Stockholm University
School of Business

Bachelor Thesis

THE EFFECT OF MONETARY LIQUIDITY ON ASSET RETURNS

Author: Martin Winiarski
Supervisor: Niclas Hagelin

HT 2002 □ 2003·01·22 □ 10 Credits

Contents

THE EFFECT OF MONETARY LIQUIDITY ON ASSET RETURNS

MARTIN WINIARSKI†

Abstract. Recently, the effect of liquidity on asset prices has been frequently discussed. This thesis investigates whether there is any linkage between monetary liquidity and asset returns. The method used is based on Vector Autoregression (VAR), a multivariate time series analysis approach. No significant relationship between liquidity, as defined in this thesis, and asset returns was found. A number of reasons may contribute to this result. It seems likely, though, that a macroeconomic variable such as liquidity have a very small effect on asset returns in general.

1. Introduction

The interaction between stock returns, interest rates, inflation and other macroeconomic variables has been extensively studied and discussed in previous literature during the last decades. The approaches have varied and so have the conclusions. This bachelor thesis in finance will look at a variable, monetary liquidity, that not has been included, to the best of my knowledge, in more than one other previous study. Since liquidity is not one of the fundamental cornerstones of the macroeconomic theory, in the same way as the monetary base, inflation, consumption or GDP, it has not at all received the same amount of attention. Practioners at the financial institutions, however, nevertheless take interest in liquidity. A common opinion being that when liquidity is up, it is a good time to buy. Intuitively, this makes sense, since when there is a large amount of money and money-like assets available for investment, the laws of supply and demand suggest rising asset prices. But intuition can be treacherous. Therefore, this thesis will investigate whether monetary liquidity is a variable to consult in the allocation process.

Vector Autoregression (VAR) will be applied to analyze the hypothesis of a positive linkage between stock returns and monetary liquidity. Other assets such as bonds are included indirectly since long interest rates are studied to some extent. This method has been favored by many researchers e.g. James, Koreisha, and Partch (1985), Patelis (1997) and Lee (1992) and its benefits and drawbacks will be discussed in the method section.

I would like to thank Lena Lindhe at Handelsbanken Asset Management for suggesting the subject and providing the CBC liquidity index.

† Contact info: Email: f98-mwi@nada.kth.se, Phone: +46 70 229 85 93.

Baks and Kramer (1999) distinguish between market liquidity and monetary liquidity. Market liquidity reflects the financial market's capacity to absorb large buy and sell orders, without unduly affecting the price, while monetary liquidity is related to the aggregate quantity of money and the conditions in the short-term credit market.

The purpose of this thesis is to evaluate the effect of liquidity and determine whether it in any way can improve asset allocation decisions. The thesis also examines a commercial liquidity index, which by the provider is claimed to be a good stock and bond return predictor. The idea behind the thesis was suggested by the macroeconomic analysts in the allocation group at Handelsbanken Asset Management.

2. Background

Prior research in this field has generally not focused directly on monetary liquidity but rather on the relationship between stock returns and variables such as inflation, real activity, nominal and real interest rates, money growth and monetary policy. Some of this research has produced remarkable results that did not agree with general beliefs.

2.1. **Inflation and Real Activity.** It used to be common wisdom that equities, representing ownership of the income generated by real assets should be a hedge against inflation (Fama 1981). This turned out to be uncertain in view of the empirical evidence of a negative relationship between stock returns and inflation (Fama and Schwert 1977). Fama argued that the negative relationship between stock returns and inflation is actually proxying for positive relations between stock returns and real variables, which have a more fundamental role in equities valuation. The negative relationship between stock returns and inflation is induced by a negative relationship between inflation and real activity.

Geske and Roll (1983) extend and supplement Fama's work and approach the problem from a slightly different angle by arguing that stock market returns signal changes in inflation through a chain of macroeconomic events. When the stock market moves in response to expected changes in the economic conditions, personal and corporate profits move in the same direction. The government's expenditures, however, remain fairly fixed, which means that a decrease in revenues will result in deficit. The Treasury will have to borrow money to be repaid later in times of surplus. Geske and Roll argue that the debt often was *monetized* by the printing of currency and and expansion of bank reserves. This increased rate of monetary growth caused the inflation. So, a decrease in the economic activity leads to an increase in the expected growth rate of the money supply, and thereby a larger increase in inflation than would have occurred if there was not any negative relation between real activity and the growth rate of the money supply.

Fama's and Geske and Rolls' models are similar in the respect that, first, changes in expected real activity are determined exogenously, secondly, changes in expected future activity are signaled through stock returns and, thirdly, there is a negative relationship between real activity and inflation.

2.2. **Monetary Policy.** Conover, Jensen, and Johnson (1999) have studied [1] the impact of international monetary policy environments on stock returns. They found, as they suspected, that there is a significant relationship between the monetary policy environment and stock returns. A restrictive policy thus suggests smaller returns and an expansive policy suggests larger returns. They studied both the impact of the local environment as well as the impact of US environment. In the case of Sweden they found at first a significant (at a 1% significance level) relationship between returns and the local monetary policy. They also found a significant (at a 1% significance level) impact of the US policy. But when combining the Swedish and US policy the effect of the Swedish policy lost its significance and only the US policy remained significant (at a 5% significance level). The effect is however quite small and the combined impact of both the local Swedish and US monetary policy never explains more than 2% ($R^2 = 0.02$) of the monthly stock returns.

Thorbecke (1997) studied the linkage between stock market returns and monetary policy on a domestic level in the US. Using VAR and impulse response analysis he examined the effect of innovations in the federal funds rate on portfolios of different industries and sizes. Thorbecke states that evidence, which shows that positive monetary shocks increase stock returns, indicates that expansionary monetary policy exert real effects by increasing future cash flows or by decreasing the discount rate used when valuing the cash flows. Thorbecke also states that the results from the size portfolios indicate that monetary shocks have larger effects on small firms than on large firms, which was a hypothesis based on Gertler and Gilchrist (1994).

If monetary policy matters, one possible reason could be that it affects stock returns through the firms' balance sheets. Gertler and Gilchrist claim, that smaller businesses are affected more than larger ones, partly because of less capital market exposure. Gertler and Gilchrist studied how a tightening of monetary policy affected small manufacturing firms. They found that these firms contract substantially relative to large firms after a tightening of the money supply. Smaller firms also account for a disproportionate amount of manufacturing decline.

Patelis (1997) studied if the observed predictability of excess stock returns over the risk free rate could be accounted for by monetary policy. Patelis

[1]They used regression with dummy variables. In the case of the combined impact of Swedish and US policy environments the equation had the form $S_t = \alpha + \beta_1 D_t^{\mathrm{SWE}} + \beta_2 D_t^{\mathrm{US}} + \epsilon_t$. Where S_t represents the stock returns and D_t is a dummy.

concludes that there is a significant relationship, but it does not fully explain the predictability.

2.3. **Prior VAR-studies.** James, Koreisha, and Partch (1985) investigated the causal relationship between stock returns, real activity, money growth, and expected inflation by using a Vector Autoregression Moving Average (VARMA) model. Their goal was to explain the negative stock return and inflation relation, which was perceived as anomalous. They found evidence of both a linkage between real activity and stock returns, as well as a linkage between real activity and inflation. They also found that stock returns signal changes in the monetary base. Since stocks derive their value from expectations of future activity, James *et al.* argue that their findings are consistent with the money supply explanation offered by Geske and Roll.

Lee (1992) considers the inherent difficulty of interpreting the causality in VAR-models consisting of more than two variables and use a somewhat extended approach to refine the findings of James *et al.*. Lee found that stock returns seem to Granger-cause[2] and explain a large fraction of the variance in real activity. Using impulse response analysis, Lee found that real activity responds positively to stock return shocks. When extending James *et al.*'s model by including interest rates not only as a measure of expected inflation, but on their own behalf, Lee found, contrary to James *et al.*'s findings, that stock returns explained little of the variation in inflation. Interest rates, on the other hand, explain a substantial amount of the variation in inflation and inflation responds negatively to shocks in real interest rates. Lee also found that inflation explains little of the variation in real activity, which responds negatively to shocks in inflation. Lee concludes there is no causal relation between stock returns and money supply and therefore no causal linkage between stock returns and inflation. Lee considers these conclusions to associate closer to the ones of Fama than to those of Geske and Roll. The conclusions also imply that inflation would not be a reliable prediction factor for stock returns.

There can be several reasons why Thorbecke concludes that monetary policy affects stock returns, while Lee claim there is no causal linkage. Even though both used variants of VAR, there still are differences in method to consider. The relations are also weak and causality is often difficult to determine.

2.4. **The Possible Effects of Liquidity.** There are several ways that monetary liquidity could effect asset prices, Baks and Kramer name the following plausible links. First, a rise in liquidity could inflate asset prices

[2]See Method section.

if the amount of assets remains fixed, through supply and demand. Secondly, increased liquidity might coincide with a cyclical upturn and improved economic prospects. Thirdly, stock prices might be affected by liquidity through an effect of liquidity on interest rates and thereby changing the CAPM discount rate.

Baks and Kramer looked primarily at two things, first, the relationship of G7[3] money and asset returns and, secondly, monetary spillovers. Their results, measured as contemporaneous correlations, point at *excess money* ($\Delta MS^4 - \Delta GDP$) is negatively correlated with interest rates, and positively correlated with stock returns, though the stock correlation is quite weak . They also found that real asset returns are generally more strongly correlated with excess narrow[5] money than excess broad[6] money.

When Baks and Kramer considered monetary spillovers, they hypothesized about two possible international transmission channels, which they call the *push* and the *pull* channels. A rapid rise in liquidity in one country may give rise to capital flows to foreign stock and bond markets. The money is pushed abroad and exerts upward pressure on foreign stocks and downward pressure on foreign interest rates. Alternatively, liquidity growth in one country may lead to domestic asset inflation, which attracts capital from foreign countries. Money is pulled into the country and depresses foreign countries asset prices. Baks and Kramer conclude that there are some indications of spillovers from excess money growth to interest rates and stock returns across G7 countries, and they seem consistent with the *push* rather than the *pull* explanation.

This thesis differs in a couple of ways from the previous research. First of all it uses Swedish data on *excess money*, which, to my knowledge, have not been included in other research. I also use a refined measure of liquidity. A commercial product claimed to be very good by the provider, making it interesting to see how well it will perform. Finally, I use a different method, than Baks and Kramer did and also include more variables.

3. Method

Vector Autoregression is based on multivariate time series analysis and was advocated by Sims (1980) for use in macroeconomics instead of the Cowles Commission's structural simultaneous equation models. The model has a number of appealing characteristics that makes it especially suited for this paper.

One of the main advantages is that the model requires no *a priori* distinction between endogenous and exogenous variables. It simply regards all

[3]Group of 7
[4]Money Supply
[5]i.e. in Sweden M0
[6]M3 is a broader measure than M0

variables as endogenous. Another important advantage of VAR-modeling is the possibility to obtain useful descriptive characteristics from a small scale example, without the need to build large models based on sometimes shaky assumptions.

The fact that the macroeconomic theory is not represented in any other way than in the choice of the included variables has evoked some criticism and the model has been called *atheoretical*. Further critique of the model can be found in Epstein (1987) and Darnell and Evans (1990). This does however not change the fact that VAR has gained enormous popularity in the research community and has at times proven to be a valuable forecasting tool.

The analysis is performed in MATLAB and for the estimation of the VAR-models a package called ARfit is used. Further details about this package is found in Schneider and Neumaier (2001) .

3.1. **Properties of VAR Processes.** In univariate time series analysis we are interested in finding a model that describes how a variable's current value is related to past values. The simplest model is the first order autoregressive process, called AR(1):

$$x_t = \phi_1 x_{t-1} + \epsilon_t, \qquad \epsilon_t \sim \mathrm{IID}(0, \sigma^2) \tag{1}$$

This says that the current value x_t is equal to a factor ϕ_1 multiplied with its previous value one time step before x_{t-1} plus a stochastic and unpredictable error term ϵ_t, which is white noise.

If we find it more likely that the variable we are interested in is not only dependent on past values of itself, but also of past values of other variables, we can extend the model and get a multivariate version. This is what is referred to as a VAR(p) model.

$$y_t = \mu + \mathbf{\Phi}_1 y_{t-1} + \mathbf{\Phi}_2 y_{t-2} + \ldots + \mathbf{\Phi}_p y_{t-p} + \boldsymbol{\epsilon}_t, \quad \boldsymbol{\epsilon}_t \sim \mathrm{IID}(0, \Sigma)$$

Where y_t is a ($\mathbb{R}^k$) vector containing the set of time series and in that way treating them as a multivariate time series. The μ ($\mathbb{R}^k$) vector is the intercept term and allows the use of series with non-zero mean ($\mathbb{E}[y_t] \neq 0$).

$$y_t = \begin{pmatrix} y_{1,t} \\ y_{2,t} \\ \vdots \\ y_{k,t} \end{pmatrix} \quad \mu = \begin{pmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_k \end{pmatrix} \quad \mathbf{\Phi}_i = \begin{pmatrix} \phi_{11,i} & \phi_{12,i} & \cdots & \phi_{1k,i} \\ \phi_{21,i} & \phi_{22,i} & \cdots & \\ \vdots & \vdots & \ddots & \\ \phi_{k1,i} & \cdots & & \phi_{kk,i} \end{pmatrix}$$

And, $\mathbf{\Phi}_i$, which is the coefficient matrix ($\mathbb{R}^{k \times k}$).

3.2. **Granger Causality.** Ever since Granger published his famous paper in 1969, it has been popular to discuss the presence of Granger causality among the variables included in a VAR. The main idea behind Granger causality is that if x affect a variable y, then x should also be able to improve a prediction of y.

Granger considered a bivariate VAR on the form

$$x_t = \sum_{j=1}^{m} a_j x_{t-j} + \sum_{j=1}^{m} b_j y_{t-j} + \epsilon_t^{(1)}$$
$$y_t = \sum_{j=1}^{m} c_j x_{t-j} + \sum_{j=1}^{m} d_j y_{t-j} + \epsilon_t^{(2)}$$

Granger (1969, p. 431) say that "... y_t is causing x_t provided some b_j is not zero. Similarly x_t is causing y_t if some c_j is not zero. If both these events occur, there is said to be a feedback relationship between x_t and y_t."

Using Hamilton's (1994) notation instead of Grangers, it is said that ordinary Granger causality exist if

$$\text{MSE}\big[\mathbb{E}_t[x_{t+s}|x_t, x_{t-1}, \ldots, y_t, y_{t-1}, \ldots]\big] \leq \text{MSE}\big[\mathbb{E}_t[x_{t+s}|x_t, x_{t-1}, \ldots]\big] \quad (2)$$

Equation (2) says that if the mean squared error (MSE) of the prediction of x_{t+s} (i.e. s-steps ahead) at the time t is reduced when information about y is included in the prediction, then y is said to Granger-cause x.

Granger causality is often only discussed in a bivariate system. If the system studied contains more than two variables, e.g. x_1, x_2, x_3, it is sometimes popular to transform it to a bivariate system by studying if $y = (x_2, x_3)$ Granger-cause x_1.

The simplest way to detect Granger-causality in a VAR(1)-model is to examine $\mathbf{\Phi}_1$.

$$\begin{pmatrix} x_t \\ y_t \\ z_t \end{pmatrix} = \begin{pmatrix} \phi_{11} & \phi_{12} & \phi_{13} \\ \phi_{21} & \phi_{22} & \phi_{23} \\ \phi_{31} & \phi_{32} & \phi_{33} \end{pmatrix} \begin{pmatrix} x_{t-1} \\ y_{t-1} \\ z_{t-1} \end{pmatrix} + \boldsymbol{\epsilon}_t$$

If all ϕ_{1i} except ϕ_{11} are zero, then (y, z) do not Granger cause x.

3.3. **Econometric Tests for Granger Causality.** Hamilton describes the following econometric test for Granger causality in a bivariate VAR.

Estimate

$$x_t = c_1 + \alpha_1 x_{t-1} + \alpha_2 x_{t-2} + \ldots + \alpha_p x_{t-p} + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \ldots + \beta_p y_{t-p} + \epsilon_t \quad (3)$$

Then conduct an F-test of the null hypothesis

$$H_0 : \beta_1 = \beta_2 = \ldots = \beta_p = 0$$

This test requires the sum of squared residuals from equation (3)

$$RSS_1 = \sum_{t=1}^{T} \hat{\epsilon}_t^2$$

and the sum of squared residuals of a univariate autoregression for x_t,

$$RSS_0 = \sum_{t=1}^{T} \hat{\xi}_t^2$$

where

$$x_t = c_0 + \gamma_1 x_{t-1} + \gamma_2 x_{t-2} + \ldots + \gamma_p x_{t-p} + \xi_t$$

If

$$S_1 = \frac{(RSS_0 - RSS_1)/p}{RSS_1/(T - 2p - 1)}$$

is larger than the 5% critical value for the $F(p, T - 2p - 1)$ distribution the null hypotheses is rejected, i.e. if $S_1 > F_{0.05}(p, T - 2p - 1)$ we draw the conclusion y Granger-cause x.

3.4. **Order Selection.** There are a number of different criteria for choosing the appropriate order p of the VAR process. These are very helpful in the case where one does not know the underlying correct order, assuming that there is such.

Two very common methods are Akaike's final prediction error (FPE) criterion and Schwartz's Bayesian criterion (SBC). Exactly how they work is perhaps not as important as what kind of results one might expect. If the primary interest is to infer the *true* order of the VAR then SBC is the most important since it is a consistent method. Consistent, meaning that the estimator $\hat{p}$ will asymptotically give the true order.

$$\operatorname*{plim}_{T\to\infty} \hat{p} = p$$

If the interest on the other hand is focused on making as accurate predictions as possible, FPE is the most important criterion, since it will minimize the prediction error. In this paper both the order selection criteria return $\hat{p}(\text{SBC}) = \hat{p}(\text{FPE}) = 1$ in all cases, which is reasonable considering that stock returns are included, and they are quite random.

3.5. **Stationarity and Residuals.** An important stability condition for the VAR process is that VAR is covariance-stationary. A VAR(1) model represents a jointly stationary multivariate time series if the eigenvalues of $\mathbf{\Phi}_1$ fall within the unit circle. This is the multivariate equivalence of $|\phi_1|$ in equation (1) being less than one, i.e. not a unit root. If the condition is not satisfied the model would be unsuitable, since it would be instable.

To apply the t-statistics and have faith in the model it is necessary to be convinced that the residuals of the fitted series can be considered unautocorrelated and normally distributed. A Li-McLeod Portmaneu (LMP) test is conducted (Schneider and Neumaier 2001) and the significance level should exceed 5%.

4. Variables and Data

4.1. **Data.** I have chosen to include a set of variables that should capture a large part of the interaction in the financial market that reflects macroeconomic reality. All data used have been retrieved from the EcoWin database, except the long (1961-2001) yearly GDP series, which is taken from Statistics Sweden (SCB).

I have used quarterly data for the GDP since this is the only available. All other data is originally monthly but has been converted to quarterly data, if needed. All data, except stock prices, interest rates and the liquidity index, have been seasonally adjusted. Whether a index of the liquidity index type should be seasonally adjusted can be discussed. In this thesis the liquidity index has not been adjusted, although some additional seasonally adjusted results are found in the appendix. The results that are not found in the appendix have been omitted because of the minimal difference between the seasonally adjusted and unadjusted. Figure A.1 in the appendix shows the liquidity index and its seasonal component. To get the relative changes I have used the customary logarithmic transformation.

$$\Delta X_t = \log X_t / \log X_{t-1}$$

Due to this transformation, a stationary time series is expected. To confirm this I run *Dickey-Fuller* and *KPSS*[7] tests. The tests indicate that stationarity is satisfied.

4.2. **Variables.**

4.2.1. *Monetary Liquidity (LIQ0 and LIQ3).* Monetary liquidity is obviously the most important variable in this study. Finding an exact definition for liquidity is probably impossible since it can include such a large set of measures. I have chosen to work with a measure of the *excess money* in the economy. That is the amount that the monetary supply changes that does not directly reflect a change in the real economy, i.e. the GDP.

$$LIQ3_t = \Delta M3_t - \Delta GDP_t$$

This is the way Baks and Kramer define liquidity in their study of international liquidity flows. It is a good measure, in the sense that it is clearly defined, easy to understand and work with. Its disadvantage is that it is rough and and not very refined.

A problem with this measure is that the GDP time series is not quite consistent. New national accounts were introduced in 1993, which affect how the GDP is measured. Even more important is the regime shift in

[7]Kwiatkowski-Phillips-Schmidt-Schin, this test has the null hypothesis that the time series is stationary, contrary to the D-F test where the null is a unit root.

monetary policy at the time. Because of this I have chosen to start the analysis at 1993.

Both the M0 and the M3 measure of the money supply are tested to see if there is any difference, such as the one Baks and Kramer noticed.

4.2.2. *Stock returns (AFGX).* Swedish stock returns are represented by the return on Affärsvärldens Generalindex (AFGX). The data is sampled monthly.

4.2.3. *Interest rates.* The Swedish short rate (SHORT) is measured as the yield on the 3 month Swedish treasury bill[8]. This data is monthly sampled and availability is not an issue. The long rate (LONG) is measured as the yield on the Swedish 10 year treasury bond. This data is monthly sampled and is only available from the late 1980s.

4.2.4. *Inflation (CPI).* The inflation is measured by the consumer price index (CPI) and is monthly sampled and availability is not an issue.

4.2.5. *CBC Swedish Liquidity Index (SLI).* As a complement to the coarse liquidity measure consisting of money supply and GDP a commercial liquidity index is included. The index comes from the financial research firm CrossBorder Capital (*www.crossbordercapital.com*) and is claimed to reflect a compound measure of central bank liquidity, private sector liquidity, a credit spread indicator and foreign liquidity. Exactly how the index is put together is not revealed, since it obviously is a trade secret. It is in place to be highly sceptical to these kinds of indices. The data is monthly and available between 1980 and August 2001.

TABLE 4.1. Basic properties of the *quarterly* data used.

	MEAN	STD
AFGX	0.0444	0.1081
CPI	0.0029	0.0040
SHORT	-0.0242	0.0999
LONG	-0.0185	0.1027
SLI	-0.0279	0.2307
LIQ0	0.0004	0.0181
LIQ3	-0.0001	0.0205

[8]i.e. Statsskuldväxel

5. Results

5.1. CBC Swedish Liquidity Index and Stock Returns, Monthly Data. In this bivariate VAR(1)-model the two components are the Cross Border Capital Swedish overall Liquidity Index (SLI) and AFGX. I have included both a VAR on data from 1980–2001 and 1993–2001.

It is clear from the coefficient matrix in Table 5.1 that SLI Granger cause AFGX in the 1980–2001 case. The test described in Section 3.3 gives $S_1 = 5.5376 > 3.8782 = F_{0.05}(1, 255)$, which also indicate a Granger causal relationship. The fact that Granger causality is evident in this case should not be given too much weight. This because the system only consists of two variables. It is possible that the relationship will disappear when more explaining variables are included. But it shows that further investigation is called for. From Table 5.1 it is also evident that the liquidity measure is autocorrelated.

To be able to compare the result with the following VARs I have also included the period 1993–2001, which most of the proceeding VARs are based upon. In this case there is no Granger causality at all. The econometric test yield $S_1 = 1.8709 < 3.9371 = F_{0.05}(1, 99)$, which also is suggested by the coefficient matrix.

Because of the significant result above a VAR is also estimated from the 1980-1992 period. One might expect that there would be a significant relationship between stock returns and liquidity in this period, because there is one in the 1980-2001 period but not in the 1993-2001 period. But with $S_1 = 3.1799 < 3.9038 = F_{0.05}(1, 151)$ there is no indication of Granger causality.

5.2. Swedish Liquidity Based on M0, Quarterly Data. This is the first of a number of VARs consisting of more than two variables. The liquidity measure is as previously stated based on the difference between the innovations in M0 and GDP. The data stretch from January 1993 to August 2001, and since the GDP data is sampled quarterly the other data is adjusted accordingly.

The resulting coefficient matrix is shown in Table 5.2. There is a number of statistically significant relationships, but the only variable that has a significant impact on stock returns (AFGX) is inflation (CPI). This relationship is clearly negative, which is in accordance with previous research. The short rate is significantly autocorrelated and is positively related to innovations in stock returns, the long rate and inflation. The long rate is also significantly autocorrelated and negatively related to innovations in the short rate, but positivley related to changes in inflation. None of these findnings is new and is only what is expected. It is also clear that the M0 liquidity measure lacks in predictive power and does not help to explain any other variable included in the VAR.

Table 5.1. The coefficient matrix of the VAR(1) consisting of Swedish Liquidity Index and AFGX. The t-statistic is given in brackets and the 95% critical two-tailed t-value is ± 1.9759 in the 80-92 period, ± 1.9845 in the 93-01 period and ± 1.9693 in the 80-01 period.

	1980–1992			1993–2001	
	$AFGX_{t-1}$	SLI_{t-1}		$AFGX_{t-1}$	SLI_{t-1}
$AFGX_t$	**0.2416**	0.0566	$AFGX_t$	0.0485	0.0917
	(3.0538)	(1.7932)		(0.4798)	(1.3642)
SLI_t	0.0114	**0.6357**	SLI_t	0.0068	**0.7201**
	(0.0690)	(9.6510)		(0.0641)	(10.2479)

	1980–2001	
	$AFGX_{t-1}$	SLI_{t-1}
$AFGX_t$	**0.1648**	**0.0654**
	(2.6664)	(2.3635)
SLI_t	0.0141	**0.6403**
	(0.1300)	(13.1780)

Note:$|\lambda| = \{0.2399, 0.6374\}$ and LMP significance is 0.9235>0.05.
$|\lambda| = \{0.6419, 0.1637\}$ and LMP significance is 0.7335>0.05.
$|\lambda| = \{0.0476, 0.7211\}$ and LMP significance is 0.6118>0.05.

Table 5.2. The coefficient matrix of the VAR(1), when the liquidity measure is based on M0. The t-statistic is given in brackets and the 95% critical two-tailed t-value is $\pm$ 2.0639.

	$AFGX_{t-1}$	$SHORT_{t-1}$	$LONG_{t-1}$	CPI_{t-1}	$LIQ0_{t-1}$
$AFGX_t$	0.1367	0.0305	0.3220	**-12.7582**	-0.7581
	(0.7299)	(0.1476)	(1.5934)	(-2.5190)	(-0.6915)
$SHORT_t$	**0.3721**	**0.3503**	**0.3270**	**13.8466**	1.1350
	(3.2383)	(2.7622)	(2.6368)	(4.4546)	(1.6868)
$LONG_t$	0.2471	**-0.4859**	**0.4908**	**11.1604**	-0.6414
	(1.5863)	(-2.8261)	(2.9182)	(2.6480)	(-0.7031)
CPI_t	-0.0007	0.0105	0.0020	0.3278	-0.0263
	(-0.1110)	(1.4503)	(0.2787)	(1.8388)	(-0.6811)
$LIQ0_t$	-0.0382	-0.0297	-0.0106	-0.6459	-0.2645
	(-1.1104)	(-0.7836)	(-0.2845)	(-0.6947)	(-1.3143)

Note:$|\lambda| = \{0.43, 0.65, 0.65, 0.01, 0.28\}$ and LMP significance is 0.1218>0.05.

5.3. **Swedish Liquidity Based on M3, Quarterly Data.** In this VAR M0 is exchanged for the broader money supply M3 in the liquidity measure. The data stretch from January 1993 to August 2001

The results, shown in Table 5.3, of this VAR is quite similar to the M0 VAR in many respects. Inflation is still the only significant impact on stock returns. The short rate is still positively related to changes in stock returns, the long rate and inflation, but the significant autocorrelation is lost. The long rate relationships still hold, with positive relation to inflation, negative relation to short rate and a positive autocorrelation.

The new and interesting fact about this VAR is that there is a significant relationship between inflation and M3 liquidity. This relationship is negative, which is quite surprising. If the M3 money supply grows faster than the real economy, here proxied for by GDP, one would expect an inflationary pressure rather than the opposite.

TABLE 5.3. The coefficient matrix of the VAR(1), when the liquidity measure is based on M3, Quarterly data. The t-statistic is given in brackets and the 95% critical two-tailed t-value is ± 2.0639.

	$AFGX_{t-1}$	$SHORT_{t-1}$	$LONG_{t-1}$	CPI_{t-1}	$LIQ3_{t-1}$
$AFGX_t$	0.1307	0.0312	0.2978	**-12.3430**	-0.3327
	(0.6807)	(0.1351)	(1.4889)	(-2.4389)	(-0.3078)
$SHORT_t$	**0.4047**	0.2912	**0.3688**	**12.9920**	-0.0575
	(3.2733)	(1.9568)	(2.8638)	(3.9870)	(-0.0826)
$LONG_t$	0.2498	**-0.5041**	**0.4720**	**11.4362**	-0.4620
	(1.5683)	(-2.6296)	(2.8452)	(2.7242)	(-0.5153)
CPI_t	0.0026	0.0018	0.0020	0.3070	**-0.0954**
	(0.4522)	(0.2596)	(0.3230)	(2.0022)	(-2.9146)
$LIQ3_t$	-0.0601	-0.0058	-0.0290	-1.4425	0.0524
	(-1.4683)	(-0.1182)	(-0.6811)	(-1.3367)	(0.2272)

Note: $|\lambda| = \{0.39, 0.68, 0.68, 0.33, 0.33\}$ and LMP significance is 0.3902>0.05.

5.4. **Swedish Liquidity Based on CBC Liquidity Index, Quarterly Data.** The liquidity measure, based on money supply, is a coarse measure and perhaps another more refined measure will yield better results. The results obtained when using CrossBorder Capitals Swedish overall liquidity index (SLI) is shown in Table 5.4.

The result shows large similarity with previous results. The short rate is siginificantly related to the same variables as when the M0 measure was used, i.e. stock returns, inflation, the long rate and it is autocorrelated. There is still a clear negative relationship between stock returns and past changes in inflation. Neither does the SLI have a significant impact on stock returns or inflation. The SLI does not contribute any useful information when quarterly data is used.

5.5. **Swedish Liquidity Based on CBC Liquidity Index, Monthly Data.** Since the SLI is sampled monthly it might be interesting to also

TABLE 5.4. The coefficient matrix of the VAR(1), when the liquidity measure is based on CBC Swedish Liquidity Index, Quarterly data. The t-statistic is given in brackets and the 95% critical two-tailed t-value is ± 2.0639.

	$AFGX_{t-1}$	$SHORT_{t-1}$	$LONG_{t-1}$	CPI_{t-1}	SLI_{t-1}
$AFGX_t$	0.1118	0.0117	0.3154	**-14.8191**	-0.0866
	(0.6091)	(0.0564)	(1.5936)	(-2.5957)	(-0.9267)
$SHORT_t$	**0.4073**	**0.3563**	**0.3455**	**15.8617**	0.0942
	(3.5734)	(2.7708)	(2.8119)	(4.4748)	(1.6237)
$LONG_t$	0.2346	**-0.4042**	**0.4476**	**14.1211**	0.0825
	(1.5436)	(-2.3581)	(2.7322)	(2.9880)	(1.0662)
CPI_t	-0.0018	0.0078	0.0026	0.1548	-0.0064
	(-0.2930)	(1.1396)	(0.3922)	(0.8218)	(-2.0629)
SLI_t	-0.1729	0.0830	-0.1788	-10.5147	**0.4578**
	(-0.4266)	(0.1816)	(-0.4095)	(-0.8345)	(2.2205)

Note: $|\lambda| = \{0.4268, 0.6333, 0.6333, 0.2900, 0.5848\}$ and LMP significance is 0.3237>0.05.

run a VAR on this data. More data points result in better accuracy, but it is also known to sometime change Granger causal relationships. Table 5.5 display the results. When monthly data is used, several of the significant relations that were present using quarterly data disappear. Stock returns are still only affected by changes in past inflation. The short rate is now only autocorrelated, the other relations are lost. This is also the case with the long rate.

The only interesting difference is the liquidity and inflation linkage, which is negative. This relation resembles the negative relation that appeared when M3 liquidity (quarterly) was used.

There is still no apparent linkage between liquidity and stock returns or interest rates. The SLI measure does not seem to contribute any information that could be useful in precion of asset returns.

5.6. **Swedish Liquidity Based on M0 and M3, Yearly Data.** In the other VARs either quarterly or monthly data between 1993 and 2001 was used. Here yearly data streching from 1961 to 2001 is used. Yearly data may be less jagged than monthly or quarterly. A longer time horizon has both its benefits and drawbacks. For prediction purposes data from the distant past may not be very useful, but to asses if a time invariant relationship exist, a long horizon is required. The problem with the GDP data series remain. So the year 1993 is omitted and also note that the way GDP is measured is inconsistent over time. Another problem that makes it difficult to compare with the previous VARs is that the long rate is excluded, since data is not available until the late 1980s.

TABLE 5.5. The coefficient matrix of the VAR(1), when the liquidity measure is based on CBC Swedish Liquidity Index, Monthly data.The t-statistic is given in brackets and the 95% critical two-tailed t-value is ± 1.9853.

	$AFGX_{t-1}$	$SHORT_{t-1}$	$LONG_{t-1}$	CPI_{t-1}	SLI_{t-1}
$AFGX_t$	0.0759	0.0758	0.0096	**-5.6353**	0.0677
	(0.7442)	(0.4676)	(0.0627)	(-2.0529)	(0.9637)
$SHORT_t$	-0.0348	**0.4355**	0.0173	1.4926	-0.0388
	(-0.5657)	(4.4484)	(0.1882)	(0.9002)	(-0.9151)
$LONG_t$	-0.0870	-0.0769	**0.4000**	2.2030	-0.0158
	(-1.2939)	(-0.7195)	(3.9759)	(1.2165)	(-0.3404)
CPI_t	-0.0000	0.0031	0.0044	-0.0018	**-0.0062**
	(-0.0012)	(0.5143)	(0.7721)	(-0.0173)	(-2.3327)
SLI_t	0.0053	-0.2172	-0.0371	-3.4271	**0.6752**
	(0.0497)	(-1.2789)	(-0.2324)	(-1.1912)	(9.1680)

Note:$|\lambda| = \{0.0467, 0.0467, 0.7542, 0.4191, 0.4191\}$ and LMP significance is 0.1218>0.05.

The results, shown in Table 5.6, are quite different from the earlier results. Very few relations are significant. The previous significant stock return and inflation relation has disappered. The only sinificant relations that exist are the inflation autocorrelation and an inflation effect on liquidity. None of these findings are very interesting.

One more significant relation is observed when M0 is exchanged for M3 in the liquidity measure. It is the one between liquidity and the short rate, this is not a very useful finding either.

TABLE 5.6. The coefficient matrix of the VAR(1), when the liquidity measure is based on M0, and yearly data 1961–2001 is used. The year 1993 is omitted, due to missing data. The t-statistic is given in brackets and the 95% critical two-tailed t-value is ± 2.0423.

	$AFGX_{t-1}$	$SHORT_{t-1}$	CPI_{t-1}	$LIQ0_{t-1}$
$AFGX_t$	0.1350	-0.0888	2.3584	-2.1226
	(0.6619	(-0.7856)	(1.4929)	(-1.6613)
$SHORT_t$	0.0669	-0.2209	-1.7434	2.7260
	(0.1940)	(-1.1574)	(-0.6534)	(1.2633)
CPI_t	0.0039	0.0097	**0.6153**	0.1829
	(0.1799)	(0.8091)	(3.6623)	(1.3459)
$LIQ0_t$	-0.0377	0.0036	**0.5588**	0.1445
	(-1.1551)	(0.1996)	(2.2133)	(0.7076)

Note:$|\lambda| = \{0.3886, 0.2953, 0.2953, 0.7774\}$ and LMP significance 0.3241>0.05

TABLE 5.7. The coefficient matrix of the VAR(1), when the liquidity measure is based on M3, and yearly data 1961–2001 is used. The year 1993 is omitted, due to missing data. The t-statistic is given in brackets and the 95% critical two-tailed t-value is ± 2.0423.

	$AFGX_{t-1}$	$SHORT_{t-1}$	CPI_{t-1}	$LIQ3_{t-1}$
$AFGX_t$	0.0393	-0.0867	1.5019	-1.1391
	(0.2008)	(-0.6984)	(1.0066)	(-1.0321)
$SHORT_t$	0.1137	-0.1053	-2.4712	**3.6917**
	(0.3688)	(-0.5390)	(-1.0527)	(2.1257)
CPI_t	0.0085	0.0152	**0.6020**	0.2043
	(0.4301)	(1.2093)	(3.9893)	(1.8303)
$LIQ3_t$	-0.0285	0.0043	**0.6412**	0.0900
	(-0.8216)	(0.1937)	(2.4247)	(0.4599)

Note: $|\lambda| = \{0.2955, 0.2955, 0.2195, 0.8018\}$ and LMP significance $0.4145 > 0.05$

6. CONCLUSIONS

There does not seem to be any evidence of a consistent positive linkage between liquidity and stock returns, which was the hypothesis of this thesis. During certain periods of history the hypothesis may hold, but those kind of short term relationships can usually be found in any data. The previous research in this field, e.g. Baks and Kramer or Conover *et al.*, may have found some relationships, but they have always been very weak. Weak predictive power of macroeconomic variables for stock returns is in no way surprising, first of all, there are numerous more or less complex factors that influence the stock markets movements. Macroeconomic variables may always have some part in the movements, but a factor such as market sentiment may explain more. During the period 1993–2001, which most of the study have been focused on, the macro economic relationships seem to be especially weak, this may have a number of explainations. Shiller (2000) discusses in his book *Irrational Excuberance*, named after Alan Greenspan's famous quote, several aspects that can help explain the unbelievable growth of the market. Factors such as the growth of mutual funds, increased media coverage of business news, change in pension plans, etc. have all lead to a change in sentiment towards the stock market, which made people, even professional investors, believe that stocks were risk free, at least in the long run. The exploding and subsequent collapse of the stock market in the 1996–2002 period indicate that other factors than macroeconomic data influence the stock market valuation. Therefore it is not surprising that a variable such as monetary liquidity does not give any better results.

The second reason why we cannot expect better results from a publicly observable variable such as liquidity is the well known efficient market hypothesis, which in its semi strong form states that all publicly known information already is incorporated in the security prices.

If one still believes in a close relationship between liquidity and stocks, a couple of other methods can be applied to gather further knowledge. Impulse response analysis is very popular to gather more information about causality in a dynamic system. I have not used this extended method, because of the lack of significance in my findings. Another popular method for dynamic system analysis such as a Kalman filter can be used. This approach may give other and perhaps more significant results, because it allows the estimated parameters to be time dependent. There are also certainly a number of ways that one can alter the liquidity measure.

References

Baks, K., and C. Kramer (1999): "Global Liquidity and Asset Prices: Measurement, Implications, and Spillovers," *Working Paper of the International Monetary Fund*.

Conover, C. M., R. Jensen, Gerald, and R. R. Johnson (1999): "Monetary Environments and International Stock Returns," *Journal of Banking & Finance*, 23, 1357–1381.

Darnell, A. C., and J. L. Evans (1990): *The Limits of Econometrics*. Edward Elgar Publishing Ltd., Aldershot.

Epstein, R. (1987): *A History of Econometrics*. North-Holland, Amsterdam.

Fama, E., and G. Schwert (1977): "Asset Returns and Inflation," *Journal of Financial Economics*, 5(2), 115–146.

Fama, E. F. (1981): "Stock Returns, Real Activity, Inflation, and Money," *The American Economic Review*, 71(4), 545–565.

Gertler, M., and S. Gilchrist (1994): "Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms," *The Quarterly Journal of Economics*, 109(2), 309–340.

Geske, R., and R. Roll (1983): "The Fiscal and Monetary Linkage Between Stock Returns and Inflation," *The Journal of Finance*, XXXVIII(1), 1–33.

Granger, C. (1969): "Investigating Causal Relations by Econometric Models and Cross-spectral Methods," *Econometrica*, 37(3), 424–438.

Hamilton, J. (1994): *Time Series Analysis*. Princeton University Press, Princeton, New Jersey.

James, C., S. Koreisha, and M. Partch (1985): "A VARMA Analysis of the Causal Relations Among Stock Returns, Real Output, and Nominal Interest Rates," *The Journal of Finance*, XI(5), 1375–1384.

Lee, B.-S. (1992): "Causal Relations Among Stock Returns, Interest Rates, Real Activity, and Inflation," *The Journal of Finance*, XLVII(4), 1591–1603.

Patelis, A. D. (1997): "Stock Return Predictability and The Role of Monetary Policy," *The Journal of Finance*, LII(5), 1951–1972.

Schneider, T., and A. Neumaier (2001): "Algorithm 808: ARFit – A MATLAB package for the estimation of parameters and eigenmodes of multivariate autoregressive models," *ACM Transactions on Mathematical Software*, 27(1), 58–65.

Shiller, R. J. (2000): *Irrational Exuberance*. Princeton University Press, Princeton, New Jersey.

Sims, C. A. (1980): "Macroeconomics and Reality," *Econometrica*, 48(1), 1–48.

Thorbecke, W. (1997): "On Stock Returns and Monetary Policy," *The Journal of Finance*, LII(2), 635–654.

Appendix A

Figure A.1. Plot of the AFGX and the CBC Swedish Liquidity Index.

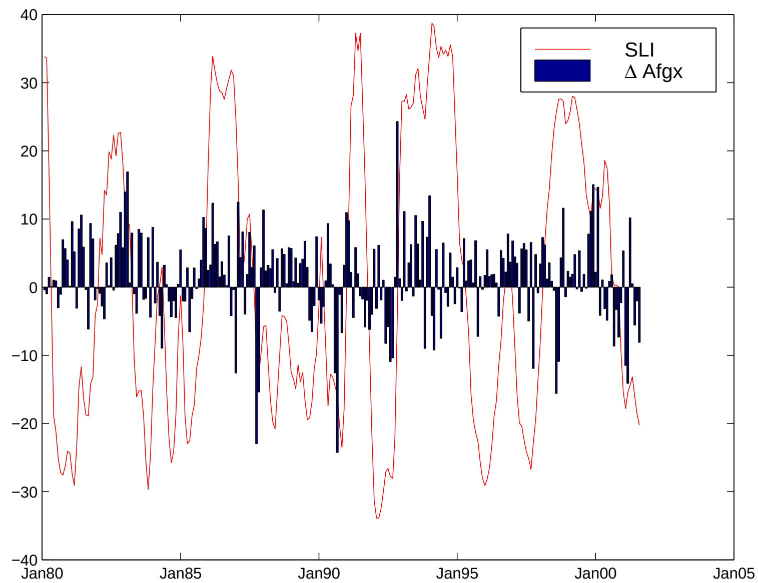

Figure A.2. Plot of AFGX returns and the absolute CBC Swedish Liquidity Index.

A.1. **Seasonally adjusted SLI and AFGX.** Table A.1 shows the interaction between stock returns and the seasonally adjusted SLI. The difference between this result and the seasonally unadjusted result is that the former lack Granger causality in the 1980-2001 period.

TABLE A.1. The coefficient matrix of the VAR(1) consisting of the *seasonally adjusted* Swedish Liquidity Index and AFGX. The t-statistic is given in brackets and the 95% critical two-tailed t-value is ± 1.9759 in the 80-92 period, ± 1.9845 in the 93-01 period and ± 1.9693 in the 80-01 period.

	1980–1992			1993–2001	
	$AFGX_{t-1}$	SLI_{t-1}		$AFGX_{t-1}$	SLI_{t-1}
$AFGX_t$	**0.2574**	0.0312	$AFGX_t$	0.0461	0.0822
	(3.2587)	(0.9888)		(0.4544)	(1.1829)
SLI_t	0.0041	**0.6286**	SLI_t	-0.0246	**0.7370**
	(0.0249)	(9.6284)		(-0.2461)	(10.7721)

	1980–2001	
	$AFGX_{t-1}$	SLI_{t-1}
$AFGX_t$	**0.1749**	0.0445
	(2.8252)	(1.5962)
SLI_t	0.0321	**0.6346**
	(0.2979)	(13.0512)

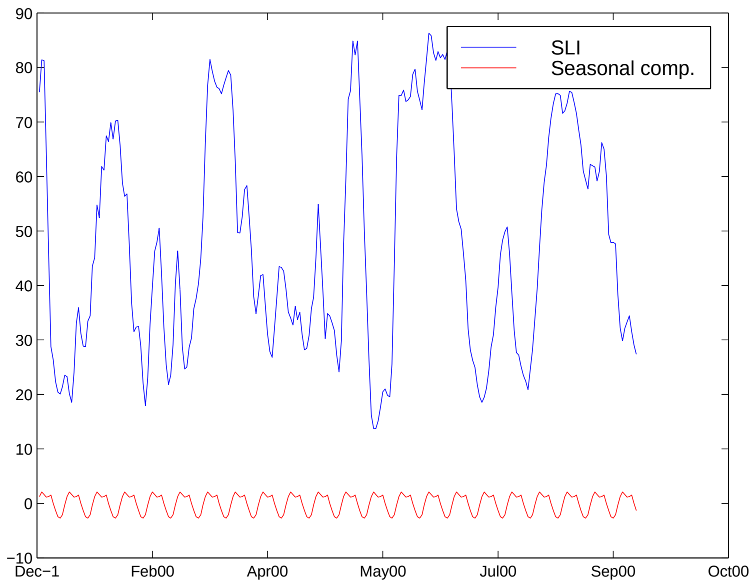

FIGURE A.3. Plot of the SLI and its seasonal component.