, due to the real life similarities of the method. This is why we separate our analysis into a training and test sample, to enable evaluation of the superior regression out-of-sample.

[34] In the POOS analysis, we focus solely on GDP as the dependent variable and disregard the INV and CONS.

For the POOS forecasting we use a recursive window, starting with the in-sample period, predicting the last quarter of 2011. Thereafter, we move on to predict 2012Q1, including 2011Q4 in our training sample. The sample thereby increases by one quarter for each new forecasting performed. This represents a recursive estimation scheme. The reason for choosing the recursive forecasting technique is due to its proven superior performance in the absence of structural breaks (Clark and McCracken, 2009).[35] Furthermore, our total sample length, as well as the length of our test sample, advocates a recursive estimation scheme. Based on previous research on the Norwegian market within this field, namely Næs et al. (2011), we have chosen to use a recursive window rather than the rolling window they use.

Data on GDP are exposed to both publication and revision lag, which imposes a modification to our model from the in-sample analysis. The publication lags usually inflict a one quarter delay of the GDP data, whereas the revision lag is more complicated to account for (SSB, 2017). Several revisions are made to mainly cope with measurement errors in earlier vintages. Thus, the ideal would be to use the final vintage, with data excluding these potential measurement errors. However, as the final vintage is published with a 21-month lag we choose to use the first vintage despite the disadvantages this may cause.[36] Accounting for the publication lag, the first vintage of GDP becomes available normally one quarter after the quarter of measurement. Thus, when we supposedly are standing in the third quarter of 2011 and want to forecast the last quarter that year, GDP data will only be available up to the second quarter of 2011. Therefore, we can only include data available when the forecast is made. Accordingly, the lag of the dependent variable will be two quarters prior to the forecast. Thus, the following modified regression is performed for the POOS forecasting:

$$dGDP_{t+1} = \alpha_0 + \beta_{SMD} SMD_t + \gamma_{dGDP} dGDP_{t-1} + \gamma_{CTRL} \underline{CTRL}_t$$

[35] See in Section 4 Methodology that we do not have structural breaks.
[36] This is in line with the unadjusted data collected from SSB.

Due to the publication lag in GDP, the regression has one modification to that of regression I and VI from the in-sample analysis. Instead of being lagged one quarter, the GDP variable needs to be lagged two quarters back and is therefore separated from the vector containing the control variables ($Macro_{t-1}$). The independent variable (SMD_t) and the other control variables ($\underline{CTRL}_t$) are unchanged. All the regressions we run out-of-sample are presented in appendix 4.

To evaluate our SMD variables we use three methods of evaluation. First, a two-sided t-test is run on the forecasting errors.[37] All mistakes deviating from zero, independent of their magnitude are thereby accounted for. The test consists of the following hypothesis.

$$H_0: Mean = 0$$
$$H_A: Mean \neq 0$$

As none of the tests could reject the null, we draw the conclusion that the forecasting errors are not significantly different from zero.[38] This indicates that on average our forecasts are very accurate and close to the observable values. Furthermore, we compute the root mean squared forecasting error (RMSFE) and Theil's U_{II} (U_{II}), and present the results in *Table 6: RMSFE and Theil´s UII* below.

$$RMSFE = \sqrt{\frac{1}{no.of\ forecasts}\sum_{i=1}^{T}(actual_i - forecast_i)^2}$$

RMSFE penalizes large errors independent of whether the deviation is negative or positive and is widely used in econometrics. Applying regression I, the RMSFE for *Roll* and *returns* are 0.0288 and 0.0293, respectively. Hence, the Roll measure performs better than returns according to this measure. However, for a simple AR(1) model we obtain RMSFE of 0.0276. Accordingly, the SMD variables are unable to contribute with improved informativeness for GDP forecasts. Using

[37] Where normal critical t-values were used.
[38] Appendix 5: table of t-tests.

regression VI, the results slightly differ, as *Roll* marginally outperforms the regression with no SMD variable. Return still performs the weakest.[39]

$$U_{II} = \frac{\sqrt{\frac{1}{T}\sum_{i=1}^{T-1}\left(\frac{forecast_{i+1} - actual_{i+1}}{actual_i}\right)^2}}{\sqrt{\frac{1}{T}\sum_{i=1}^{T-1}\left(\frac{actual_{i+1} - actual_i}{actual_i}\right)^2}}$$

The measure of Theil´s U_{II} compares the forecast error of a naive no-change model in comparison with our modified model including *Roll* or *returns*, respectively. The model is constructed so that the current U_{II} measure is dependent on next period's forecast. Hence, calculations of the measure is lagged to the preceding period. The measure ranges from a lower bound of zero, but with no finite upper bound. However, the naive no-change model yields a value of one, when no new contribution is made. The proposed model should be rejected if U_{II} exceeds one, due to its inferior performance compared to the no-change model (Bliemel 1973). On the contrary, the model forecasts perfectly if the value of the measure is zero. Using the first regression, we get a U_{II} of 0.6244 and 0.7786 for *Roll* and *return*, respectively. Running a simple AR(1) model with a one-quarter publication lag, this yields a U_{II} value of 0.7641. These results imply that our model contribute with improved *GDP* forecasts beyond those attainable for a naive no-change model for both SMD variables. However, only *Roll* performs superior to the AR(1) model. The results we obtain from the sixth regression supports the findings from regression I. All the models still outperform the naive no-change model, but only Roll performs superior to the model using only GDP and the other control variables.[40]

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[39] RMSFE Roll is 0.0292, RMSFE GDP is 0.0293 and RMSFE asset prices is 0.0305.
[40] UII GDP is 0.7641, UII Roll is 0.6244 and UII asset prices is 0.7786.

Table 6: RMSFE and Theil´s UII

The table below shows the RMSFE and Theil's UII when predicting real GDP growth out-of-sample. In the POOS analysis both a modified version regression I and VI are used. Furthermore, three versions of these regressions have been tested, totalling to a number of six regression run for the POOS. On the first row, results from the modified regressions excluding the SMD variable, expressed as GDP in the table below, are presented. For modified regression I the model excluding the SMD variables equates an AR(1) model, whereas for regression VI all of the other control variables are also included. Hence, dGDP lagged two quarters, TERM, ER and VOLA is included. The SMD variable is omitted in both regressions. The results from the modified regressions including Roll as the only SMD variable are presented on the second row. On the last row, the results from the modified regressions including asset prices (using returns) as the only SMD variable. Both the evaluation metrics aim to be as close to zero as possible. These means of evaluation are used for the POOS analysis, hence on data for the period 2011Q4 to 2016Q3. For regression specifications, revisit appendix 4.

	Regression I		**Regression VI**	
	RMSFE	**Theil's U_{II}**	**RMSFE**	**Theil's U_{II}**
GDP	0.0276	0.7641	0.0293	0.5826
Roll	0.0288	0.6244	0.0292	0.5606
Asset Prices	0.0293	0.7786	0.0305	0.6239

Examining the results from our POOS analysis, we obtain somewhat ambiguous results. Looking at Theil's U_{II} we find evidence to reject the second null hypothesis presented in *Section 3 Hypotheses*, as the Roll measure is the superior when running both regressions. Accordingly, the regression including *Roll* improves the naive model by the most. The ambiguity appears when examining the RMSFE. Running regression VI, RMSFE is approximately equal for the regressions including Roll compared to the one where Roll is excluded. Furthermore, examining the RMSFEs obtained from regression I, the superior regression is the one incorporating only GDP. Thus, the AR(1) model is superior to the ones including either of the SMD variables, as its forecasting errors are smaller. Despite the fact that we do obtain some evidence advocating the rejection of the null hypothesis, we do not find this sufficient to carry through. Thus, afraid of committing a type 1 error (Stock & Watson, 2015), we keep the null hypothesis, supporting that SMD does not contribute to an improved out-of-sample prediction of GDP.

7. Conclusion

In this thesis, our main objective is to test whether SMD can improve the forecast of GDP, both in- and out-of-sample, by performing a horse race. Testing *asset prices* and illiquidity measures, including *ILR*, *RS* and *Roll*, our in-sample prediction of GDP is greatly improved by the inclusion of *Roll* and *asset prices*. In order to avoid being too sturdy we acknowledge the ambiguous results amongst the illiquidity measures. Even though the measures capture different aspects of illiquidity, we expect them to have somewhat similar predictive power of GDP, as they all attempt to measure illiquidity. However, where *Roll* and *asset prices* strongly indicated an existing relationship, *ILR* and *RS* yield completely insignificant, and occasional contradictory, results. Furthermore, in light of the article by Næs et al. (2011), we find it surprising that the Roll measure outperforms both *RS* and *ILR*. However, other researchers have obtained results differing from theirs.

As discussed in *Section 2 Literature review*, Galariotis and Giouvris (2015) could not confirm the relationship between liquidity and the business cycle in all the markets they tested. However, unable to confirm the results suggested by Næs et al, they refer to country specific characteristics as a possible explanation, that does not apply for our differences. However, with trust in our analysis, we still feel confident to confirm our first alternative hypothesis, as *Roll* and *asset prices*' impact on GDP is significantly different from zero.

For the out-of-sample horse race, we continue with *Roll* and *asset prices*, due to their superiority in-sample. The two variables are compared to an AR(1) model, to see if they contribute with improvements in the forecasting of GDP. Examining the measures of evaluation, RMSFE and Theil´s U_{II} yield somewhat conflicting results. According to the RMSFE, none of the SMD variables improves the forecast of GDP. However, when investigating Theil´s U_{II}, the regression including *Roll* outperforms both the other. Our out-of-sample evidence, indicating that Roll outperforms asset prices, may confirm the more recent literature within the predictions of GDP. Due to an isolated focus on certain matters within the stock market, some of the noise captured in asset prices is seemingly avoided using liquidity, which is arguably more influential to the real economy. However, despite the latter, we do not confirm our second hypothesis due to the ambiguous evidence and our eagerness to be conservative, in order not to commit a type 1 error. Hence, the simple AR(1) model is deemed slightly superior compared to a model including either *asset prices* or *Roll*. We find some support for the hypothesis; however, we do not consider it sufficient. Anyhow, we still believe that an improvement of GDP accuracy may be present when including Roll, due to the marginally improvement of RMSFE from regression VI.

For further research, we will strongly recommend to look for improvements in a model incorporating SMD to forecast GDP in order to provide robust results out-of-sample. Even though we choose to keep the second null hypothesis, indicating that our chosen SMD variables does not contribute to the improvement of GDP forecasts in excess of a model excluding SMD, we believe the relationship to be prominent and evidence is possible to obtain. Even though the RMSFE for regression VI including Roll and GDP are basically the same, the regression including Roll has a RMSFE that is 0.0001 lower. This made us contemplate about the fact that the regression incorporating Roll becomes superior to the one without the SMD variable, when control variables are included, namely regression VI. Advocating the inclusion of additional control variables, we believe this may contribute to superior predictions of GDP growth with Roll as the main independent variable.

Furthermore, we would recommend examining the link between stock market liquidity and the business cycle more closely, by investigating the channels through which liquidity affects the business cycle. This is to get a more comprehensive understanding on the mechanisms working in such a relationship.

Another interesting area for further research would be to extend our horse race by conducting it on other countries, e.g. countries in Scandinavia, to investigate if the relationship is prominent for other markets and a stronger association may be found. This may be further extended by employing the horse race on countries with business cultures that differ largely from that in Norway. Thus, one could potentially examine how the differences in business culture transfer to the predictability of SMD in forecasting GDP.

As a concluding remark, we are unable to confirm SMD to be a good leading indicator of the Norwegian real economy, despite the presence of some evidence. Finally, we find Roll and asset prices to be the SMD variables with the most superior performance in-sample, while the former marginally outperformed the latter for out-of-sample predictions.

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9. Appendix

Appendix 1 – Overview of Datastream Variables

Table 7: Variables from Datastream

Turnover by volume (VO)	This shows the number of shares traded for a stock on a particular day. The figure is expressed in thousands of local currency. Both daily and non-daily figures are adjusted for capital events.
Price (P)	Official closing price. Adjusted for subsequent capital actions
Price - Ask (PA)	The asking price quoted at close of market. Values are adjusted for subsequent capital actions and this adjusted figure then becomes the default value.
Price - Bid (PB)	This is the bid price offered at close of market. Values are adjusted for subsequent capital actions and this adjusted figure then becomes the default value
Market Value (MV)	Market value is the share price multiplied by the number of ordinary shares in issue. The amount in issue is updated whenever new tranches of stock are issued or after a capital change. - For companies with more than one class of equity capital, the market value is expressed according to the individual issue. - Market value is displayed in millions of units of local currency.
Common Shares outstanding (WC05301)	Common shares outstanding represent the number of shares outstanding at the company's year end. It is the difference between issued shares and treasury shares.

Appendix 2 – Regressions for the In-Sample Analysis

This appendix shows all the regression run for the in-sample analysis, namely the general regression.

$$Macro_{t+1} = \alpha_0 + \beta_{SMD}SMD_t + \gamma_{CTRL}\underline{CTRL}_t$$

Extended Panel A: Amihud Illiquidity Ratio – ILR

dGDP	
Regression I	$dGDP_{t+1} = \alpha_0 + \beta_{ILR}ILR_t + \beta_{dGDP}dGDP_t$
Regression II	$dGDP_{t+1} = \alpha_0 + \beta_{ILR}ILR_t + \beta_{dGDP}dGDP_t + \gamma_{TERM}TERM_t$
Regression III	$dGDP_{t+1} = \alpha_0 + \beta_{ILR}ILR_t + \beta_{dGDP}dGDP_t + \gamma_{ER}ER_t$
Regression IV	$dGDP_{t+1} = \alpha_0 + \beta_{ILR}ILR_t + \beta_{dGDP}dGDP_t + \gamma_{VOLA}VOLA_t$
Regression V	$dGDP_{t+1} = \alpha_0 + \beta_{ILR}ILR_t + \beta_{dGDP}dGDP_t + \gamma_{ER}ER_t + \gamma_{VOLA}VOLA_t$
Regression VI	$dGDP_{t+1} = \alpha_0 + \beta_{ILR}ILR_t + \beta_{dGDP}dGDP_t + \gamma_{TERM}TERM_t + \gamma_{ER}ER_t + \gamma_{VOLA}VOLA_t$

dCONS	
Regression I	$dCONS_{t+1} = \alpha_0 + \beta_{ILR}ILR_t + \beta_{dCONS}dCONS_t$
Regression II	$dCONS_{t+1} = \alpha_0 + \beta_{ILR}ILR_t + \beta_{dCONS}dCONS_t + \gamma_{TERM}TERM_t$
Regression III	$dCONS_{t+1} = \alpha_0 + \beta_{ILR}ILR_t + \beta_{dCONS}dCONS_t + \gamma_{ER}ER_t$
Regression IV	$dCONS_{t+1} = \alpha_0 + \beta_{ILR}ILR_t + \beta_{dCONS}dCONS_t + \gamma_{VOLA}VOLA_t$
Regression V	$dCONS_{t+1} = \alpha_0 + \beta_{ILR}ILR_t + \beta_{dCONS}dCONS_t + \gamma_{ER}ER_t + \gamma_{VOLA}VOLA_t$
Regression VI	$dCONS_{t+1} = \alpha_0 + \beta_{ILR}ILR_t + \beta_{dCONS}dCONS_t + \gamma_{TERM}TERM_t + \gamma_{ER}ER_t + \gamma_{VOLA}VOLA_t$

dINV	
Regression I	$dINV_{t+1} = \alpha_0 + \beta_{ILR}ILR_t + \beta_{dINV}dINV_t$
Regression II	$dINV_{t+1} = \alpha_0 + \beta_{ILR}ILR_t + \beta_{dINV}dINV_t + \gamma_{TERM}TERM_t$
Regression III	$dINV_{t+1} = \alpha_0 + \beta_{ILR}ILR_t + \beta_{dINV}dINV_t + \gamma_{ER}ER_t$
Regression IV	$dINV_{t+1} = \alpha_0 + \beta_{ILR}ILR_t + \beta_{dINV}dINV_t + \gamma_{VOLA}VOLA_t$
Regression V	$dINV_{t+1} = \alpha_0 + \beta_{ILR}ILR_t + \beta_{dINV}dINV_t + \gamma_{ER}ER_t + \gamma_{VOLA}VOLA_t$
Regression VI	$dINV_{t+1} = \alpha_0 + \beta_{ILR}ILR_t + \beta_{dINV}dINV_t + \gamma_{TERM}TERM_t + \gamma_{ER}ER_t + \gamma_{VOLA}VOLA_t$

Extended Panel B: Relative Quoted Spread – hpRS

dGDP	
Regression I	$dGDP_{t+1} = \alpha_0 + \beta_{hpRS}hpRS_t + \beta_{dGDP}dGDP_t$
Regression II	$dGDP_{t+1} = \alpha_0 + \beta_{hpRS}hpRS_t + \beta_{dGDP}dGDP_t + \gamma_{TERM}TERM_t$
Regression III	$dGDP_{t+1} = \alpha_0 + \beta_{hpRS}hpRS_t + \beta_{dGDP}dGDP_t + \gamma_{ER}ER_t$
Regression IV	$dGDP_{t+1} = \alpha_0 + \beta_{hpRS}hpRS_t + \beta_{dGDP}dGDP_t + \gamma_{VOLA}VOLA_t$
Regression V	$dGDP_{t+1} = \alpha_0 + \beta_{hpRS}hpRS_t + \beta_{dGDP}dGDP_t + \gamma_{ER}ER_t + \gamma_{VOLA}VOLA_t$
Regression VI	$dGDP_{t+1} = \alpha_0 + \beta_{hpRS}hpRS_t + \beta_{dGDP}dGDP_t + \gamma_{TERM}TERM_t + \gamma_{ER}ER_t + \gamma_{VOLA}VOLA_t$

dCONS	
Regression I	$dCONS_{t+1} = \alpha_0 + \beta_{hpRS}hpRS_t + \beta_{dCONS}dCONS_t$
Regression II	$dCONS_{t+1} = \alpha_0 + \beta_{hpRS}hpRS_t + \beta_{dCONS}dCONS_t + \gamma_{TERM}TERM_t$
Regression III	$dCONS_{t+1} = \alpha_0 + \beta_{hpRS}hpRS_t + \beta_{dCONS}dCONS_t + \gamma_{ER}ER_t$
Regression IV	$dCONS_{t+1} = \alpha_0 + \beta_{hpRS}hpRS_t + \beta_{dCONS}dCONS_t + \gamma_{VOLA}VOLA_t$
Regression V	$dCONS_{t+1} = \alpha_0 + \beta_{hpRS}hpRS_t + \beta_{dCONS}dCONS_t + \gamma_{ER}ER_t + \gamma_{VOLA}VOLA_t$
Regression VI	$dCONS_{t+1} = \alpha_0 + \beta_{hpRS}hpRS_t + \beta_{dCONS}dCONS_t + \gamma_{TERM}TERM_t + \gamma_{ER}ER_t + \gamma_{VOLA}VOLA_t$

dINV	
Regression I	$dINV_{t+1} = \alpha_0 + \beta_{hpRS}hpRS_t + \beta_{dINV}dINV_t$
Regression II	$dINV_{t+1} = \alpha_0 + \beta_{hpRS}hpRS_t + \beta_{dINV}dINV_t + \gamma_{TERM}TERM_t$
Regression III	$dINV_{t+1} = \alpha_0 + \beta_{hpRS}hpRS_t + \beta_{dINV}dINV_t + \gamma_{ER}ER_t$
Regression IV	$dINV_{t+1} = \alpha_0 + \beta_{hpRS}hpRS_t + \beta_{dINV}dINV_t + \gamma_{VOLA}VOLA_t$
Regression V	$dINV_{t+1} = \alpha_0 + \beta_{hpRS}hpRS_t + \beta_{dINV}dINV_t + \gamma_{ER}ER_t + \gamma_{VOLA}VOLA_t$
Regression VI	$dINV_{t+1} = \alpha_0 + \beta_{hpRS}hpRS_t + \beta_{dINV}dINV_t + \gamma_{TERM}TERM_t + \gamma_{ER}ER_t + \gamma_{VOLA}VOLA_t$

Extended Panel C: Roll Implicit Spread Estimator – Roll

dGDP	
Regression I	$dGDP_{t+1} = \alpha_0 + \beta_{Roll}Roll_t + \beta_{dGDP}dGDP_t$
Regression II	$dGDP_{t+1} = \alpha_0 + \beta_{Roll}Roll_t + \beta_{dGDP}dGDP_t + \gamma_{TERM}TERM_t$
Regression III	$dGDP_{t+1} = \alpha_0 + \beta_{Roll}Roll_t + \beta_{dGDP}dGDP_t + \gamma_{ER}ER_t$
Regression IV	$dGDP_{t+1} = \alpha_0 + \beta_{Roll}Roll_t + \beta_{dGDP}dGDP_t + \gamma_{VOLA}VOLA_t$
Regression V	$dGDP_{t+1} = \alpha_0 + \beta_{Roll}Roll_t + \beta_{dGDP}dGDP_t + \gamma_{ER}ER_t + \gamma_{VOLA}VOLA_t$
Regression VI	$dGDP_{t+1} = \alpha_0 + \beta_{Roll}Roll_t + \beta_{dGDP}dGDP_t + \gamma_{TERM}TERM_t + \gamma_{ER}ER_t + \gamma_{VOLA}VOLA_t$

dCONS	
Regression I	$dCONS_{t+1} = \alpha_0 + \beta_{Roll}Roll_t + \beta_{dCONS}dCONS_t$
Regression II	$dCONS_{t+1} = \alpha_0 + \beta_{Roll}Roll_t + \beta_{dCONS}dCONS_t + \gamma_{TERM}TERM_t$
Regression III	$dCONS_{t+1} = \alpha_0 + \beta_{Roll}Roll_t + \beta_{dCONS}dCONS_t + \gamma_{ER}ER_t$
Regression IV	$dCONS_{t+1} = \alpha_0 + \beta_{Roll}Roll_t + \beta_{dCONS}dCONS_t + \gamma_{VOLA}VOLA_t$
Regression V	$dCONS_{t+1} = \alpha_0 + \beta_{Roll}Roll_t + \beta_{dCONS}dCONS_t + \gamma_{ER}ER_t + \gamma_{VOLA}VOLA_t$
Regression VI	$dCONS_{t+1} = \alpha_0 + \beta_{Roll}Roll_t + \beta_{dCONS}dCONS_t + \gamma_{TERM}TERM_t + \gamma_{ER}ER_t + \gamma_{VOLA}VOLA_t$

dINV	
Regression I	$dINV_{t+1} = \alpha_0 + \beta_{Roll}Roll_t + \beta_{dINV}dINV_t$
Regression II	$dINV_{t+1} = \alpha_0 + \beta_{Roll}Roll_t + \beta_{dINV}dINV_t + \gamma_{TERM}TERM_t$
Regression III	$dINV_{t+1} = \alpha_0 + \beta_{Roll}Roll_t + \beta_{dINV}dINV_t + \gamma_{ER}ER_t$
Regression IV	$dINV_{t+1} = \alpha_0 + \beta_{Roll}Roll_t + \beta_{dINV}dINV_t + \gamma_{VOLA}VOLA_t$
Regression V	$dINV_{t+1} = \alpha_0 + \beta_{Roll}Roll_t + \beta_{dINV}dINV_t + \gamma_{ER}ER_t + \gamma_{VOLA}VOLA_t$
Regression VI	$dINV_{t+1} = \alpha_0 + \beta_{Roll}Roll_t + \beta_{dINV}dINV_t + \gamma_{TERM}TERM_t + \gamma_{ER}ER_t + \gamma_{VOLA}VOLA_t$

Extended Panel D: Asset Prices – dP

dGDP	
Regression I	$dGDP_{t+1} = \alpha_0 + \beta_{dP} dP_t + \beta_{dGDP} dGDP_t$
Regression II	$dGDP_{t+1} = \alpha_0 + \beta_{dP} dP_t + \beta_{dGDP} dGDP_t + \gamma_{TERM} TERM_t$
Regression III	$dGDP_{t+1} = \alpha_0 + \beta_{dP} dP_t + \beta_{dGDP} dGDP_t + \gamma_{ER} ER_t$
Regression IV	$dGDP_{t+1} = \alpha_0 + \beta_{dP} dP_t + \beta_{dGDP} dGDP_t + \gamma_{VOLA} VOLA_t$
Regression V	$dGDP_{t+1} = \alpha_0 + \beta_{dP} dP_t + \beta_{dGDP} dGDP_t + \gamma_{ER} ER_t + \gamma_{VOLA} VOLA_t$
Regression VI	$dGDP_{t+1} = \alpha_0 + \beta_{dP} dP_t + \beta_{dGDP} dGDP_t + \gamma_{TERM} TERM_t + \gamma_{ER} ER_t + \gamma_{VOLA} VOLA_t$

dCONS	
Regression I	$dCONS_{t+1} = \alpha_0 + \beta_{dP} dP_t + \beta_{dCONS} dCONS_t$
Regression II	$dCONS_{t+1} = \alpha_0 + \beta_{dP} dP_t + \beta_{dCONS} dCONS_t + \gamma_{TERM} TERM_t$
Regression III	$dCONS_{t+1} = \alpha_0 + \beta_{dP} dP_t + \beta_{dCONS} dCONS_t + \gamma_{ER} ER_t$
Regression IV	$dCONS_{t+1} = \alpha_0 + \beta_{dP} dP_t + \beta_{dCONS} dCONS_t + \gamma_{VOLA} VOLA_t$
Regression V	$dCONS_{t+1} = \alpha_0 + \beta_{dP} dP_t + \beta_{dCONS} dCONS_t + \gamma_{ER} ER_t + \gamma_{VOLA} VOLA_t$
Regression VI	$dCONS_{t+1} = \alpha_0 + \beta_{dP} dP_t + \beta_{dCONS} dCONS_t + \gamma_{TERM} TERM_t + \gamma_{ER} ER_t + \gamma_{VOLA} VOLA_t$

dINV	
Regression I	$dINV_{t+1} = \alpha_0 + \beta_{dP} dP_t + \beta_{dINV} dINV_t$
Regression II	$dINV_{t+1} = \alpha_0 + \beta_{dP} dP_t + \beta_{dINV} dINV_t + \gamma_{TERM} TERM_t$
Regression III	$dINV_{t+1} = \alpha_0 + \beta_{dP} dP_t + \beta_{dINV} dINV_t + \gamma_{ER} ER_t$
Regression IV	$dINV_{t+1} = \alpha_0 + \beta_{dP} dP_t + \beta_{dINV} dINV_t + \gamma_{VOLA} VOLA_t$
Regression V	$dINV_{t+1} = \alpha_0 + \beta_{dP} dP_t + \beta_{dINV} dINV_t + \gamma_{ER} ER_t + \gamma_{VOLA} VOLA_t$
Regression VI	$dINV_{t+1} = \alpha_0 + \beta_{dP} dP_t + \beta_{dINV} dINV_t + \gamma_{TERM} TERM_t + \gamma_{ER} ER_t + \gamma_{VOLA} VOLA_t$

Panel E: Relative Quoted Spread – dRS

dGDP	
Regression I	$dGDP_{t+1} = \alpha_0 + \beta_{dRS} dRS_t + \beta_{dGDP} dGDP_t$
Regression II	$dGDP_{t+1} = \alpha_0 + \beta_{dRS} dRS_t + \beta_{dGDP} dGDP_t + \gamma_{TERM} TERM_t$
Regression III	$dGDP_{t+1} = \alpha_0 + \beta_{dRS} dRS_t + \beta_{dGDP} dGDP_t + \gamma_{ER} ER_t$
Regression IV	$dGDP_{t+1} = \alpha_0 + \beta_{dRS} dRS_t + \beta_{dGDP} dGDP_t + \gamma_{VOLA} VOLA_t$
Regression V	$dGDP_{t+1} = \alpha_0 + \beta_{dRS} dRS_t + \beta_{dGDP} dGDP_t + \gamma_{ER} ER_t + \gamma_{VOLA} VOLA_t$
Regression VI	$dGDP_{t+1} = \alpha_0 + \beta_{dRS} dRS_t + \beta_{dGDP} dGDP_t + \gamma_{TERM} TERM_t + \gamma_{ER} ER_t + \gamma_{VOLA} VOLA_t$

dCONS	
Regression I	$dCONS_{t+1} = \alpha_0 + \beta_{dRS} dRS_t + \beta_{dCONS} dCONS_t$
Regression II	$dCONS_{t+1} = \alpha_0 + \beta_{dRS} dRS_t + \beta_{dCONS} dCONS_t + \gamma_{TERM} TERM_t$
Regression III	$dCONS_{t+1} = \alpha_0 + \beta_{dRS} dRS_t + \beta_{dCONS} dCONS_t + \gamma_{ER} ER_t$
Regression IV	$dCONS_{t+1} = \alpha_0 + \beta_{dRS} dRS_t + \beta_{dCONS} dCONS_t + \gamma_{VOLA} VOLA_t$
Regression V	$dCONS_{t+1} = \alpha_0 + \beta_{dRS} dRS_t + \beta_{dCONS} dCONS_t + \gamma_{ER} ER_t + \gamma_{VOLA} VOLA_t$
Regression VI	$dCONS_{t+1} = \alpha_0 + \beta_{dRS} dRS_t + \beta_{dCONS} dCONS_t + \gamma_{TERM} TERM_t + \gamma_{ER} ER_t + \gamma_{VOLA} VOLA_t$

dINV	
Regression I	$dINV_{t+1} = \alpha_0 + \beta_{dRS} dRS_t + \beta_{dINV} dINV_t$
Regression II	$dINV_{t+1} = \alpha_0 + \beta_{dRS} dRS_t + \beta_{dINV} dINV_t + \gamma_{TERM} TERM_t$
Regression III	$dINV_{t+1} = \alpha_0 + \beta_{dRS} dRS_t + \beta_{dINV} dINV_t + \gamma_{ER} ER_t$
Regression IV	$dINV_{t+1} = \alpha_0 + \beta_{dRS} dRS_t + \beta_{dINV} dINV_t + \gamma_{VOLA} VOLA_t$
Regression V	$dINV_{t+1} = \alpha_0 + \beta_{dRS} dRS_t + \beta_{dINV} dINV_t + \gamma_{ER} ER_t + \gamma_{VOLA} VOLA_t$
Regression VI	$dINV_{t+1} = \alpha_0 + \beta_{dRS} dRS_t + \beta_{dINV} dINV_t + \gamma_{TERM} TERM_t + \gamma_{ER} ER_t + \gamma_{VOLA} VOLA_t$

Appendix 3 - In-Sample Evidence

Our in-sample results using all the SDM variables in eight different regressions to obtain all possible combinations

Extended Table 4

Extended Panel A: Amihud Illiquidity Ratio – ILR

Macro (t+1)		$\hat{\alpha}_0$	$\hat{\beta}^{SMD}$	$\hat{\beta}^{MD}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{ER}$	$\hat{\gamma}^{VOLA}$	$\bar{R}^2$	$\bar{R}^2_{Ex.SMD}$	$RMSE$	$RMSE_{Ex.SMD}$
I	dGDP	0.0275	-0.0097	-0.4582				0.1956	0.2009	0.0327	0.0326
		(3.59)	(-0.74)	(-4.96)							
	dCONS	0.0201	-0.002	-0.352				0.1076	0.1234	0.0519	0.0514
		(3.16)	(-0.19)	(-7.43)							
	dINV	0.0507	-0.049*	-0.5368				0.278	0.2424	0.0672	0.0689
		(3.41)	(-1.99)	(-7.10)							
II	dGDP	0.0252	-0.0077	-0.4552	0.1698			0.1842	0.1937	0.033	0.0328
		(2.81)	(-0.54)	(-4.85)	(0.80)						
	dCONS	0.016	0.0015	-0.3533	0.304			0.0959	0.1123	0.0522	0.0517
		(2.29)	(0.16)	(-7.50)	(1.10)						
	dINV	0.039	-0.039	-0.5419	0.8821			0.2844	0.2692	0.0669	0.0676
		(2.36)	(-1.45)	(-7.69)	(1.31)						
III	dGDP	0.0284	-0.0114	-0.4631		-0.0107		0.1825	0.1863	0.033	0.0329
		(3.64)	(-0.84)	(-5.08)		(-0.58)					
	dCONS	0.0167	0.0051	-0.3488		0.0478		0.1066	0.1219	0.0519	0.0514
		(2.39)	(0.47)	(-6.66)		(1.36)					
	dINV	0.0492	-0.046*	-0.531		0.0189		0.2658	0.2417	0.0678	0.0689
		(3.20)	(-1.69)	(-6.61)		(0.40)					
IV	dGDP	0.0697	0.0095	-0.4211			-1.7727	0.2525	0.2603	0.0315	0.0314
		(4.90)	(0.76)	(-4.46)			(-3.24)				
	dCONS	0.1068	0.0360***	-0.3647			-3.5767	0.2228	0.1987	0.0484	0.0491
		(4.32)	(2.89)	(-6.59)			(-3.95)				
	dINV	0.1678	0.0026	-0.534			-4.8436	0.381	0.3922	0.0622	0.0617
		(4.80)	(0.12)	(-8.51)			(-3.52)				
V	dGDP	0.0768	0.0071	-0.4307		-0.0301	-1.9707	0.2516	0.2623	0.0316	0.0313
		(4.56)	(0.57)	(-4.69)		(-1.26)	(-3.24)				
	dCONS	0.1041	0.0368***	-0.3632		0.0112	-3.4991	0.2089	0.1838	0.0488	0.0496
		(3.98)	(2.75)	(-6.33)		(0.32)	(-3.72)				
	dINV	0.1765	-0.0004	-0.5448		-0.0353	-5.0855	0.3731	0.3847	0.0626	0.0621
		(3.94)	(-0.02)	(0.00)		(-0.52)	(-3.08)				
VI	dGDP	0.0757	0.0071	-0.4311	0.0425	-0.0316	-1.9473	0.2374	0.2485	0.0319	0.0316
		(4.28)	(0.57)	(-4.65)	(0.16)	(-1.14)	(-3.22)				
	dCONS	0.1137	0.0366***	-0.3633	-0.3948	0.025	-3.7131	0.2	0.1752	0.0491	0.0499
		(3.65)	(2.70)	(-6.00)	(-0.86)	(0.60)	(-3.51)				
	dINV	0.1671	-0.0005	-0.5518	0.4047	-0.0502	-4.8704	0.3642	0.3762	0.0631	0.0625
		(4.05)	(-0.02)	(-9.80)	(0.67)	(-0.66)	(-3.14)				

Extended Panel B: Relative Quoted Spread – hpRS

Macro (t+1)		$\hat{\alpha}_0$	$\hat{\beta}^{SMD}$	$\hat{\beta}^{MD}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{ER}$	$\hat{\gamma}^{VOLA}$	$\bar{R}^2$	$\bar{R}^2_{Ex.SMD}$	$RMSE$	$RMSE_{Ex.SMD}$
I	*dGDP*	0.022	-0.261	-0.4521				0.2006	0.2009	0.0326	0.0326
		(7.98)	(-1.27)	(-4.92)							
	dCONS	0.019	-0.2598	-0.3504				0.1136	0.1234	0.0517	0.0514
		(6.23)	(-0.84)	(-7.17)							
	dINV	0.0236	-1.2955**	-0.5341				0.3021	0.2424	0.0661	0.0689
		(3.32)	(-2.50)	(-6.72)							
II	*dGDP*	0.0211	-0.2212	-0.4509	0.1296			0.1876	0.1937	0.0329	0.0328
		(7.59)	(-0.92)	(-4.84)	(0.59)						
	dCONS	0.0177	-0.2008	-0.3508	0.1921			0.0991	0.1123	0.0521	0.0517
		(4.75)	(-0.64)	(-7.23)	(0.68)						
	dINV	0.0187	-1.0864*	-0.5385	0.6903			0.3006	0.2692	0.0662	0.0676
		(2.76)	(-1.92)	(-7.26)	(1.04)						
III	*dGDP*	0.0219	-0.3209	-0.4577		-0.0157		0.1893	0.1863	0.0329	0.0329
		(7.75)	(-1.36)	(-5.06)		(-0.71)					
	dCONS	0.0194	-0.115	-0.3484		0.0383		0.1067	0.1219	0.0519	0.0514
		(6.44)	(-0.35)	(-6.57)		0.98					
	dINV	0.0235	-1.3039*	-0.5248		-0.0021		0.2892	0.2417	0.0667	0.0689
		mar.22	(-1.87)	(-6.42)		(-0.03)					
IV	*dGDP*	0.0765	0.2168	-0.4269			-1.8238	0.2524	0.2603	0.0315	0.0314
		mar.92	(0.90)	(-4.62)			(-2.81)				
	dCONS	0.1255	0.6665**	-0.375			-3.5305	0.208	0.1987	0.0489	0.0491
		mai.29	(2.11)	(-6.53)			(-4.48)				
	dINV	0.1627	-0.0892	-0.5365			-4.6237	0.3812	0.3922	0.0622	0.0617
		apr.51	(-0.27)	(-8.59)			(-3.79)				
V	*dGDP*	0.0809	0.1434	-0.4354		-0.0297	-1.9762	0.2508	0.2623	0.0316	0.0313
		mar.92	(0.58)	(-4.83)		(-1.27)	(-2.90)				
	dCONS	0.1236	0.6957**	-0.3739		0.0124	-3.4633	0.194	0.1838	0.0493	0.0496
		mai.16	(2.05)	(-6.36)		(0.37)	(-4.28)				
	dINV	0.1688	-0.1897	-0.5482		-0.0393	-4.8352	0.374	0.3847	0.0626	0.0621
		(4.20)	(-0.47)	(-8.80)		(-0.54)	(-3.51)				
VI	*dGDP*	0.0798	0.1457	-0.4359	0.0492	-0.0314	-1.9517	0.2366	0.2485	0.0319	0.0316
		mar.76	(0.57)	(-4.78)	(0.18)	(-1.14)	(-2.83)				
	dCONS	0.1318	0.6778*	-0.3737	-0.3686	0.025	-3.6442	0.1839	0.1752	0.0496	0.0499
		apr.44	(1.99)	(-6.07)	(-0.79)	(0.62)	(-3.97)				
	dINV	0.1602	-0.1758	-0.5548	0.3963	-0.0536	-4.645	0.365	0.3762	0.0631	0.0625
		apr.27	(-0.43)	(-9.56)	(0.67)	(-0.66)	(-3.54)				

Extended Panel C: Roll Implicit Spread Estimator – Roll

Macro (t+1)		$\hat{\alpha}_0$	$\hat{\beta}^{SMD}$	$\hat{\beta}^{MD}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{ER}$	$\hat{\gamma}^{VOLA}$	$\bar{R}^2$	$\bar{R}^2_{Ex.SMD}$	$RMSE$	$RMSE_{Ex.SMD}$
I	*dGDP*	0.0831	-3.5532***	-0.4272				0.2797	0.2009	0.031	0.0326
		(5.59)	(-4.16)	(-4.76)							
	dCONS	0.1229	-6.0217***	-0.3323				0.226	0.1234	0.0483	0.0514
		(3.57)	(-3.12)	(-6.82)							
	dINV	0.1751	-8.775***	-0.5185				0.3501	0.2424	0.0638	0.0689
		(6.16)	(-5.12)	(-7.84)							
II	*dGDP*	0.0834	-3.5646***	-0.4272	-0.0092			0.2664	0.1937	0.0313	0.0328
		(5.38)	(-4.09)	(-4.72)	(-0.05)						
	dCONS	0.1269	-6.1942***	-0.3319	-0.1405			0.2127	0.1123	0.0487	0.05172
		(3.12)	(-2.81)	(-6.70)	(-0.36)						
	dINV	0.1566	-7.9753***	-0.5262	0.6603			0.3493	0.2692	0.0638	0.0676
		(4.21)	(-3.75)	(-8.39)	(1.00)						
III	*dGDP*	0.0956	-4.2900***	-0.4344		-0.0373		0.2867	0.1863	0.0308	0.0329
		(6.07)	(-4.73)	(-5.02)		(-1.97)					
	dCONS	0.126	-6.2073**	-0.3326		-0.0093		0.2122	0.1219	0.0487	0.0514
		-3.05	(-2.62)	(-6.91)		(-0.21)					
	dINV	0.1821	-9.1901***	-0.5233		-0.0205		0.3393	0.2417	0.0643	0.0689
		(4.80)	(-3.97)	(-7.95)		(-0.43)					
IV	*dGDP*	0.0833	-2.8395*	-0.4271			-0.4166	0.2685	0.2603	0.0312	0.0314
		(5.51)	(-1.86)	(-4.70)			(-0.50)				
	dCONS	0.1231	-5.0202	-0.3379			-0.5804	0.2135	0.1987	0.0487	0.0491
		(3.47)	(-1.45)	(-6.91)			(-0.46)				
	dINV	0.1775	-1.7534	-0.534			-4.109	0.3827	0.3922	0.0622	0.0617
		(7.10)	(-0.42)	(-8.75)			(-1.69)				
V	*dGDP*	0.0967	-3.2988**	-0.4347		-0.0398	-0.6074	0.2778	0.2623	0.031	0.0313
		(5.89)	(-2.14)	(-4.96)		(-1.96)	(-0.69)				
	dCONS	0.1272	-5.1562	-0.3388		-0.012	-0.6398	0.1996	0.1838	0.0491	0.0496
		(3.05)	(-1.40)	(-6.97)		(-0.28)	(-0.48)				
	dINV	0.1913	-2.2073	-0.5441		-0.0399	-4.3159	0.3759	0.3847	0.0625	0.0621
		(5.16)	(-0.52)	(-9.15)		(-0.63)	(-1.68)				
VI	*dGDP*	0.0939	-3.5117**	-0.4362	0.172	-0.0463	-0.4355	0.2665	0.2485	0.0312	0.0316
		(5.42)	(-2.07)	(-4.95)	(0.63)	(-1.84)	(-0.45)				
	dCONS	0.1308	-4.8649	-0.3402	-0.2291	-0.0033	-0.8718	0.1862	0.1752	0.0495	0.0499
		(2.89)	(-1.36)	(-6.73)	(-0.60)	(-0.08)	(-0.65)				
	dINV	0.1836	-2.8426	-0.5529	0.5131	-0.0601	-3.8201	0.3687	0.3762	0.0629	0.0625
		(4.79)	(-0.67)	(-10.26)	(0.90)	(-0.88)	(-1.56)				

Extended Panel D: Asset Prices – dP

	Macro (t+1)	$\hat{\alpha}_0$	$\hat{\beta}^{SMD}$	$\hat{\beta}^{MD}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{ER}$	$\hat{\gamma}^{VOLA}$	$\bar{R}^2$	$\bar{R}^2_{Ex.SMD}$	$RMSE$	$RMSE_{Ex.SMD}$
I	*dGDP*	0.02165	0.0328***	-0.4194				0.2414	0.2009	0.0318	0.0326
		(8.77)	(3.12)	(-4.68)							
	dCONS	0.019	0.0418**	-0.3435				0.1476	0.1234	0.0507	0.0514
		(6.04)	(2.02)	(-7.27)							
	dINV	0.0233	0.0723***	-0.5114				0.2865	0.2424	0.0668	0.0689
		(3.25)	(3.17)	(-5.84)							
II	*dGDP*	0.0224	0.0353***	-0.4178	-0.1044			0.2285	0.1937	0.0320	0.0328
		(7.99)	(2.67)	(-4.66)	(-0.47)						
	dCONS	0.0201	0.0455*	-0.3429	-0.1526			0.1329	0.1123	0.0511	0.0517
		(4.49)	(1.80)	(-7.12)	(-0.43)						
	dINV	0.0187	0.0561*	-0.5185	0.6655			0.2828	0.2692	0.067	0.0676
		(3.12)	(1.98)	(-6.39)	(0.86)						
III	*dGDP*	0.0212	0.0489***	-0.4201		-0.049		0.2559	0.1863	0.0315	0.0329
		(9.05)	(2.78)	(-5.06)		(-1.89)					
	dCONS	0.0191	0.0408*	-0.3435		0.003		0.1319	0.1219	0.0511	0.0514
		(6.12)	(1.75)	(-7.19)		(0.08)					
	dINV	0.0233	0.079**	-0.5162		-0.0201		0.2743	0.2417	0.0674	0.0689
		(3.12)	(2.05)	(-6.02)		(-0.30)					
IV	*dGDP*	0.0559	0.0203*	-0.4183			-1.1401	0.2643	0.2603	0.0313	0.0314
		(3.76)	(1.86)	(-4.49)			(-2.31)				
	dCONS	0.0841	0.0181	-0.3568			-2.1576	0.1901	0.1987	0.0494	0.0491
		(3.74)	(1.02)	(-6.79)			(-2.98)				
	dINV	0.1544	0.0251	-0.5355			-4.3454	0.3868	0.3922	0.062	0.0617
		(4.51)	(1.09)	(-8.23)			(-3.77)				
V	*dGDP*	0.0639	0.0384***	-0.419		-0.0643	-1.4276	0.298	0.2623	0.0306	0.0313
		(4.06)	(2.91)	(-4.96)		(-2.57)	(-2.74)				
	dCONS	0.0867	0.0241	-0.3578		-0.0213	-2.2532	0.1771	0.1838	0.0498	0.0496
		(3.53)	(1.24)	(-7.01)		(-0.48)	(-2.76)				
	dINV	0.1645	0.0461*	-0.5553		-0.0745	-4.6977	0.3884	0.3847	0.0619	0.0621
		(3.91)	(1.86)	(-8.90)		(-1.03)	(-3.30)				
VI	*dGDP*	0.0665	0.0398***	-0.4169	-0.1225	-0.0611	-1.4845	0.2858	0.2485	0.0308	0.0316
		(3.86)	(2.85)	(-4.87)	(-0.46)	(-2.22)	(-2.74)				
	dCONS	0.0981	0.0297	-0.3568	-0.5316	-0.0072	-2.4992	0.1722	0.1752	0.0499	0.0499
		(3.14)	(1.37)	(-6.58)	(-1.13)	(-0.16)	(-2.53)				
	dINV	0.1596	0.0437*	-0.5588	0.2362	-0.0811	-4.5935	0.3776	0.3762	0.0624	0.0625
		(4.03)	(1.74)	(-9.45)	(0.41)	(-1.04)	(-3.36)				

Panel E: Relative Quoted Spread – dRS

Macro (t+1)		$\hat{\alpha}_0$	$\hat{\beta}^{SMD}$	$\hat{\beta}^{MD}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{ER}$	$\hat{\gamma}^{VOLA}$	$\bar{R}^2$	$\bar{R}^2_{Ex.SMD}$	$RMSE$	$RMSE_{Ex.SMD}$
I	*dGDP*	0.0221	0.3594	-0.4599				0.2024	0.2009	0.0326	0.0326
		(6.94)	(1.37)	(-4.93)							
	dCONS	0.0191	0.1871	-0.3607				0.1093	0.1234	0.0518	0.0514
		(6.36)	(0.39)	(-7.19)							
	dINV	0.0231	0.4183	-0.5087				0.2332	0.2424	0.0693	0.0689
		(2.48)	(1.02)	(-6.48)							
II	*dGDP*	0.0189	0.5378*	-0.4625	0.4436			0.2098	0.1937	0.0324	0.0328
		(6.65)	(1.79)	(-4.84)	(2.09)						
	dCONS	0.0161	0.3633	-0.3663	0.4292			0.1019	0.1123	0.052	0.0517
		(4.10)	(0.72)	(-7.30)	(1.45)						
	dINV	0.0117	1.097**	-0.5416	1.6448			0.2827	0.2692	0.067	0.0676
		(1.75)	(2.64)	(-8.44)	(2.59)						
III	*dGDP*	0.0225	0.7681*	-0.4573		0.0471		0.2055	0.1863	0.0325	0.0329
		(7.49)	(1.83)	(-4.74)		(1.59)					
	dCONS	0.0206	1.2746**	-0.3877		0.1228		0.1456	0.1219	0.0507	0.0514
		(6.68)	(2.41)	(-6.43)		(2.97)					
	dINV	0.0247	2.0397***	-0.4961		0.1875		0.279	0.2417	0.0672	0.0689
		(2.89)	(4.05)	(-6.11)		(2.90)					
IV	*dGDP*	0.0758	0.6147**	-0.4481			-1.7943	0.2909	0.2603	0.0307	0.0314
		(5.25)	(2.16)	(-4.86)			(-3.90)				
	dCONS	0.1032	0.6076	-0.3856			-2.7883	0.2024	0.1987	0.049	0.0491
		(4.54)	(1.36)	(-6.71)			(3.78)				
	dINV	0.1873	1.2315***	-0.5585			-5.4388	0.4184	0.3922	0.0603	0.0617
		(5.39)	(2.67)	(10.78)			(-4.70)				
V	*dGDP*	0.074	0.7174*	-0.4478		0.0129	-1.7303	0.2787	0.2623	0.031	0.0313
		(4.58)	(1.88)	(-4.76)		(0.43)	(-3.29)				
	dCONS	0.0931	1.2215**	-0.3989		0.0756	-2.4224	0.2058	0.1838	0.0489	0.0496
		(3.75)	(2.35)	(-6.58)		(1.64)	(-3.00)				
	dINV	0.1747	1.9111***	-0.5487		0.08621	-4.9965	0.419	0.3847	0.0603	0.0621
		(4.23)	(3.29)	(-9.42)		(0.91)	(-3.52)				
VI	*dGDP*	0.0727	0.7193*	-0.4484	0.0561	0.11	-1.6987	0.2651	0.2485	0.0313	0.0316
		(4.04)	(1.87)	(-4.71)	(0.22)	(0.36)	(-3.02)				
	dCONS	0.1026	1.209**	-0.3986	-0.3881	0.0884	-2.6402	0.1966	0.1752	0.0492	0.0499
		(3.19)	(2.30)	(6.38)	(-0.87)	(1.84)	(-2.66)				
	dINV	0.1642	1.9264***	-0.5565	0.4487	0.0707	-4.7587	0.4116	0.3762	0.0607	0.0625
		(4.15)	(3.22)	(-10.08)	(0.78)	(0.70)	(-3.44)				

Appendix 4 – Regressions for the POOS Analysis

This appendix shows the modified regressions run for the POOS analysis using only growth in GDP as the dependent variable. We proceed with the two superior SMD variables, namely Roll and asset prices (dP), running the modified regression I and VI. Accounting for the publication lag the dependent variable, dGDP, is lagged two quarters back. Thus, this variable is now omitted from the vector $\underline{CTRL}_t$. This is the only modification done to the general regression.

$$dGDP_{t+1} = \alpha_0 + \beta_{SMD}SMD_t + \gamma_{Macro}dGDP_{t-1} + \gamma_{CTRL}\underline{CTRL}_t$$

Regression I	
GDP (dGDP)	$dGDP_{t+1} = \alpha_0 + \beta_{dGDP}dGDP_{t-1}$
Roll	$dGDP_{t+1} = \alpha_0 + \beta_{Roll}Roll_t + \beta_{dGDP}dGDP_{t-1}$
Asset prices (dP)	$dGDP_{t+1} = \alpha_0 + \beta_{dP}dP_t + \beta_{dGDP}dGDP_{t-1}$

Regression VI	
GDP (dGDP)	$dGDP_{t+1} = \alpha_0 + \beta_{dGDP}dGDP_{t-1} + \gamma_{TERM}TERM_t + \gamma_{ER}ER_t + \gamma_{VOLA}VOLA_t$
Roll	$dGDP_{t+1} = \alpha_0 + \beta_{Roll}Roll_t + \beta_{dGDP}dGDP_{t-1} + \gamma_{TERM}TERM_t + \gamma_{ER}ER_t + \gamma_{VOLA}VOLA_t$
Asset prices (dP)	$dGDP_{t+1} = \alpha_0 + \beta_{dP}dP_t + \beta_{dGDP}dGDP_{t-1} + \gamma_{TERM}TERM_t + \gamma_{ER}ER_t + \gamma_{VOLA}VOLA_t$

Appendix 5 - Table of T-tests

T-test of the forecast error

H_0: *Mean (forecast error) = 0*

H_A: *Mean (forecast error) ≠ 0*

	Regression I	***Regression VI***
	P-value	***P-value***
GDP	0.5212	0.1298
Roll	0.5313	0.3322
Asset Prices	0.7887	0.4249

The underlying mean is not zero with a significance level of 52.12%, 53.13% and 78.87%, when testing with GDP, *Roll* and *asset prices*, respectively for regression I. Thereby we cannot reject the null hypothesis in either of the cases. The same applies when running the three versions of regression VI, the null hypothesis cannot be rejected in either of the versions.

Appendix 6 – Stata

The Stata input is delivered as an attachment to the thesis in DigiEx. Following is the Stata do-file.

```
*Set time to quarterly:
gen TIME = quarterly(DATE, "YQ")
tsset TIME, quarterly

*Plot liquidity measures
tsline ILR
tsline ROLL
tsline RS
tsline GDP
tsline INV
tsline CONS

*Winsorise liquidity measures at 1 and 99 percentile
winsor2 ILR, replace cuts(1 99)
winsor2 ROLL, replace cuts(1 99)
winsor2 RS, replace cuts(1 99)

*From plot - macro variables and asset prices are non-stationary
*Log difference macro variables and asset prices:
gen lnGDP = log(GDP)
gen dGDP=D.lnGDP

gen lnCONS= log(CONS)
gen dCONS=D.lnCONS

gen lnINV= log(INV)
gen dINV=D.lnINV

gen lnP = log(P)
```

```
gen dP = D.lnP
gen ldP =L.dP


*Testing for stationarity in the financial variables
*ILR
varsoc ILR
* optimal lag of 1 by SBIC
dfuller ILR, lag(1)
kpss ILR
*no unit root detected

*Roll
varsoc ROLL
* optimal lag of 1 by SBIC
dfuller ROLL, lag(1)
kpss ROLL
*no unit root detected

*RS
varsoc RS
* optimal lag of 1 by SBIC
dfuller RS, lag(1)
kpss RS
*unit root detected

*RS is non-stationarity - we use log difference
*Log difference
gen lnRS = log(RS)
gen dlnRS = D.lnRS
dfuller dlnRS, lag(1)
kpss dlnRS
```

```
*Generate lagged independent variables
gen ldlnRS = L.dlnRS
gen lROLL=L.ROLL
gen lILR=L.ILR

gen lVOLA=L.VOLA
gen lTERM=L.TERM
gen lER=L.ER

** Examining the correlation **
*Correlation between market and macro variables
corr ldlnRS lROLL lILR lVOLA lTERM lER dGDP dCONS dINV

*Illogical correlation between the log differenced RS and growth in GDP and INV
*We test other methods of handling unit root

*Difference
gen dRS = D.RS
dfuller dRS, lag(1)
kpss dRS
gen ldRS = L.dRS

*Hodrick-Prescott filter
tsfilter hp hpRS = RS
dfuller hpRS, lag(1)
kpss hpRS
gen lhpRS = L.hpRS

*Square root differenced
gen sRS = sqrt(RS)
gen dsRS = D.sRS
dfuller dsRS, lag(1)
kpss dsRS
```

gen ldsRS =L.dsRS

** Examining the correlation **
corr ldRS lhpRS ldsRS dGDP dCONS dINV

*Solely the RS with Hodrick-Prescott filter yielded correlation in line with economic intuition

*Final correlation
corr lhpRS lROLL lILR lVOLA lTERM lER dGDP dCONS dINV

****
** IN-SAMPLE (Using Newey-West standard errors, 4 lags)**

*Finding optimal lag selection of macro variables
varsoc dGDP
varsoc dCONS
varsoc dINV
*Yielding an optimal lag of 4

reg L(0/4). dGDP
reg L(0/4). dCONS
reg L(0/4). dINV
*High adjusted R^2 and an indication of a informative first lag

*Testing this by examining the autocorrelation and partial autocorrelation
corrgram dGDP
corrgram dCONS
corrgram dINV
*Confirmation of a informative first lag – Thereby we continue the analysis with solely one lag of the macro variables.

newey L(0/1).dGDP lILR in 1/60, lag(4)

```
newey L(0/1).dGDP lILR  lTERM in 1/60, lag(4)
newey L(0/1).dGDP lILR  lER in 1/60, lag(4)
newey L(0/1).dGDP lILR  lVOLA in 1/60, lag(4)
newey L(0/1). dGDP lILR  lVOLA lTERM in 1/60, lag(4)
newey L(0/1). dGDP lILR  lVOLA lER in 1/60, lag(4)
newey L(0/1). dGDP lILR  lTERM lER in 1/60, lag(4)
newey L(0/1). dGDP lILR  lTERM lER lVOLA in 1/60, lag(4)
*The same regressions are run with the other dependent variables and stock market data

reg L(0/1). dGDP lILR in 1/60
reg L(0/1). dGDP lILR lTERM in 1/60
reg L(0/1). dGDP lILR lER in 1/60
reg L(0/1). dGDP lILR lVOLA in 1/60
reg L(0/1). dGDP lILR lVOLA lTERM in 1/60
reg L(0/1). dGDP lILR lVOLA lER in 1/60
reg L(0/1). dGDP lILR lTERM lER in 1/60
reg L(0/1). dGDP lILR lTERM lER lVOLA in 1/60
*These regressions are run to obtain adjusted R2, RMSE

/Standard deviation/
sum ROLL in 1/60
sum dP in 1/60

***************************************************************
** Granger Causality test (one lag and a constant term) **
/ILR/
var dGDP ILR in 1/60, lag(1/1)
vargranger

var dCONS ILR in 1/60, lag(1/1)
vargranger
```

```
var dINV ILR in 1/60, lag(1/1)
vargranger

*The same regressions are run with the other stock market variables

******************************************************************
** PSEUDO OUT-OF-SAMPLE **
*75% of sample "training set" - 60 quarters (1996q4 - 2011q3)
*25% of sample "test set" - 20 quarters (2011q4 - 2016q3)

*Recursive window*
drop forecasts fcError fcError2
cap program drop POOS
program define POOS
	args regressionCommand startOfPredictionSample dateOfFirstPrediction
dateOfLastPrediction
	cap drop forecasts
	gen forecasts = .
	local i = 0
	while `i'<=`dateOfLastPrediction' {
		qui `regressionCommand' if TIME >= `startOfPredictionSample' &
TIME <= (`dateOfFirstPrediction'+`i'-1)
		qui predict pred
		cap replace forecasts = pred if TIME ==
(`dateOfFirstPrediction'+`i')
		drop pred
		local i = `i' + 1
	}
end
POOS "reg dGDP lROLL L2.dGDP" tq(1996q4) tq(2011q4) tq(2016q3)
*Evaluating poos by computing the RMSFE ;
 cap gen fcError = dGDP - forecasts
 sum fcError
```

```
ttest fcError = 0
cap gen fcError2 = fcError*fcError
sum fcError2
sca m_ = r(mean)
dis sqrt(m_)
```

*Theil´s UII is calculated in Excel.

*The program is run with the following modified regressions

```
/ reg dCONS lROLL L2.dCONS
/ reg dINV lROLL L2. dINV

/ reg dGDP ldP L2.dGDP
/ reg dCONS ldP L2. dCONS
/ reg dINV ldP L2.dINV

/ reg dGDP L2.dGDP
/ reg dCONS L2.dCONS
/ reg dINV L2.dINV
```

Appendix 7 Preliminary

ID number: **0939593**
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Preliminary

Stock Market Liquidity as a Leading Indicator of the Real Economy - a Norwegian Study

Hand-in date:
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Abstract

In this thesis we will study whether stock market liquidity can be used as a valuable prediction for the business cycle, measured by real Gross Domestic Product. We will examine the Norwegian market by using data on all equities listed on the Oslo Stock Exchange for the past 20 years. The core of our research is to see if we can find predictive power for economic growth in market illiquidity. To capture the effect of stock market liquidity we will use several known measures of illiquidity. Dependent on this result we will proceed to in-sample forecasting, with special focus on discussing the results associated with the financial crises of 2007-2009. Furthermore, an out-of-sample forecast of growth in real Gross Domestic Product will be provided.

1. Introduction

Over the past 15 years there have been several contributions to the research on using asset prices to forecast economic activity and inflation (Stock & Watson, 2003). Their article presents an extensive overview of the historical development, as well as the different angles on this matter. As a result of the instabilities in the 1970-80s, this research blossomed. Despite the focus on forecasting the business cycle in light of asset prices, the relationship between stock market liquidity and the business cycle has still not been extensively covered, in particular for the Norwegian market. Nevertheless, a relationship between the real economy and the liquidity in the U.S. stock market has been present from the Second World War (Næs, Skjeltorp, & Ødegaard, 2011). Liquidity is defined by Pastor and Stambaugh (2001, p. 1) as *"a broad and elusive concept that generally denotes the ability to trade large quantities quickly, at low cost, and without moving the price."*, referring to the characteristics of a liquid stock market. The research within the field of the latter relationship, is somewhat divided with regards to the focus and the empirical findings on whether stock market liquidity is a good leading indicator of the real economy. Thus, leading up to our research question:

"Is stock market liquidity a good leading indicator of the Norwegian real economy and can illiquidity measures forecast growth in GDP?"

We base our master thesis on the article written by Næs et al. (2011). To distinguish our research from existing, we use updated data on the Norwegian market, Oslo Stock Exchange (further referred to as "OSE"). Furthermore, we intend to highlight the period after the financial crisis of 2007-2009 in our research, as this is not extensively studied. Another reason we have chosen to investigate this particular issue is that it could be beneficial to society. As Shi (2015) emphasize, liquidity as a good leading indicator on the business cycle could have immediate policy implications. Thereby, aiding government in regulating and attenuating the cycle, or the Central Bank when setting the interest rate. In connection to this, we also wish to forecast real Gross Domestic Product (GDP) by using liquidity in the stock market by performing a pseudo-out-of-sample forecast.

More generally this research area contributes to at least two different fields. One being the field of macroeconomic forecasting as mentioned above. By forecasting e.g. real GDP, using stock market measures of trading activity. Whereas the other field would relate to the more financial aspect and the market microstructure literature, which up to this point has mainly focused on commonalities as a way of explaining liquidity (Galariotis & Giouvris, 2015). Co-movement between the liquidity of the security and the market as a whole is referred to as the term commonality in liquidity (Hoesli, Kadilli, & Reka, 2014). The general concept of market microstructure concerns the transaction process and its impact on price formation and volumes traded in the market (Naes & Skjeltorp, 2006). However, to refine our thesis we will solely focus on the former part.

2. Background and literature review

Næs et al. (2011) studied the relationship between stock market liquidity and the business cycle for both the Norwegian and the US economy in the period of 1980-2008 and 1947-2008 respectively, contributing with two empirical observations. Firstly, they provide evidence that useful information can be extracted from stock market liquidity in estimating current and future states of the economy. Secondly, they observe behaviour consistent with the concept of “flight to quality”, where the participation in the stock market, especially with regards to the smallest firms, decrease when liquidity worsens. There are several explanations as to why stock market liquidity may be a good leading indicator of the real economy, further on we will outline some of the research in this field which we deem relevant.

During periods of financial distress, the stock market has been observed drying up, with latest evidence from the financial crisis of 2007-2009. Brunnermeier and Pedersen (2009) provide an alternative explanation as opposed to Næs et al. (2011) where they created a model establishing a relationship between the stock market liquidity and trader´s funding liquidity. Their view is that the traders are those providing the market with liquidity. However, in order to trade they are in need of funding, which is naturally limited by capital and margin requirements.

This results in one of their findings, being that market liquidity is positively correlated to the economy, as its funding depends on the latter.

Another contributor to the phenomenon of “flight to quality”, as opposed to Næs et al. (2011), is Longstaff (2004), emphasizing the individuals’ expectations of the real economy. The article studies the relationship between the liquidity premium in Treasury bonds and the value of some Treasury bonds, trying to identify whether there is any connection between the two. Their result suggests that the popularity of the bonds is directly affecting the value. In the concept of “flight to liquidity” investors will prefer to hold highly liquid assets rather than less liquid ones. However, this is not consistent with standard asset-pricing theory, which states that the value of a security should only depend on the expected value of its cash flows, not on how often the security is traded.

Studying asset prices in relation to forecasting output and inflation, Stock and Watson (2003) present many valid and relevant results. Amongst others are their findings on the instability in the predictive power of asset prices. Even though they conclude that the forecasting power asset prices has is stronger for output growth than for inflation, forecasting based on an individual indicator is unstable. Even when combining various predictors, problems with instability are still present. Thereby, their results are important to keep in mind, as this could also apply for our research.

Other researchers such as Aastveit and Trovik (2012) have focused on how asset prices can improve the estimates for the real economy as measured with real GDP. This study is done for the Norwegian market only, where they found support to their hypothesis. Thus, hopefully it will provide us with valuable insight into the forecasting part of our thesis. On the other hand, Kiyotaki and Moore (2012) provide research with a somewhat different perspective. They present a model explaining how the relationship between aggregate activity and asset prices behave, with regards to shocks to productivity and liquidity. Another aspect of their research is to look at which role the government has to influence the open market and investors' portfolio compositions. It is important to point out that these authors have focused their studies on asset prices and not liquidity.

Galariotis and Giouvris (2015) expanded the research from Næs et al. (2011) by performing additional tests as well as incorporating the following six G7 countries; Canada, France, Germany, Italy, Japan and UK. Their findings discovered that different markets do not behave similarly, i.e. the results are country dependent. It was only in Canada that Galariotis found that liquidity variables were able to consistently predict a recession. Whereas for the other economies, the relationship went in both directions. Hence, this researcher provides critics to the Næs et al. article, by not being able to confirm the relationship as predicted by Næs et al.

According to Eisfeldt (2004) market liquidity is assumed to be varying with the state of the economy, documented by the presence of liquidity crisis in economic downturns. Another explanation of illiquidity in long-term risky assets is due to adverse selection. The problem of adverse selection causes market illiquidity as lower quality products are more likely to be sold as a result of information asymmetry. To what extent this problem is present relies on the amount of trade. The findings of this study are that markets are generally more liquid in good times. Lastly, the article links the productivity in industries and economies to liquid asset markets, where higher productivity increases liquidity. The relationship goes both ways.

"A sudden drop in asset market liquidity, which may not necessarily be related to changes in economic fundamentals, causes the equity price to fall. The lower equity price reduces the funds for investment that a firm can raise by issuing equity and/or using equity as collateral on borrowing. Thus, investment falls, output falls and an economic recession starts."

This quote is from Shi´s article from 2015 (p. 116) where he investigates this *liquidity shock hypothesis* to evaluate the importance of frictions in the financial market and how this affects the real economy. He provides empirical support of his hypothesis.

3. Methodology

To answer our research question, whether stock market liquidity could be a good leading indicator of the Norwegian real economy, we plan on using four different measures to calculate liquidity, as done in the Næs et al. article. Due to multiple theoretical definitions of liquidity, there are also many different methods of measurement. As the liquidity measure is such an important part of our research, we have decided to use various methods to capture liquidity. Additionally, using numerous measures gives more credibility to our study, as it provides a basis for comparison and enables us to be critical to the individual measurement method.

Furthermore, the frequency of the data we plan to use limits us somewhat in the choice of model. Due to the great timespan of our data and the fact that we want to look at trends in stock market liquidity to compare with real GDP, we have chosen to use daily data on the stock market. However, there are only quarterly data available for the GDPR. Many of the empirical measures require intraday information. However, as we aim to have a time period that, at least, includes the financial crisis of 2007-2009 such information is difficult, if not impossible, to find. Moreover, using such high frequency data could lead to spurious results, as this many observations may include a vast amount of noise. Hence, we have chosen to use the following measures of liquidity, which only requires daily information: The Amihud (2002) illiquidity ratio (ILR), The Roll (1984) implicit spread estimator (Roll), Relative Spread (RS) and The Lesmond, Ogden, and Trzcinka (1999) measure (LOT). All the measures used are “illiquidity measures” meaning that when they produce high values this coincides with a higher degree of illiquidity in the stock market. As we plan on using multiple measures we will compare their results, calculating their covariation and correlation. Further discussion is dependent on the results of the measures and will be presented in our thesis.

3.1 Price impact measure

The rationale behind the use of price impact measures for liquidity is that prices are sensitive to trading activity and thereby captures liquidity.

3.1.1 The Amihud (2002) illiquidity ratio (ILR)

Amihud´s illiquidity ratio measures how much prices move in response to the trading volume of that specific security. When the price moves substantially as a response to trade, the stock is viewed as having low liquidity.

$$ILR_{i,T} = 1/D_T \sum_{t=1}^{T} \frac{|R_{i,t}|}{VOL_{i,t}}$$

D_T is the number of trading days within a timeframe T, $|R_{i,t}|$ is the absolute return on day t for security i, and $VOL_{i,t}$ is the trading volume on day t.

As ILR has low requirements to data and is easy to calculate, it has become very popular. However, the ratio faces some disadvantageous, explaining price changes being one of them. Changes in price are not necessarily due to illiquidity, but may be a result of new information provided to the market, e.g. an earning announcement. Thereby, as the model does not distinguish between the reasons for changes in prices, it may yield erroneous results. Another drawback of ILR is that it does not control for inflation, as percentage return per dollar of trading volume is used as the unit of measurement. This could in particular be a problem in our studies as we plan on using data going 20 years back.

3.2 Spread based measures:

An intuitive measure of liquidity is the bid-ask spread, being the difference between the best bid price and the best ask price. However, due to biased results, which may occur solely from using this spread, alternative measures have been developed.

3.2.1 Relative spread (RS)

The relative quoted spread captures the average of the best bid and ask price, as a fraction of the quote midpoint. Hence, being a forward-looking measure. As opposed to using alternative measures, RS enables comparison of shares with different price levels.

$$s_t^{qr} = \frac{A_t - B_t}{M_t};\ M_t = \frac{A_t + B_t}{2}$$

In order to apply the measure two assumptions must be fulfilled:

1. The volume available exceeds the transaction size
2. Other prices more favourable than the best bid and ask, viz. price improvement, may not occur.

If either of the assumptions are violated, alternative models may be used to solve the issue; A spread using a volume-weighted average of the prices is a solution if assumption one is violated and an effective bid-ask spread to solve price improvement, which is not in compliance with assumption two. A closer description of either of the models will be presented if required by our data.

3.2.2 The Roll (1984) implicit spread estimator (Roll)

The Roll measure captures the implicit spread, estimated as the effective bid-ask spread calculated from data on daily returns using transaction data. The reason for this choice is that bid and ask prices are not always possible to obtain for all markets. A high value gives an indicator that the market is not very liquid, hence the costs of trading is higher. The measure is developed from the serial covariance of successive price changes.

$$S = 2\sqrt{-Cov(\Delta p_t, \Delta p_{t-1}}$$

$$\hat{s} = \sqrt{-Scov}$$

Only defined for Scov < 0

The bid-ask spread is the market maker´s gross revenue and is a source of transaction costs for investors. Including several types of costs the market maker wants to be compensated for, the bid-ask spread is constituted by the following components; costs of doing business, viz. order processing costs (including e.g. fixed and variable costs, and the opportunity cost of time), compensations related to the risk of holding inventory, viz. inventory holding cost, and finally compensation tied to the risk of trading with more informed counterparties, viz. adverse selection component. The shortcoming of the Roll measure is that it does not incorporate the last two components making up the bid-ask spread in practice, hence violating one the model's assumptions.

3.2.3 The Lesmond, Ogden, and Trzcinka (1999) measure (LOT)

The LOT measure captures the implicit transaction costs of trading. It is calculated by the interval around the current stock price, in which the return of the stock remains unchanged when the market moves. A wider interval, in which the stock price does not move, is an indicator of a less liquid security. To obtain this measure the use of data on the total transaction costs, e.g. including fees for brokerage and exchange, are required. The rationale behind this measure is that the trader with the highest expected benefit from the trade, known as the marginal trader, is only willing to undertake the trade as long as the expected return exceeds the transaction expenditures. When this is not the case, there will be no trade observable in the market and a zero return is obtained.

$$LOT = \alpha_{2,i} - \alpha_{1,i}$$

$\alpha_{1,i}$ is transaction cost for a sale, and $\alpha_{2,i}$ is transaction cost for a purchase.

3.3 Adjustments of time series data

Before starting to analyse the data we need to plot it and provide a descriptive in order to get an overview and an idea on how to proceed. Firstly, we plan on filtering our data from OSE based on the same criteria Næs et al. (2011) used, removing stocks below NOK 10 and stocks with less than 20 trading days a year. As we use all equities listed at the OSE, we expect some of the assets to be highly illiquid, thus considered outliers that will disturb the data if included. Nevertheless, as our data includes more of the financial crisis than the dataset of Næs et al. (2011), we will remain critical to this exclusion method, as what may be considered relevant data might have changed. The macroeconomic data will also be checked and potential outliers removed.

Secondly, in order to work with and be able to compare the data across time, *stationary* is required. Stationarity consists of the absence of a unit root and structural breaks. Thereby, the fourth moments of the probability distribution need to be time invariant; mean, standard deviation, kurtosis and skewness. Furthermore, heteroscedasticity need to be absent, as the variables need to have a constant mean, variance and autocovariance. Thus “shocks” inflicted on the variables will gradually die out for stationary series, i.e. mean revert.

When testing for the presence of a *unit root*, the Augmented Dickey-Fuller (hereby referred to as “ADF”) test will be applied. The reason why the standard Dickey-Fuller (hereby referred to as “DF”) test is not used, is due to the high autocorrelation that is normally present in large samples. Hence, the null hypothesis is frequently rejected incorrectly, yielding a type I error. The new theory tested is thereby acknowledged even though it is untrue, which is considered the gravest mistake in econometrics. However, this problem is resolved by using the ADF. In order to perform this test we need to choose number of max lags for the variables, which will be done using Akaike Information Criterion (hereby referred to as “AIC”). Even though AIC tends to overfit and thereby adding noise, the probability of omitting relevant variables is considerably reduced. This model is considered superior for large sample sizes, as opposed to Bayesian Information Criterion and Hannan-Quinn Information Criterion. The hypothesis testing for a unit root is as follows:

$$H_0 = \textit{The data contains at least one unit root}$$
$$H_A = Stationarity$$

As a complementary test to ADF, we will perform the test developed by Kwiatkowski, Phillips, Schmidt, and Shin (1992) (hereafter referred to as “KPSS”), where the null hypothesis considers the data to be stationary, while the alternative hypothesis is the existence of a unit root.

If the result of our hypothesis testing confirms the presence of a unit root, we need to transform the data. The transformation depends on whether the data contains a stochastic trend, in which we will have to difference the data, or a deterministic trend, when the optimal choice would be to de-trend the data. In order to insure a successful transformation, one would have to check for moving averages in the residuals. Moving averages in the residuals is a problem arising when a deterministic trend is differenced instead of de-trended. The test for a unit root is performed repeatedly until the data is stationary. The number of transformations performed on the data determines the order of integration. Furthermore, the data should not include any structural breaks in order to be stationary. This is tested for through the Quandt Likelihood Ratio. We will consider potential solutions if we find structural breaks in our data, e.g. to trim the sample at different levels or exclude different parts of the data to avoid the break.

Moreover, we need to test for cointegration. Cointegration is highly relevant when variables move in the same direction, where they share a common trend with equilibrium forces tying them together. It is relevant that the two variables are integrated of the same order and move together, where one leads and the other is a lagged variable. Checking the order of integration is done through an ADF-test on the data as described thoroughly above. As we want to test whether stock market liquidity is a precursor to real GDP and the business cycle, we consider this test to be highly relevant at this moment in time. If there is a presence of cointegration the residuals will be stationary, checking for this through an ADF on the residuals. To correct for cointegration it is common to use an error correction model, estimating the speed of the equilibrium forces.

3.4 Forecasting GDP

Depending on the results regarding the predictive power of stock market liquidity on the business cycle, we will forecast growth in real GDP. In order to do so we have chosen to work with the autoregressive distributed lag (hereafter referred to as "ADL (p,q)") where we include previous lags of the dependent variable, GDP, as well as lags of the independent variable, stock market liquidity. Firstly, we are going to perform in-sample forecasting, selecting the optimal illiquidity measure. We will evaluate the different models comparing the mean squared forecast error (hereafter referred to as "MSE"), which measures the size of the forecast error. Lastly, we are going to test this forecasting method´s pseudo out-of-sample performance on growth in real GDP for the first and second quarter of 2017. The forecasting timeframe is based on what we intuitively think we have data for. However, adjustments may occur.

4. Data

In order to contribute to Næs et al. (2011) and in particular look at the aftermath of the financial crisis, we have chosen to use data on all equities listed at OSE in the period spanning from 1996 to 2016. We have limited our sample to cover about 20 years, due to the availability of data. The data we plan on using are daily returns, trading volume as well as the bid-ask spread. Moreover, we considered only using the OSE Benchmark Index, OSEBX. However, as this is the main index at OSE, we are afraid it will not provide us with a representative view on the Norwegian stock market as a whole.

For the macroeconomic data measuring the economic situation of the country, here Norway, we will use real GDP. Quarterly data will be used, due to availability. As real GDP measures the market value of all final goods and services produced in a country and we thereby consider it a suitable measure to use in presenting the business cycle. By using other measures, like real consumption (CONSR) and real investments (INV), this enables us to substantiate our results and aid in the interpretation them. Due to instabilities in prior research, we want to affirm our results to strengthen our findings. As Norway's total real GDP is highly dependent on the level and price fluctuations of oil, we have decided to use real GDP for Mainland Norway, believing this will yield more accurate results.

5. Thesis progress

Post preliminary submission the following is our progression plan for the remainder of the thesis:

What:	**Time:**
Data collection and processing	16. January - 16. March
Data analyzing and writing thesis	17. March - 31. May
Deliver first draft of thesis to supervisor	1. June
Finalizing thesis	1. June - 1. July

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