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Money Growth and Aggregate Stock Returns

Tobias Böing and Georg Stadtmann*

Abstract

We empirically evaluate the predictive power of money growth measured by M2 for stock returns of the S&P 500 index. We use monthly US data and predict multiperiod returns over 1, 3, and 5 years with long-horizon regressions. In-sample regressions show that money growth is useful for predicting returns. Higher recent money growth has a significantly negative effect on subsequent returns of the S&P 500. An out-of-sample analysis shows that a simple model with money growth as a single predictor performs as goods as the constant expected returns model, while models with several predictor variables perform worse than those simple models.

Geldmengenwachstum und Aktienmarktrenditen

Zusammenfassung

In diesem Artikel wird die Vorhersagekraft des Geldmengenwachstums, welches mit dem Geldmengenaggregat M2 gemessen wird, für die Aktienrenditen des S&P 500 Indices gemessen. Wir verwenden Monatsdaten der USA und prognostizieren Mehrperiodenrenditen über 1, 3 und 5 Jahre mit Regressionsmodellen. Die Ergebnisse im gesamten Schätzzeitraum zeigen, dass das Geldmengenwachstum Aktienrenditen prognostizieren kann. Demnach sind bei einem hohen Geldmengenwachstum geringere Aktienrenditen in den Folgejahren zu erwarten. Die Out-of-Sample-Analyse zeigt, dass die Prognosen eines Modells mit Geldmengenwachstum als einziger Prädiktor etwa so gut abschneidet wie das Modell mit konstanten erwarteten Renditen. Die komplexeren Modelle mit mehreren Prädiktoren zeigen in der Out-of-Sample-Analyse dagegen eine schlechte Prognosefähigkeit.

Keywords: Money growth, M2, Stock Market, S&P 500, Stock Returns, Out-of-Sample

JEL classification: C58, E44, E47, G14, G17

* Dr. Tobias Böing, European-University Viadrina, Große Scharrnstraße 59, 15230 Frankfurt (Oder), E-Mail: toboeing@gmail.com.

Prof. Dr. Georg Stadtmann, European-University Viadrina, Große Scharrnstraße 59, 15230 Frankfurt (Oder), and University of Southern Denmark, Odense, E-Mail: stadtmann@europa-uni.de.

I. Introduction

In this article we evaluate the predictive value of money growth for stock returns in subsequent periods for the United States. Money growth is measured by the monetary aggregate M2 and stock returns are measured by the S&P 500 index. We use monthly data and consider multiperiod returns over subsequent 1, 3, and 5 years.

This analysis is relevant for monetary policy and portfolio investors. There is the notion that liquidity has an impact on asset prices (*Adalid/Detken* 2007; *Adrian/Shin* 2009). Accordingly, excess liquidity leads to asset price increases or even asset price bubbles, while a reduction of liquidity lowers asset prices. If liquidity dries up on markets, even financial crisis occur (*Brunnermeier/Pederson* 2009).

Central banks are interested in the effect of their monetary policy on asset prices. There is evidence that money and monetary policy has an immediate effect on asset prices (*Sellin* 2001). But there is less evidence on the effect on asset returns in subsequent periods. It is interesting to know whether there is a further increase of asset prices or a reversal in the years after the initial shock.

Portfolio investors, such as private households or institutional investors, are interested in predicting returns of indices such as the S&P 500. This knowledge is helpful for the allocation of capital across different asset classes (strategic and tactical portfolio investing). If an investor expects lower stock returns in subsequent periods, for example before the bust of a bubble, the investor should allocate less capital to the stock market.[1]

Based on in-sample regressions, we find a significantly negative relationship between money growth and subsequent stock returns. This relationship holds for all time horizons of 1, 3, and 5 years and it is robust to the addition of the dividend yield, GDP growth and the inflation rate to the regression.

In an out-of-sample analysis, a model with money growth as a single predictor variable performs worse than the constant expected returns model on a time horizon of one year. On a time horizon of three and five years, however, a model with money as a single predictor variable outperforms the constant expected returns model. The forecasting performance of models with additional predictor variables is worse than the performance of the simple model with money or the constant expected returns model.

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[1] Portfolio optimization can be used to compute the optimal amount of capital invested in the stock market or, more generally, in risky asset classes. Here, using multiperiod forecasts in two-period models would ignore the possibility of rebalancing the portfolio during the investment horizon so that multiperiod portfolio optimization is more appropriate, but also more difficult, to solve the problem.

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We proceed as follows. In chapter 2, we briefly review empirical and theoretical literature. Chapter 3 discusses the data set and chapter 4 includes the in-sample regression analysis. Finally, we perform an out-of-sample analysis in chapter 5 before concluding in chapter 6.

II. Literature Review

1. Empirical Evidence

Empirical evidence – see *Sellin* (2001) for a comprehensive survey – documents the importance of money and other monetary variables for the stock market. *Jensen* et al. (1996) analyze for the US how the monetary environment, which is classified as either expansive or restrictive, influences the effect of some predictor variables on stock returns. They use the dividend yield, the default spread and the term premium as predictor variables. Their findings show that the effects differ across the monetary environment. *Patelis* (1997) measures the effects of monetary policy indicators on stock returns for longer time horizons of up to two years for the US. He finds that monetary variables, especially the Federal Funds Rate, predict stock returns. *Belke/Beckmann* (2015) apply a cointegrated vector autoregressive model to a set of eight economies. They find, however, a limited importance of liquidity for stock prices.

Other studies analyze the dynamic pattern between monetary aggregates and stock prices by a structural vector autoregressive model (*Rapach* 2001; *Neri* 2004). They find a pattern of an initial jump in stock prices after an expansionary monetary shock and a decrease of stock prices in subsequent years. This result suggests a negative relationship between money growth and subsequent stock returns. *Rapach* (2001)[2] focuses on the US, while *Neri* (2004) documents that pattern for several major economies. In five out of eight economies, in Germany, Italy, Spain, the UK, and the US, he finds that pattern.

The contribution of this study is to analyze the predictive power of money growth for stock returns in some other dimensions. We explicitly assess the predictive power over different time horizons, with a set of control variables to increase robustness, and to assess the out-of-sample predictive power. For the interpretation of the results, it is important to mind the negative relationship between the price and the return of a stock (*Cochrane* 2005). Hence, if – ceteris paribus – money growth increases the current price of a stock, then the return decreases.[3]

[2] *Rapach* (2001) uses a long-run identification scheme so that money is neutral on stock prices in the long run. Hence, he finds a reversal of stock prices by construction of his model.

2. Theoretical Explanations

Although the contribution of this paper is empirical, we review some theories which explain the relationship between money growth and stock returns to motivate control variables.

The nominal return r_t of a stock can be decomposed into a risk-free interest rate r_t^f, which can be measured by money market rates or rates for short-term government debt, and the excess return or risk premium r_t^e:[4]

$$r_t = r_t^f + r_t^e \tag{1}$$

Effect through risk-free interest rates: The textbook liquidity preference theory describes a negative relationship between money and the interest rate (*Blanchard* et al. 2013). Since money demand depends negatively on the interest rate, and since money demand equals money supply in equilibrium, the interest rate depends negatively on the quantity of money. An increase in money supply leads to a decrease of the interest rate. However, this explains just the contemporaneous effect. By assuming persistent interest rates, recent money growth can also predict subsequent interest rates and stock returns, if the risk premium does not change.

Effect through risk premia: Theories of risk premia connect them with the business cycle/consumption growth (*Cochrane* 2005). If the economy is in a downturn or a recession, people are afraid of taking risks so that prices decrease and expected risk premia in subsequent periods increase. If a downturn or a recession occurs and money demand goes back as well, a negative correlation between the quantity of money and subsequent stock returns can be explained.

Effect through inflation: The Fisher equation shows the relationship between nominal and real returns (*Sellin* 2001):

$$\mathrm{E}r_t^{e,\,nominal} = \mathrm{E}r_t^{e,\,real} + \mathrm{E}\pi_{t+1} \tag{2}$$

The nominal expected return $\mathrm{E}r_t^{e,\,nominal}$ equals the sum of the expected real return $\mathrm{E}r_t^{e,\,real}$ and the expected inflation rate $\mathrm{E}\pi_{t+1}$. Monetarist theory argues

[3] In formal terms, the negative relationship between the price and the returns of an asset can be stated as follows (Cochrane 2005): The price of an asset is p_t and the payoff this asset in the subsequent period is x_{t+1}. The gross return R_{t+1} is defined by $R_{t+1} = \frac{x_{t+1}}{p_t}$. If the price increases, the return decreases by definition.

[4] $r_t = r_t - r_t^f + r_t^f$ holds. Since $r_t^e = r_t - r_t^f$, equation holds by definition.

based on the quantity equation[5] that higher money growth leads to a higher inflation rate. Assuming inflation inertia, higher money growth increases inflation expectations and, thereby, increases expected nominal stock returns.

Furthermore, the relationship between money growth and stock returns can be explained by the portfolio balance effect and the behavior of financial institutions. Following the portfolio balance effect, households or financial institutions receiving money do not want to hold that money but demand assets such as stocks instead. The prices of those assets go up to balance money holdings and holdings of other assets. Since the fundamental value of those assets does not change, assets are mispriced and a correction might take place in subsequent periods. Hence, returns in subsequent periods should decrease following an expansionary liquidity shock. However, this view regards the creation of money as exogenous rather than endogenous. When central banks seek to control interest rate instead of money supply, the assumption of exogenous money supply is questionable.

Finally, the behavior of financial institutions might also explain the relationship between money and the stock market. *Adrian/Shin* (2009) observe for financial institutions such as investment banks that an increase in asset valuations increases the volume of short-term funding which relies on instruments that are part of M2. However, those institutions are typically invested in credit securities rather than stocks.

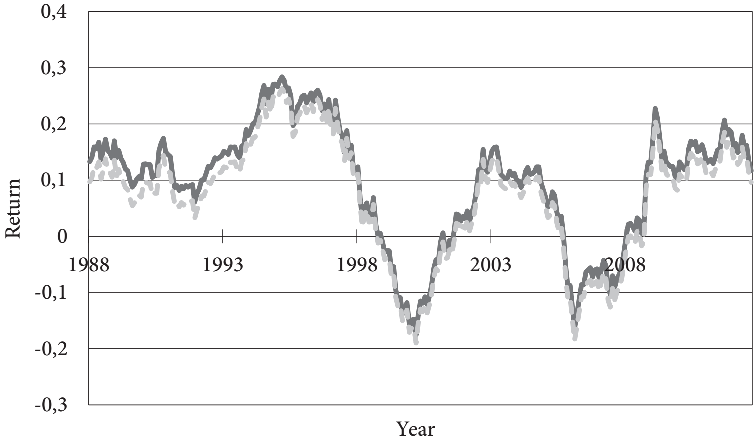
III. Data

Data of the monetary aggregate M2, GDP and consumer prices come from the FRED database (Federal Reserve Bank of St. Louis). The remaining series (S&P 500 index, dividend yield, and interest rates) are obtained from Thomson Reuters Datastream.

We measure aggregate stock returns based on the S&P 500 index. We use a price index instead of a total return index. The advantage of the price index lies in the availability of a longer time series. However, the price index does not account for dividend payments. Figure 1 shows annualized 3-year returns of the price index and of the total return index. The variation of both return series is almost identical with a correlation coefficient of 0.998.[6] The main difference is a level effect so that the return based on the total return index is slightly higher

[5] The quantity equation in growth rates is $m^g + v^g = \pi + y^g$ with the money growth m^g, the growth of the velocity of money v^g, real GDP growth y^g, and the inflation rate π.

[6] This also holds for 1 year and 5 year returns with correlation coefficients of 0.999 and 0.998, respectively.



Notes: The black line shows 3-year returns of the S&P 500 total return index. The dashed grey line shows 3-year returns of the S&P 500 price index.

Figure 1: Comparison of Return Measures

with a relatively constant premium. Hence, the difference in the variation between both indices is negligible so that we use the price index with a longer time series.

Based on the price index, we compute annualized continuously compounded multi-period returns for the subsequent 1, 3, or 5 years.[7] For computing excess returns, we use 3-month T-bills rates as a risk-free rate. We use 3-month rates in favor of monthly rates due to the availability of a longer time series.

Money growth is computed based on the monetary aggregate M2, which is a broad measure of liquid assets including savings deposits, small-denomination time deposits, and balances in retail money market mutual funds in addition to M1, which is a narrowly defined monetary aggregate. We consider M2 as the natural starting point, since it is likely the widely used monetary aggregate for the US. Of course, alternative measures of money can be used as well such as the aggregate MZM or measures of excess liquidity. We measure money growth by the annual growth rate of M2.

[7] The formula is $\ln\left(\frac{p_{t+h}}{p_t}\right) \cdot \frac{h}{12}$. For example in the case of 3 year returns, h is 36 since we have monthly data.

The dividend yield (dividend payments in a period divided by prices) refers to stocks of the S&P 500 index. The inflation rate is the annual growth rate[8] of the Consumer Price Index (for all urban customers). GDP growth is computed by the annual growth rate of real GDP. In order to generate monthly observations of the GDP, we apply a simple linear interpolation.[9]

Table 1 gives an overview of the series we downloaded from the FRED database and Thomson Reuters Datastream.

Table 1

Data Sources

Variable	*Measurement*	*Sample*	*Data Source*
S&P 500	Composite Price Index	1964:01–2015:09	Thomson Reuters Datastream
Dividend Yield	Based on S&P 500	1965:01–2012:09	Thomson Reuters Datastream
M2	Monetary Aggregate (M2SL)	1964:01–2015:09	FRED, Federal Reserve St. Louis
Interest Rate	3-month T-bill	1972:01–2015:09	Thomson Reuters Datastream
GDP	real (GDPC1)	1964:01–2015:09	FRED, Federal Reserve St. Louis
Consumer Price Index	All urban Customers (CPIAUCSL)	1964:01–2015:09	FRED, Federal Reserve St. Louis

For our analysis we transformed the data. Table 2 shows the final series for our statistical analysis:[10]

[8] The annual growth rate refers to the percentage change from the respective month of the previous year.

[9] The data of the second month in a quarter equals the level of the GDP in this quarter. The data of the first month in a quarter is computed by 2/3 of GDP of the current quarter and 1/3 of the GDP of the previous quarter. The data of the third month in a quarter is computed by 2/3 of GDP of the current quarter and 1/3 of the GDP of the following quarter.

[10] The returns series are stationary for monthly returns according to the augmented Dickey-Fuller test (p-value < 0.01). For longer time horizons, the transformation with overlapping multiperiod returns produces persistent returns series. Since multiperiod returns are computed by the mean of stationary monthly returns, we also assume multiperiod returns series to be mean stationary.

Table 2
Data for Regression Analysis

Variable	*Basis*	*Sample*
1-year Return	S&P 500 Price Index	1965:01-2012:09
3-year Return	S&P 500 Price Index	1965:01-2012:09
5-year Return	S&P 500 Price Index	1965:01-2010:09
1-year Excess Return	S&P 500 Price Index/T-bill Rate	1972:01-2012:09
3-year Excess Return	S&P 500 Price Index/T-bill Rate	1972:01-2012:09
5-year Excess Return	S&P 500 Price Index/T-bill Rate	1972:01-2010:09
Money Growth	M2	1965:01-2012:09
Dividend Yield	S&P 500 Divdend Yield	1965:01-2010:09
Inflation Rate	CPI	1965:01-2012:09
GDP Growth	GDP	1965:01-2012:09

IV. In-Sample Regression Analysis

1. Methodology

The goal is to predict the returns of the S&P 500 index in subsequent periods. We apply a linear regression with returns over the next year, 3 years and 5 years as the dependent variable. A problem of autocorrelation arises since we use monthly observations and multiperiod returns over at least one year. For example, with annual returns we have to compute the returns from January 2000 to January 2001, February 2000 to February 2001, etc. A price shock in January 2001 influences the returns in twelve month (from January 2000 to January 2001, February 2000 to February 2001, …, December 2000 to December 2001), so that the error terms are correlated with each other. However, we use long-horizon regressions, because the predictability of aggregate stock returns improves with the time horizon (*Cochrane* 2005) and we can assess the predictability over different time horizons.[11] The set of predictors varies across specifications:

(3.1) $$r_{t+h} = \beta_0 + \beta_1 \cdot m_t + \in_{t+h}$$ *S1: Money model*

(3.2) $$r_{t+h} = \beta_0 + \beta_1 \cdot m_t + \beta_2 \cdot dy_t + \beta_3 \cdot y_t + \beta_3 \cdot \pi_t + \in_{t+h}$$ *S2: Model with all variables*

[11] In addition, using observations with a spacing of 1, 3, or 5 years would shrink the number of observations drastically.

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(3.3) $r_{t+h} = \beta_0 + \beta_2 \cdot dy_t + \beta_3 \cdot y_t + \beta_3 \cdot \pi_t + \in_{t+h}$ *S3: Model without money*

with

- r_{t+h}: Returns or excess returns of the S&P 500 price index with time horizon h of either 1, 3, or 5 years
- m_t: Annual growth rate of M2
- dy_t: Dividend Yield of the S&P 500 index
- y_t: Real GDP growth
- π_t: Consumer price inflation

We use the ordinary least squares (OLS) estimator to fit the model.[12] To accommodate for autocorrelation, we use robust standard errors following *Andrews* (1991) with a relatively long bandwidth of 10 years (*Hayashi* 2000).[13] The first goal is to assess the significance of money growth for stock returns. In order to increase the robustness, we add the dividend yield, real GDP growth, and the inflation rate to the regression. In principle, the effect of money growth could be explained by its correlation with one of these variables. If this is the case, the predictive value of money growth for stock returns is very limited. We add the dividend yield because it can reflect some degree of mispricing or time-varying risk premium and it is widely used to predict stock returns (*Cochrane* 2005). GDP growth and inflation might be correlated with both money growth and stock returns. By using excess returns, we also control for interest rates. The null hypotheses regarding money growth is that it has no effect on stock returns ($H_0 : \beta_1 = 0$).

Second, we also assess the model fit. In particular, we compare the model S2 including money growth with model S3 without money growth. We consider the adjusted R^2 and the Akaike information criterion (AIC) to assess the model fit.

2. Results

Tables 3 and 4 show the results of OLS regressions of models S1, S2, and S3 for returns and excess returns:

[12] The goal is to predict stock returns, so that causal inference is not the primary concern of this study,

[13] This is a non-parametric methodology like the Newey-West estimator with slightly better asymptotic properties. We use a bandwidth of 10 years, since the autocorrelation function indicates an autocorrelation structure of more than few years. The degrees of freedom are still high enough for statistical inference purposes.

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Table 3

Regression Results for Returns
(Author's Own Processed from Thomson Reuters Datastream and Federal Reserve St. Louis)

Horizon	1 year			3 years			5 years		
	S1	S2	S3	S1	S2	S3	S1	S2	S3
Money Growth	–0.99*	–1.44***	–	–0.88	–1.28***	–	–0.62	–0.99*	–
	(–2.571)	(–3.864)		(–1.520)	(–3.984)		(–1.133)	(–2.411)	
Dividend Yield	–	8.62***	7.42***	–	5.88***	4.82***	–	5.42***	4.57***
		(5.827)	(6.486)		(8.088)	(6.334)		(8.904)	(9.982)
GDP Growth	–	–1.02	–1.38	–	–0.33	–0.65	–	–0.65*	–0.91***
		(–1.093)	(–1.176)		(–1.196)	(–1.706)		(–2.254)	(–4.566)
Inflation	–	–2.87***	–2.82***	–	–1.70***	–1.65***	–	–1.43***	–1.39***
		(–7.947)	(–8.903)		(–4.197)	(–3.977)		(–4.754)	(–3.817)
Intercept	0.13***	0.05	–0.01	0.12**	0.05	0.00	0.11*	0.04	0.01
	(4.408)	(1.217)	(–0.168)	(3.187)	(1.843)	(0.181)	(2.436)	(1.315)	(0.344)
Adjusted R squared	0.03	0.23	0.16	0.09	0.38	0.21	0.07	0.53)	0.37
AIC	–463.03	–587.48	–544.20	–1182.27	–1396.35	–1263.79	–1404.81	–1777.46	–1714.39

Notes: The models are estimated by OLS. Standrad errors are corrected for autocorrelation by Andrew's robust standard errors with a bandwidth of 10 years. The t-values are shown in parantheses. One/two/three stars refer to significance levels of 0.001, 0.01, and 0.05, respectively.

Table 4

Regression Results for Excess Returns
(Author's Own Processed from Thomson Reuters Datastream and Federal Reserve St. Louis)

Horizon	1 year			3 years			5 years		
	S1	S2	S3	S1	S2	S3	S1	S2	S3
Money Growth	−1.45**	−1.80***	–	−1.07*	−1.25***	–	−1.06*	−1.27***	–
	(−3.070)	(−3.687)		(−2.103)	(−3.958)		(−2.828)	(−5.696)	
Dividend Yield	–	8.22***	6.64***	–	5.07***	3.97**	–	4.66***	3.49***
		(5.633)	(6.786)		(4.718)	(3.068)		(9.313)	(3.972)
GDP Growth	–	−1.19	−1.54	–	−0.78*	−1.03*	–	−1.04**	−1.31***
		(−1.264)	(−1.156)		(−2.428)	(−2.194)		(−3.041)	(−4.670)
Inflation	–	−3.51***	−3.44***	–	−2.30***	−2.25***	–	−1.84***	−1.79***
		(−7.412)	(−7.698)		(−5.107)	(−4.258)		(−6.738)	(−4.277)
Intercept	0.11***	0.07*	0.00	0.09*	0.07***	0.03	0.09**	0.06**	0.01
	(4.177)	(2.476)	(0.096)	(2.766)	(3.517)	(1.034)	(3.002)	(5.381)	(1.857)
Adjusted R squared	0.06	0.25	0.17	0.12	0.39	0.25	0.23	0.69	0.41
AIC	−327.79	−433.82	−383.42	−979.70	−1158.54	−1054.77	−1282.89	−1696.84	−1402.11

Notes: The models are estimated by OLS. Standrad errors are corrected for autocorrelation by Andrew's robust standard errors with a bandwitdth of 10 years. The t-values are shown in parantheses. One/two/three stars refer to significance levels of 0.001, 0.01, and 0.05, respectively.

The results are listed for 1, 3, and 5 year multiperiod returns. For each horizon, the first column represents the model S1 with money growth as the single predictor variable. The second and third column show the model S2 with *all* predictor variable and model S3 without money growth. The samples begin in 1965:01 for returns and in 1972:01 for excess returns. For both return measures, the sample ends 2012:09 (1 and 3 year returns) or 2010:09 (5 year returns).

Money growth has a negative effect on subsequent stock returns in all specifications. This result is consistent with findings in previous studies (*Rapach* 2001; *Neri* 2004). The size of the coefficient is around -1 so that an increase in money growth by one percentage point predicts lower annualized stock return by around one percentage point.

The t-statistics for money growth range between –1.133 to –5.696. The coefficient of money growth is only insignificant for returns on a time horizon of 3 and 5 years for model S1. In 10 out of 12 cases money growth is significant on a significance level of 5 %.

The predictive power of money growth is relatively constant over the three time horizons. When increasing the time horizon from one year to three or five years, the effect of money growth decreases slightly. Hence, the adjustment of stock prices after a monetary shock takes place within the first year after the shock.

The absolute values of money growth coefficients are a bit higher for excess returns than for returns.[14] This holds especially for the model S1 with money growth as the only predictor. Hence, the interpretation that money growth has a negative effect on the risk-free interest rate and thereby an effect on stock returns can be rejected.

The effect of money growth remains robust after the addition of the dividend yield, GDP growth, and the inflation rate to the regression. The absolute value of the coefficient even increases. The predictive power of money growth is not explained by the correlation with those variables. Furthermore, the estimated coefficients of the additional predictor variables are consistent with previous evidence.[15]

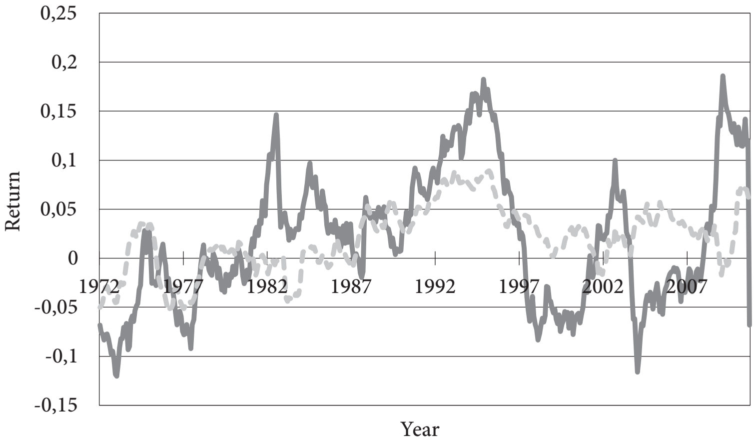
The model fit measured by the adjusted R^2 is increasing with the time horizon. The model S2 with all predictor variables reaches an adjusted R^2 of 0.69 for excess returns. Hence, almost 70 % of the variation in 5 year excess returns can be explained by four predictor variables. These results are in line with previous literature (*Cochrane* 2005).

[14] A possible explanation is that the begin and the length of the sample varies between the results in Table 3 and 4. However, the statement also holds when analyzing the same sample period.

[15] See *Cochrane* (2005) for the dividend yield and *Sellin* (2001) for inflation.

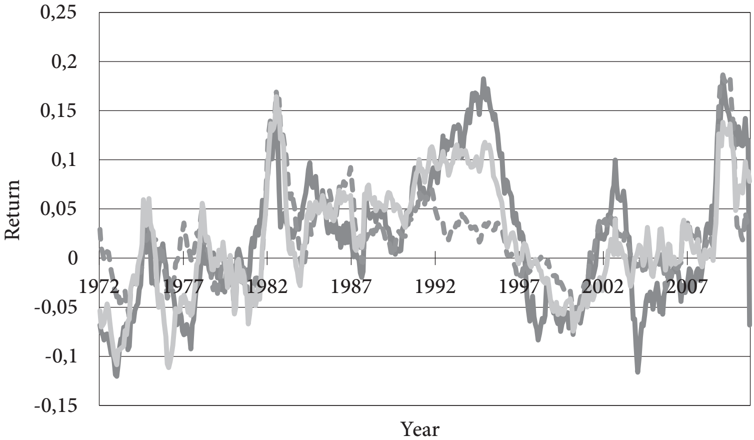
The comparison of model S2 including money growth and the model S3 without money growth provides further evidence for the importance of money growth. The fit of the model including money growth is better in every specification according to the adjusted R^2 and the Akaike information criterion (AIC).

Figures 2 and 3 show the predicted 5-year excess returns by the models.



Notes: The dark grey line shows actual 5-year returns. The dashed grey line shows the returns predicted by the model S1 with money growth and without any other predictors.

Figure 2: Actual vs. Predicted 5-year Excess Returns



Notes: The dark grey line shows actual 5-year returns. The bright grey line shows the returns predicted by model S2 which represents the model with our whole set of predictor variables. The dashed grey line shows the returns predicted by model S3 which represents the model without money growth as a predictor variable.

Figure 3: Actual vs. Predicted 5-year Excess Returns

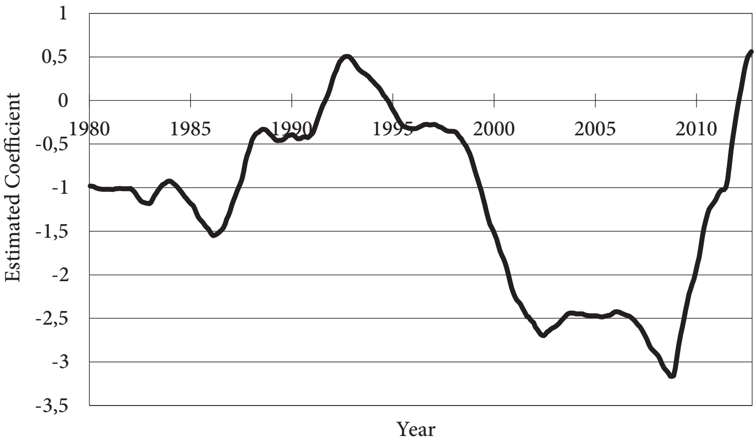
Figure 2 compares the prediction of model S1 (dashed grey line) with the actual 5-year excess return (dark grey line). The plot shows some predictive power of money growth. For example, the model predicts actual returns in the seventies and the first years of the eighties well.

The stock price boom in the late nineties and the bust afterwards can also be partly explained by money growth. Figure 3 shows predicted excess returns by the models S2 and S3 as well as the actual return. The bright grey line shows the predicted return by the model with *all* variables including money. First, the line is very close to the actual return (dark grey line) so that the fit is very good which graphically represents the high R^2 of 0.69. Second, the bright grey line predicts actual returns better than the dashed grey line, which represents the prediction by the model without money. This is especially true for the late seventies and the early nineties.

3. Parameter Stability

Two potential problems for prediction are overfitting and parameter instability (*James* et al. 2013). Since we have many degrees of freedom, we do not consider overfitting as a major problem.

Figure 4 shows the stability of the estimated coefficient ($\hat{\beta}_1$) of money growth in model 1 S1. The estimated coefficient in each period is based on the data of the previous 15 years.



Notes: The line shows the estimated β_1-coefficient of model S1 with returns. The length of the estimation window is constant so that every observation represents the estimate over the last 15 years.

Figure 4: Parameter Stability of the Estimated β_1-coefficient

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The estimated coefficient varies from negative values of around –3 to slightly positive values. Hence, the effect of money growth on stock returns is unstable. One reason for this instability might be the changing structure of the financial and monetary system. For example, there has been a shift towards market-based institutions of financial intermediation, in particular in credit based financial services, which accounts for an important portion of the money supply M2 (*Adrian/Shin* 2009).

The in-sample analysis suggests that the predictor variables have predictive power for subsequent stock returns. In the presence of parameter instability, however, the estimated coefficients based on an estimation window might be misleading for forecasts of stock returns out-of-sample. As a consequence, a model with a superior in-sample performance can have an inferior out-of-sample performance.

V. Out-of-Sample Analysis

1. *Methodology*

To evaluate the forecasting performance, we perform an out-of-sample analysis. We consider the three models S1, S2, and S3 estimated with OLS and, in addition, the constant expected returns (cer) model. The cer model prediction is the mean return over the estimation window (training period) and it serves as a benchmark for all models.[16]

The estimation window is set to 15 years, which accounts for around two business cycles. Based on the estimated parameter and the values of the predictor variables at the end of the estimation window, we compute a single prediction over the specified time horizon for each model. This procedure is repeated by a rolling estimation window so that the estimation window always covers the previous 15 years of data. We use all subsamples for which we have the previous 15 years of data available for all variables. For each model, we generate a vector of forecasts and compare those forecasts with the vector of actual returns in those periods.

We compute the root mean square error (RMSE) to evaluate the forecasting performance of each model:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(\hat{r}_t - r_t)^2} \tag{4}$$

[16] The cer model for continuously compounded returns is the equivalent to the random walk model of log prices. Note that the models S1, S2, and S3 nest the cer model as a special case if all regression coefficients expect the intercept are zero.

$\hat{r}_t$ is the model forecast in period t. A low RMSE indicates a good forecasting performance. In addition, we compute the mean absolute error. We evaluate the importance of money growth by two comparisons. First, the model S1 with money should have a better forecasting performance than the cer model. Second, the model S2 with money growth should perform better than model S3 without money growth.

2. Results

Tables 5 and 6 present the results of the out-of-sample analysis.

Table 5

Out-of-Sample Analysis for Returns: RMSE in Percent (Author's Own Processed from Thomson Reuters Datastream and Federal Reserve St. Louis)

Model	1 year	3 years	5 years
Constant Excepected Returns	*17.77*	11.40	9.04
S1: Money	18.38	*10.86*	*7.99*
S2: All	22.68	12.78	10.77
S3. All without Money	21.98	14.11	12.65

Notes: The estimation window (training sample) is 15 years.

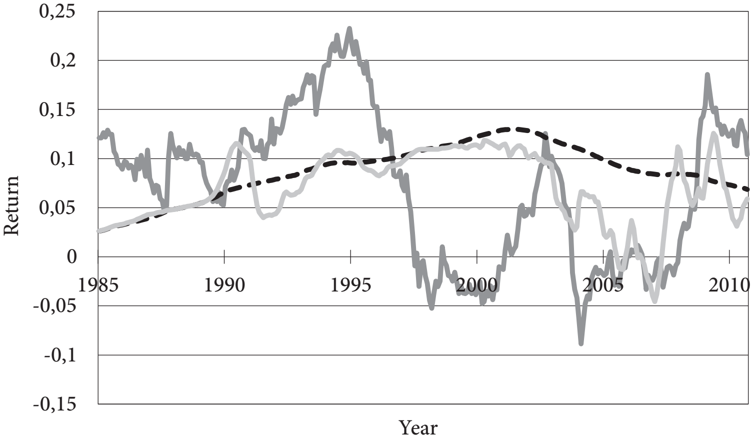
Table 6

Out-of-Sample Analysis for Excess Returns: RMSE in Percent (Author's Own Processed from Thomson Reuters Datastream and Federal Reserve St. Louis)

Model	1 year	3 years	5 years
Constant Excepected Returns	*18.61*	12.25	9.47
S1: Money	19.63	*11.70*	*8.65*
S2: All	22.65	11.88	9.62
S3. All without Money	21.58	12.79	9.81

Notes: The estimation window (training sample) is 15 years.

The best performing models to forecast returns are the two simplest models, the cer model and the model S1. For annual returns, the constant expected returns model works best.



Notes: The dark grey line shows actual 5-year returns. The grey line shows forecasts by the model S1 with money as a single predictor variable. The dashed black line represents the constant expected returns model forecast. The estimation window (training sample) is 15 years.

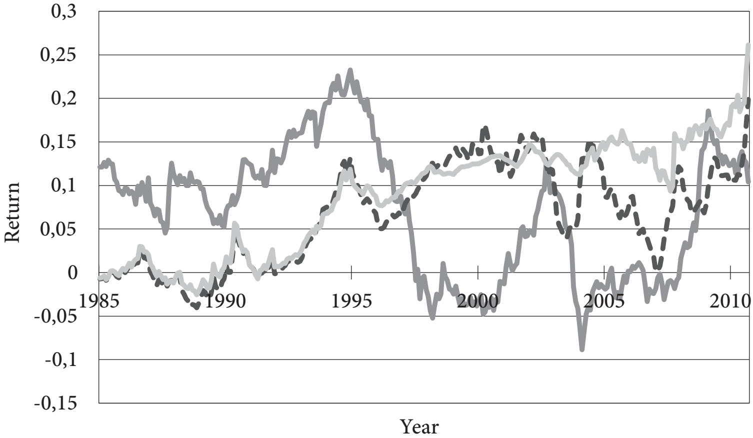
Figure 5: Out-of-Sample Forecasts of Different Models for 5-year Return

For 3 and 5 year returns, the model S1 with money growth as a single predictor variable beats the cer model in all cases. Especially for returns and over a longer time horizon, money growth might be useful to predict aggregate stock returns. Figure 5 shows the series of out-of-sample forecasts of the cer model and S1 model as well as the actual return.

Until 2000, the deviations of the forecasts of both models are relatively small. The forecasting performance of model S1 is, however, better from 2003 to 2008. Generally, the volatility of the cer model forecast is the lowest among all considered model, which partly explains its relatively small RMSE.

The models S2 and S3 perform in most cases worse than its two competitors, although those are the two models with the best in-sample fit. For annual returns, the model S2 with all predictor variable performs slightly worse than the model S3. When comparing both models on a time horizon of 3 or 5 years, the model including money growth performs better than the model without money growth. Hence, when using forecasting models with some predictor variables, it is reasonable to consider money growth as a predictor. Figure 6 also shows that the model with money growth (dashed grey line) outperforms the model without money growth (bright grey line), especially from 2008 on.

When using the mean absolute error, the results do not change. When comparing the in-sample performance of our models with their out-of-sample performance, we find a much better in-sample performance which can be seen by high adjusted R^2 values. When going out-of-sample, models such as the models



Notes: The dark grey line shows actual 5-year returns. The bright grey shows the forecast by the model S3 without money as a predictor variable. The dashed grey line represents the forecast by the model S2 with all predictor variable. The estimation window (training sample) is 15 years.

Figure 6: Out-of-Sample Forecasts of Different Models for 5-year Returns

S2 and S3 with a good in-sample fit perform poorly out-of-sample. This result is well-known and can be attributed to parameter instability, which has been found in this article (see 4.3), or overfitting (*Goyal/Welch* 2007; *James* et al. 2013).

VI. Conclusions

In-sample regressions show a relatively high level of predictability of subsequent stock returns, especially over a longer forecasting horizon. Higher money growth predicts lower stock returns. If an expansionary monetary shock increases stock prices immediately, there is a reversal of stock prices in subsequent periods, since stock returns are lower in subsequent periods. Hence, concerns that liquidity shocks push stock prices permanently to either too high or too low levels are not justified.

While the in-sample regression analysis points to a reasonable degree of predictability of subsequent stock returns, the out-of-sample analysis shows a different picture. The models with several predictor variables perform worse than the constant expected returns model and the model with money as the single predictor variable. The out-of-sample-performance of the model with money growth as the single predictor variable performs as good as the constant expected returns model. Especially from 2003 to 2008, money growth has been a valuable variable to assess the stock market. For financial analysts who consider a broad set of variables to assess the stock market, money growth or other measures of money might be interesting.

Our analysis is simple in order to have a high level of interpretability. In future research, more sophisticated models such as non-linear models (regime-switching models, non-parametric models, etc.) or shrinkage models can be analyzed to improve the forecasting performance, since they can reduce problems of parameter instability, which we document, or overfitting. The analysis can also be extended to different measures of money or to different samples with respect to indices or countries.

Finally, it is difficult to provide a reasonable theoretical explanation for our empirical results. Some simple explanations such as the effect of money on interest rates or GDP growth can be rejected. However, we cannot give a detailed explanation of the mechanism based on the empirical methods we use, which is beyond the scope of this article.

Table 7

Out-of-Sample Analysis for Returns: Mean Absolute Error in Percent (Author's Own Processed from Thomson Reuters Datastream and Federal Reserve St. Louis)

Model	1 year	3 years	5 years
Constant Excepected Returns	*13.12*	8.98	7.91
S1: Money	13.65	*8.54*	*6.73*
S2: All	17.39	10.71	9.62
S3. All without Money	16.52	11.89	10.58

Notes: The estimation window (training sample) is 15 years.

Table 8

Out-of-Sample Analysis for Excess Returns: Mean Absolute Error in Percent (Author's Own Processed from Thomson Reuters Datastream and Federal Reserve St. Louis)

Model	1 year	3 years	5 years
Constant Excepected Returns	*13.82*	10.37	8.53
S1: Money	14.74	*9.64*	*7.49*
S2: All	17.28	10.02	8.31
S3. All without Money	16.15	10.52	8.60

Notes: The estimation window (training sample) is 15 years.

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