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Essays on Stock Return Predictability and Market Efficiency

By

Lei Jiang
Doctor of Philosophy

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Esfandiar Maasoumi, Ph.D.
Advisor

Tetyana Molodtsova, Ph.D.
Advisor

Tarun Chordia, Ph.D.
Committee Member

Stefan Krause, Ph.D.
Committee Member

Richard Luger, Ph.D.
Committee Member

Accepted:

Lisa A. Tedesco, Ph.D.
Dean of the James T. Laney School of Graduate Studies

Date

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Lei Jiang

M.A., Emory University, 2010

M.A., University of Virginia, 2006

M.A., Harbin Institute of Technology, 2005

B.A., Harbin Institute of Technology, 2003

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Committee Member: Richard Luger, Ph.D.

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Abstract

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I explore how the Taylor rule fundamentals affect stock liquidity at the market level and at the individual stock level, commonality in stock liquidity, stock return predictability and financial market efficiency.

In the paper, "Stock Liquidity and the Taylor Rule", I establish the linkage between stock liquidity and real time macroeconomic variables through the Taylor rule. Contractionary monetary policy as indicated by Taylor rule fundamentals changes the funding liquidity and financial constraints faced by market makers in the stock market, which affects their ability and incentive to provide liquidity and commonality in liquidity. A one percentage point rise in the output gap (inflation) lowers market liquidity by 4.3 percentage points (4.6 percentage points). An increase in the output gap (inflation) by one percentage point drives up commonality in liquidity by 1.6% (1%) from the supply side. When commonality of liquidity is evaluated from the demand side, the effect of the Taylor rule is not as strong as the wealth effect.

In the "Stock Return Predictability and the Taylor Rule" paper co-authored with Tetyana Molodtsova, we link the business condition variables to stock returns via monetary policy channels. We use real time data for inflation and output gap, which precisely mimic the decision making environment of investors in the stock market, to test for stock return predictability. The Taylor rule model has higher forecasting ability than the constant return model and long term yield model. The predictability of Taylor rule fundamentals during recent 30 years is robust to different measures of the output gap and different window sizes.

In the paper, "Order imbalance, liquidity and market efficiency: evidence from the Chinese stock market", I evaluate the Chinese stock market efficiency by past stock return information and order imbalance information. Order imbalance may predict returns when there is no designated market maker. It takes longer for information regarding past returns and order imbalance to be incorporated into stock prices in China than in the U.S.. The process of converging to efficiency depends highly on stock liquidity.

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Preface

My research focuses on the financial market and its efficiency. More specifically I am interested in how the business cycle affects stock liquidity at the market level and at the individual stock level, commonality in stock liquidity, stock return predictability and other related stock market microstructure issues such as stock order imbalances.

In my first paper, I examine how Taylor Rule fundamentals affect stock market liquidity. While some papers link stock liquidity to the business cycle and monetary policy, to my knowledge, there is no paper providing evidence on how Taylor Rule fundamentals, i.e. inflation and the output gap, change the liquidity of individual stocks. Moreover, scholars do not know whether business cycle variables have an effect on commonality in stock liquidity.

Stock liquidity measures the ease with which investors can either sell stocks without conceding a large proportion of the price or buy stocks without paying a large price premium. It can be measured from the following five perspectives: width, immediacy, depth, resiliency, and tightness. Chordia, Roll, and Subrahmanyam (2000), Hasbrouck and Seppi (2001) and Huberman and Halka (2001) find that liquidity of different stocks co-move with each other and in response to common factors. The commonality in liquidity measures the effect of common factors on individual stock liquidity. Stock liquidity and commonality in liquidity are central issues in the microstructure of stock markets.

My first paper addresses whether macroeconomic variables and business cycle variables have an effect on the microstructure of the stock market, especially stock liquidity and commonality in liquidity.

Many papers identify microstructure variables, such as exogenous transaction costs, inventory risk for market makers and asymmetric information, as factors which move asset liquidity. A rise in order processing fee, inventory risk, and insider trading can reduce asset liquidity (for example, see Amihud and Mendelson, 1980; Stoll, 1978; Ho and Stoll, 1983; Glosten and Milgrom, 1985; Easley and O'Hara, 1987, 1991; and Back and Baruch, 2004). In addition, funding liquidity and financial constraints faced by market makers from the perspective of liquidity supply can also be determinants of stock liquidity when assuming that liquidity demand is exogenous. Because of decreasing funding availability, market makers have less ability and incentive to provide liquidity to the stocks they specialize in.

Fewer papers address the relationship between stock liquidity and the business cycle and monetary policy. Watanabe (2004) argues that macroeconomic variables are a source of systematic liquidity variation. She finds that market liquidity responds to inflation and the federal funds rate using a vector autoregression model. Goyenko and Ukhov (2009) connect stock market liquidity and bond market liquidity with macroeconomic variables. They find that monetary policy variables first influence short term bond liquidity, through which the shocks to monetary policy transfer to stock liquidity. These papers all examine how macroeconomic variables affect asset liquidity at the stock market level, but to my knowledge, there is no paper on how Taylor rule fundamentals (inflation and the output gap) change the liquidity of individual stocks. Moreover, scholars still do not know whether business cycle variables have an effect on commonality in stock liquidity.

Brunnermeier and Pedersen (2009) provide a theoretical model to explain how a funding liquidity crisis from 2007 transferred to a financial crisis. During the financial crisis, the stock market suffered a sudden loss of liquidity and the co-movement of liquidity increased between different stocks. The main implication of their paper is that a decline in funding liquidity can result in a drop in asset liquidity and an increase in commonality in asset liquidity. With the implicit assumption that monetary policy is the main determinant of funding liquidity in a closed economy, or a big economy like the United States whose funding liquidity is not largely affected by international capital flow, Chordia, Roll and Subrahmanyam (2001) use short and long term interest rates as measures of funding liquidity. Brennan, Chordia, Subrahmanyam and Tong (2009) use the Ted spread, which is the difference between interest rates on interbank loans and short-term U.S. government debt as a measure of funding availability, and find that it is positively related to both buy-side and sell-side illiquidity.

In my paper, I propose that the Taylor rule fundamentals are alternative measures of funding liquidity, since Taylor rule fundamentals are one of the best measures of monetary policy in the United States. According to the Federal Reserve Act, the Board of Governors and the FOMC (Federal Open Market Committee) should promote "maximum employment, stable price and moderate long-term interest rates". Since the last goal can be achieved automatically by decreasing inflation, the Federal Reserve can limit its responsibility to "dual mandate" by targeting inflation and output gap. This dual mandate makes Taylor rule the best guidance for monetary policy. The Taylor rule goals can be achieved by a combination of monetary policy tools including reserve requirements, discount rates, and margin requirements, such as Term Asset-Backed Securities Loan Facility in addition to the federal funds rate. Furthermore, the federal funds rate has a lower bound, and the zero interest rate policy which happened in Japan since 1998 and United States since 2008 makes the federal funds rate not as informative as Taylor rule fundamentals. Therefore, I successfully connect business cycle variables with stock market microstructure using a Brunnermeier and Pedersen (2009) model and Taylor rule fundamentals as the measures of funding liquidity. This new monetary policy path is important since through the path, inflation and output gap (business cycle variables) influence stock liquidity and commonality in liquidity at both the market and individual stock level.

Most of the business cycle variables are periodically revised because of definitional change, the change of benchmark or other statistical reasons. At the time when market participants make investment decisions, only real-time data is available to them. Our Taylor rule model depends on the policy the Federal Reserve formulated with their available information, which makes the real-time data even more suitable for our empirical analysis. Many papers argue that the economically and statistically different results can be achieved using real-time data and revised data. Although most of the previous literature uses revised data on macroeconomic variables, I fill this gap by using real-time data on inflation and the output gap from the Philadelphia Fed Real-Time Database for Macroeconomists to precisely utilize the information available to investors in the stock market and policymakers to avoid forward looking bias.

Using an extensive empirical measures of stock liquidity, including Amihud Ratio by Amihud (2002), return reversal by Pastor and Stambaugh (2003), effective costs by Hasbrouck (2009) and the theory based liquidity measure by Chordia, Huh, and Subrahmanyam (2009), I find that a one percentage point rise in the output gap (inflation) lowers market liquidity by 4.3 percentage points (4.6 percentage points). The result is also robust for stocks with different characteristics. When I form portfolios by market capitalization or individual stock illiquidity levels, I find not only that Taylor rule fundamentals affect stock liquidity in different portfolios but also that the effect of Taylor rule fundamentals on small stocks and illiquid stocks is much higher than large stocks and liquid stocks. My finding provides support for the flight to quality and flight to liquidity phenomena. When contractionary monetary policy is used because of a growth in the output gap or inflation, the funding constraints of market makers tighten. This forces the market makers to provide liquidity only to large stocks and highly liquid stocks, which makes small stocks and illiquid stocks suffer more.

In order to evaluate the effect of Taylor rule fundamentals on commonality in liquidity, I follow the literature and use the market liquidity which is equal-weighted averages of liquidity for all stocks, as common factor of stock liquidity from the supply side. Results indicate that an increase in the output gap (inflation) by one percentage point drives up commonality in liquidity by 1.6% (1%). The results for liquidity level and commonality in liquidity are economically and statistically significant, which effectively supports my Taylor rule extended Brunnermeier and Pedersen (2009) model.

I also provide evidence about how Taylor rule fundamentals change commonality in asset liquidity from the demand side. Koch, Ruenzi and Starks (2010) identify mutual funds as a group of intuitional investors who demand liquidity of stocks at the same time due to shocks in net inflow, net outflow or information. Mutual fund managers simultaneously buy or sell a certain group of stocks and force the relevant stock liquidity to co-move with each other. In Fed model, where stocks and bonds compete for space in a mutual fund's portfolio, an expansion in Taylor rule fundamentals or contractionary monetary policy increases the yield of the bonds, cuts the demand for stocks in general and decreases commonality in liquidity from the demand side if the monetary policy effect dominates the business cycle effect. I follow Koch, Ruenzi and Starks (2010) and use mutual fund ownership, which is the ratio of shares of the stock held by all the mutual funds to all shares outstanding to rank stocks. I pick up the top 25% of stocks highly held by mutual funds to form the portfolio and rebalance the portfolio every quarter. Then I calculate the common factor of liquidity from the demand side by using equal-weighted averages of stock liquidity for the mutual fund highly held portfolio.

I firstly find that a rise in the federal funds rate by 1 percentage point lessens the commonality in liquidity by 2.1% from the demand side, which explicitly supports the Fed model. However, an increase in inflation and the output gap by 1 percentage points boosts commonality in liquidity by 3.4% and 5.5% respectively. An increase in inflation and the output gap indicates that the economy is booming and the representative consumer invests more money both in the stock market and in the bond market in order to smooth consumption. Although the proportion of investment in stock market shrinks, the absolute amount of money grows compared with low Taylor rule fundamental scenarios. It increases the demand for stocks and augments the commonality in liquidity from the demand side. The conclusion that the effect of the monetary policy is not as strong as the wealth effect can be achieved from liquidity demand side.

The above-mentioned empirical results are new and exciting, since they connect macroeconomic variables with the microstructure of stock market liquidity and partially explain the liquidity crisis starting in 2007. Additionally, there is an ongoing debate about whether the Federal Reserve should consider the stock market when it formulates monetary policy. My paper identifies a side effect of monetary policy on stock liquidity. A contractionary monetary policy can cut the funding availability for market makers in the stock market, drive down stock liquidity, and drive up commonality in stock liquidity. Since both the liquidity level and commonality in liquidity affect stock returns (Amihud and Mendelson, 1986 and Acharya and Pedersen, 2004), the Federal Reserve may inject risk in the stock market when it tries to dampen the business cycle and stabilize the economy. Investors should be careful with monetary policy' effect on their asset liquidity and take the shock of monetary policy into account when making their investment choices and form portfolios.

My second paper examines Taylor rule fundamentals and stock market returns. Since Taylor rule fundamentals are more informative than the federal funds rate in predicting stock liquidity, can the output gap and inflation also predict stock returns? Stock returns are not quite as easy to predict, since predictability means arbitrage opportunities. The excessive arbitrage behavior can render the previously useful information redundant. However, the literature on stock return predictability is far from consistent. Although some studies find evidence of out-of-sample predictability with business condition variables (Fama and French, 1989), monetary policy variables (Patelis,1998) and valuation ratios, these findings are not robust to sample period and estimation methodology. Furthermore, Goyal and Welch (2008) exam an extensive list of traditional predictive variables for stock returns and conclude that none of the conventional macroeconomic or financial variables can predict excess returns in-sample or out-of-sample in the past 30 years.

Several recent papers connect exchange rates with the Taylor rule. Engel and West (2006), Mark (2009), Engel, Mark, and West (2007), Molodtsova and Papell (2009), and Molodtsova, Nikolsko-Rzhevskyy, and Papell (2008) examine the predictive information of Taylor rule fundamentals on exchange rates either in-sample or out-of-sample and find that the Taylor rule has a better performance than a constant return model when explaining exchange rate behavior. In the "Stock Return Predictability and the Taylor Rule" paper co-authored with Tanya Molodtsova, we want to find out whether the predictability of stock return by Taylor rule fundamentals is as successful as in predicting exchange rate.

Using monthly and quarterly real-time data from 1970 to 2008, we find that Taylor rule fundamentals can predict stock returns not only in-sample but also out-of-sample, although Inoue and Kilian (2004) argue that in-sample predictability does not necessarily mean out-of-sample predictability, and vice versa. Following Clarida, Gali, and Gertler (1998), we also assume partial adjustment of the interest rate to its target within a period by including lagged interest rate in the model in addition to inflation and the output gap. We find the evidence that stock return predictability is stronger using the Taylor rule model without smoothing than with smoothing in the tests based on first two moments, but it is stronger with smoothing than without based on the dependence test.

In order to evaluate in-sample predictability, we use traditional t-statistics and F-statistics. In addition, we use adjusted R-squared, Akaike's Information Criterion (AIC) and the Bayesian Information Criterion (BIC) to verify that the Taylor rule fundamentals include more predictive information than long term yields. We compare Taylor rule fundamental information with a constant return model using tests based on mean squared prediction error (MSPE) comparisons such as Diebold and Mariano (1995) and West (1996) (DMW test), Clark and West (2006, 2007) and out-of-sample R^2 . We find that with monthly data, predictability of Taylor rule fundamentals on stock return is stronger than with quarterly data and stock return predictability improves toward the end of the sample when the U.S. monetary policy is generally characterized by the Taylor rule. Using the above mentioned statistics, we find that Taylor rule model also statistically outperforms long term yield models. In addition, we test for the dependence of stock returns on Taylor rule predictors using the information about the whole distribution. The Matusita-Bhattacharya-Hellinger measure of dependence by Maasoumi and Racine (2002) is used. The result still indicates that stock return depends on Taylor rule fundamentals.

One of the problems scholars often face is that there is no perfect measure for the output gap. In order to solve this issue, we use extensive estimates of the output gap including a linear time trend detrended output gap, a quadratic time trend detrended output gap, a Hodrick-Prescott (1997) (HP) trend detrended output gap, a Baxter-King (BK) Filter adjusted for the end-of-sample uncertainty for the output gap and the unemployment rate. The robust results give us more confidence that Taylor rule fundamentals indeed include information about stock returns. Since stock prices, which reflect the discounted future dividends, are determined in a forward-looking manner, monetary policy is likely to influence stock prices through the interest rate (discount) channel, and indirectly through its influence on market participants' expectations of the future economic activity, which has an effect on the determinants of dividends and the stock return premium. Using Taylor rule fundamentals information, risk-averse representative investors in the stock market can get higher certainty equivalence than by using a constant return model or a long term yield model.

In my third paper, I compare the U.S. stock market, the most advanced and mature market, with the Chinese stock market, the emerging market in the world's second-largest economy. I evaluate market efficiency by stock return information and order imbalance information. Order imbalance is the difference between the volume of buyer-initiated trades and seller-initiated trades. I calculate the actual speed for the Chinese market to incorporate the order imbalance information. This by itself is quite important to further understand the Chinese stock market and interesting to Chinese policymakers and market participants in China and other countries. Order imbalance information should be more informative than traditionally used trading volume, since order imbalance not only includes information on trading volume, but also includes information about trading direction. However, how useful it is in Chinese stock market still need to be investigated.

Using the unique tick-by-tick data for every security transaction made in the Shanghai and Shenzhen Stock Exchange in 2006, I find that on average it takes more than 15 minutes but less than 30 minutes for the past price information to be incorporated into the current stock price. With the “constant return” asset-pricing model, the Chinese stock market takes more than 15 minutes to converge to weak form efficiency. Compared to the convergence time in the U.S. market, which was less than 5 minutes in 2002 (Chordia, Roll and Subrahmanyam, 2005), the Chinese stock market takes much more time to incorporate past price information.

With respect to order imbalance information, the microstructure difference in the Chinese stock market and the U.S. market renders the comparison even more interesting. There is neither a designated market maker nor specialists to provide liquidity in the Chinese stock market, and according to Chordia and Subrahmanyam (2004), it is the inventory adjustment behavior of risk-averse market makers that generates the predictability of order imbalance. However, I still find the existence of predictability of order imbalance in the Chinese stock market. The predictability indicates that the inventory effect theory may still be valid if people who want to gain the liquidity fee and trade for reasons other than insider information or liquidity demand can be seen as market makers in China. The results show that Chinese stock traders’ propensity to act as a market maker is quite high.

The Chinese stock market is also unique, because the direction of trade is publicly available information released by the exchanges at the moment of trade. This can therefore be observed by every participant in the market. In contrast, in the U.S., this information is kept in the books which can be accessed only by specialists or at most guessed by very sophisticated floor traders. According to Chordia, Roll and Subrahmanyam (2002), this could be seen as private information. From this perspective, the predictability of stock returns in the U.S. by order imbalance would be a violation of strong form efficiency (Fama 1970, 1991). However, the predictability of stock returns in China only reflects the failure of a semi-strong form efficiency. Generally speaking, achieving a strong form efficiency should be more difficult than a semi-strong form. Therefore, it should take more time. However, our results indicate that in China, it takes 15 to 30 minutes to converge to efficiency which is substantially slower than the 5 to 10 minutes needed in the United States (Chordia, Roll and Subrahmanyam, 2005). The result is robust to different econometric models, which brings to question what factors might change the time to converge to efficiency.

Inventory effect models indicate that stock liquidity in the market can be one of the factors that affect the time to converge to market efficiency. When the market is liquid, the market makers can adjust their inventory relatively easily and in a relatively short time, and sophisticated investors can also use the information of past return more quickly. The predictability of order imbalance and past returns in liquid market cannot last as long as in illiquid market. Using the Amihud ratio as measure of liquidity, I provide evidence that the predictability of order imbalance and past returns is stronger when market liquidity declines. The empirical results provide policy implications for the Chinese stock market. The China Securities Regulatory Commission could increase stock liquidity through decreasing the transaction costs in the market to enhance stock market efficiency.

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Chapter1

Stock Liquidity and the Taylor Rule

Lei Jiang

Abstract

Recent theoretical models have linked stock liquidity and commonality in liquidity to the market makers' funding availability and financial constraints from liquidity supply side. This paper establishes the linkage between stock liquidity and real time macroeconomic variables through the Taylor rule, the monetary policy rule that Federal Reserve uses to determine federal funds rate. Tightness in the funding market as indicated by Taylor rule fundamentals changes the funding liquidity and financial constraints faced by market makers in the stock market, which will affect their ability and incentive to provide liquidity. We document the evidence that Taylor rule fundamentals can influence stock liquidity at both the market and individual stock level. We show that a rise in the output gap and inflation lowers stock liquidity. Contemporaneous Taylor rule fundamentals also affect commonality in liquidity from the liquidity supply side. We find that when Taylor rule fundamentals indicate a tighter monetary policy, commonality in liquidity in the stock market intensifies. These results are robust to various measures of liquidity, output gap and specifications of the Taylor rule models. The result is especially important in a ZIRP (zero interest rate policy) situation as in Japan since 1995 and U.S. since 2008. However, when commonality of liquidity is determined by contemporaneous federal funds rate from the liquidity demand side, the effect of the Taylor rule is not as strong as the wealth effect.

Keywords: Stock liquidity, Taylor rule, Commonality in liquidity.

JEL Classification: G10, G21, E58

1. Introduction

The financial crisis from 2007 to the present started from a funding liquidity crisis which quickly spreads to stock market characterized by a sudden loss of liquidity along with the co-movement of liquidity in different stocks within the market. As such, it attracted much research on the determinants of stock liquidity and commonality in liquidity, and potential monetary policy preemption and responses.

Many scholars have studied the factors that affect stock liquidity from the perspective of liquidity supply and generally assume that liquidity demand is exogenous. The determinants of liquidity in the stock market can be due to the market structure and exogenous transaction costs. From the perspective of market makers, sources of illiquidity can arise from inventory risk and asymmetric information (Amihud and Mendelson 1980; Stoll 1978; Ho and Stoll 1983; Glosten and Milgrom 1985; Easley and O'Hara 1987, 1991; and Back and Baruch 2004). In addition, "flight to liquidity" and "flight to quality" identify that current liquidity and fundamental risk are also determinants of future liquidity, since during the period of a liquidity crisis, investors and market makers tend to run to stocks with high liquidity and small risk, thus causing low liquidity and highly volatile stocks to suffer even more (Amihud, Mendelson and Pedersen 2005).

More recent studies have focused on the funding of liquidity and financial constraints faced by market makers. Brunnermeier and Pedersen (2009) provide a theoretical model that links asset liquidity to a market makers' funding availability, which depends on capital and marginal requirement. They argue that a negative funding shock can reduce stock liquidity, and potentially result in a liquidity spiral. Many researchers have attempted to identify the determinants of stock liquidity. Hameed, Kang, and Viswanathan (2010) argue that stock market return is a determinant of liquidity, since negative stock market returns lessens the funding available to market makers and drives down the asset liquidity. Comerton-Forde, Hendershott, Jones, Moulton and Seasholes (2010) on the other hand argue that the market-maker's inventory and revenue are also determinants of stock market liquidity, since too much inventory and too little revenue impose a constraint on the funding availability for the market maker. The effect is nonlinear, and it is especially significant when the market maker faces a large loss or takes large inventory.

Several papers also try to link stock liquidity to the business cycle and monetary policy. Chordia, Roll and Subrahmanyam (2001) find that short and long term interest rates influence stock market liquidity. Watanabe (2004) argues that macroeconomic variables can also be sources of systematic liquidity variation. She examines the effects of an extensive list of macroeconomic fundamentals on stock market liquidity using a Vector Autoregression model and concludes that market liquidity responds to inflation and the federal funds rate. Goyenko and Ukhov (2009) connect liquidity in both the stock and bond market with macroeconomic variables. They find that monetary policy variables first influence short term bond liquidity, through which the shocks to monetary policy transfer to stock liquidity. According to Chordia, Sarkar, and Subrahmanyam (2005), both stock and bond market liquidity exhibits seasonality and day of the week effect, and they are significantly correlated with each other. In addition, they find the effect of the federal funds rate surprise on liquidity. Brennan, Chordia, Subrahmanyam and Tong (2009) use the Ted spread as measure of funding availability and find that it is positively related to both buy-side and sell-side illiquidity. Næs, Skjeltorp, Ødegaard (2010) connect business cycle variables and stock market liquidity from an opposite direction finding that stock market liquidity is the leading indicator for the business cycle. The predictive information in liquidity for economic growth is not nested in many other stock market variables such as excessive market return, market volatility, term spread, and credit spread.

According to Acharya and Pedersen (2005), commonality in liquidity is one of asset pricing factors. Chordia, Roll, and Subrahmanyam (2000), Hasbrouck and Seppi (2001) and Huberman and Halka (2001) have documented the existence of commonality in liquidity. Coughenour and Saad (2004) argue that the existence of commonality in the liquidity of stocks is due to specialists sharing capital and information within specialist firms. If these specialist firms had deeper pockets, the commonality in liquidity would disappear as the financial constraint is no longer binding. Brunnermeier and Pedersen (2009) also suggest that capital tightness can explain commonality in liquidity: when capital constraint is tight, more co-movement of liquidity in different stocks can be observed. Hameed, Kang, and Viswanathan (2010) use stock market returns as a measure of funding liquidity and conclude that when stock market returns decrease, commonality in liquidity grows.

This paper studies the empirical implication of Taylor (1993) rule, the rule Federal Reserve uses to determine federal funds rate, on stock liquidity and commonality in liquidity from both the liquidity demand and supply side. According to the Federal Reserve Act, the Board of Governors and the FOMC (Federal Open Market Committee) should promote “maximum employment, stable price and moderate long-term interest rates”. Since the last goal can be achieved automatically by decreasing inflation, the Federal Reserve’s “dual mandate” with federal funds rate as primary monetary policy instrument makes Taylor rule the best guidance for monetary policy. The objective of this paper is fourfold. First, we link the macroeconomic fundamentals to stock market microstructure by evaluating the response of stock market liquidity to Taylor rule fundamentals such as inflation and output gap using real time data. Second, we illustrate how the Taylor rule influences individual stock liquidity. Thirdly, we studied determinants of stock liquidity and commonality in liquidity, especially in a ZIRP (zero interest rate policy) situation as in Japan since 1995 and U.S. since 2008. Fourthly, we provide evidence on how the Taylor rule fundamentals influence commonality in liquidity through the liquidity demand and supply and how this effect compares with the wealth effect.

Starting with Taylor (1993), the interest rate reaction function where the nominal interest rate responds to the difference between inflation and its target, the output gap, the equilibrium real interest rate, and (sometimes) the lagged interest rate and real exchange rate, has become a prevailing method for evaluating monetary policy. Several recent papers connect Taylor-type monetary policy rules and asset price models. Jiang and Molodtsova (2010) found the Taylor rule fundamentals have predictive power for stock market return. Engel and West (2006), Mark (2009), Molodtsova and Papell (2009) and Molodtsova, Nikolsko-Rzhevskyy, and Papell (2008) examine the empirical performance of Taylor-rule based exchange rate models and find that the Taylor rule variables have a potential for explaining exchange rate behavior both in-sample and out-of-sample.

In this paper, we use monthly real-time data from 1965 to 2008 to examine the relationship between stock liquidity and Taylor rule variables in the U.S.. The purpose of the Taylor rule is to dampen the business cycle and stabilize the economy. In order to mitigate any effect of the output gap and inflation as business cycle indicators, and to achieve a relatively clean effect of monetary policy, we utilize monthly data. The Taylor rule model of market liquidity is derived by substituting the Taylor rule fundamentals for the U.S. federal funds rate. The results indicate the presence of effect of Taylor rule fundamentals on stock liquidity, especially, in a ZIRP (zero interest rate policy) situation, when federal fund rate is not as effective as before. The Taylor rule implied federal fund rate could be achieved by central bank lending facilities such as Term Asset-Backed Securities Loan Facility (TALF). Since Clarida, Gali, and Gertler (1998), it has become common practice to assume a partial adjustment of the interest rate to its target within a period. To incorporate gradual adjustment of the federal funds rate, we include lagged interest rates in the model in addition to inflation and the linear output gap or unemployment rate. Alternatively, we can derive a model with no smoothing that does not include the lagged interest rate.

Although it makes sense to evaluate liquidity models using real-time data which reflects available information to market participants when they form their expectations, most of the previous literature uses revised data on macroeconomic variables. We fill this gap by using real time data on inflation and output gap to precisely utilize the information available for investors in the stock market and avoid forward looking bias. Since our Taylor rule model depends on the policy the Federal Reserve made with their available information, it makes the real time data even more suitable for our empirical analysis.

The estimated output gap depends on one’s measure of potential output. The linear output gap can be calculated as the percentage deviation of actual output from a linear time trend. Alternatively, Blinder and Reis (2005) measure the output gap as the difference between the unemployment rate and natural rate of unemployment. We find that when the output gap and inflation goes up, market liquidity goes down. Moreover, from the liquidity supply side, a rise in the output gap and inflation also raises commonality in liquidity, as the federal funds rate is driven up by the Taylor rule, thus tightening the financial constraint for market makers. From the demand side, when federal funds rate goes up, the "Fed model" would result in a fall in stock demand and a decrease in the severity of commonality in liquidity. However, empirical evidence shows that effect of inflation and output gap on commonality in liquidity actually counters the implication of "Fed model", since the wealth effect overweighs any effect from monetary policy (Taylor rule). To our best of knowledge, no paper has previously attempted to provide evidence for the stock liquidity and commonality in liquidity's reaction to business condition variables via the Taylor rule.

The rest of the paper consists of seven sections. In section 2, we introduce the financial market liquidity model and hypothesis in our empirical research. In section 3, we describe the data sources and measurements for stock market liquidity. In section 4, we provide evidence on the Taylor rule's influence on stock market liquidity. In section 5, we provide support that the Taylor rule influences liquidity of individual stocks. In section 6, we check the robustness of our model with different measurements of market liquidity. Then we form a portfolio by market capitalization and liquidity of stock to see the effect of Taylor rule fundamentals on stocks with different characteristics. In section 7, we test whether the Taylor rule affects commonality in liquidity in the stock market from demand and supply side. Section 8 concludes.

2. Model of Liquidity with Taylor rule

Funding liquidity is not only important to market makers in specialist firms, but it is also important to other investors who behave like a market maker, such as hedge funds and investment banks. A monetary policy shock can influence the funding availability to all of them. Specifically, the funding cost to market makers including the cost to finance inventory and the cost of margin depends on the current short term borrowing interest rate. For example, when a certain seller arrives at the stock market, a market maker can take her sell order for a future resell, if there is no buyer available at that time. The market maker needs capital (or margin) to provide this liquidity. The capital availability for her depends on the interest rate. When the interest rate goes up, the funding cost grows. This creates an incentive for the market maker to widen the spread, lessening stock market liquidity (Chordia, Roll, and Subrahmanyam 2001). The Federal funds rate which is the overnight rate for interbank borrowing is a good proxy for the interest rate faced by market makers.

$$IL_t = \alpha + \beta \times i_t + \varepsilon_t \qquad (1)$$

where i_t is federal funds rate, the interest rate on loans from banks with excess reserves to banks with insufficient reserves. A $\beta > 0$ indicates that the raise in federal funds reduces stock liquidity.

Following Taylor (1993), the central bank should set the federal funds rate in response to inflation gap and output gap

$$i_t^* = \pi_t + \phi(\pi_t - \pi^*) + \gamma y_t + r^* \qquad (2)$$

where i_t^* is the target level of the federal funds rate with the zero as lower bound, π_t is the inflation rate, π^* is inflation target, y_t is the output gap, defined as a percent deviation of actual output from an estimate of its potential level, and r^* is the equilibrium level of the real interest rate. It follows that $\phi > 0$ and $\gamma > 0$, since stabilizing the economy requires the central bank to raise the federal funds rate when inflation and/or output is above the target.

We can combine π^* and r^* in equation (2) into a constant term, $\mu = r^* - \phi\pi^*$. The short term nominal interest rate follows the equation

$$i_t^* = \mu + \lambda\pi_t + \gamma y_t \qquad (3)$$

where $\lambda = 1 + \phi$.

Following Clarida, Gali and Gertler (1998), we allow for the possibility that the interest rate adjusts gradually to achieve its target level as follows

$$i_t = (1-\rho)i_t^* + \rho i_{t-1} + v_t \qquad (4)$$

where $0 \leq \rho < 1$. Substituting equation (3) into (4), gives the following equation,

$$i_t = (1-\rho)(\mu + \lambda\pi_t + \gamma y_t) + \rho i_{t-1} + v_t \qquad (5)$$

To derive the Taylor-rule-based equation for stock liquidity, we substitute equation (5) into equation (1). The Taylor Rule model with smoothing is then

$$IL_t = \omega + \omega_\pi \pi_t + \omega_y y_t + \omega_i i_{t-1} + \eta_t \qquad (6)$$

Where $\omega_\pi = \beta \times (1-\rho)\lambda > 0$, $\omega_y = \beta \times (1-\rho)\gamma > 0$, and $\omega_i = \beta \times \rho > 0$

If the interest rate adjusts to its target level within a period, $\rho = 0$. Then, the Taylor Rule model without partial adjustment assumption would become.

$$IL_t = \omega + \omega_\pi \pi_t + \omega_y y_t + \eta_t \qquad (7)$$

As liquidity is persistent over time (Amihud 2002), then

$$IL_{t+1} = c + d \times IL_t + u_{t+1}$$

$$IL_{t+1} = c + d(\omega + \omega_\pi \pi_t + \omega_y y_t + \omega_i i_{t-1} + \eta_t) + u_{t+1} \quad (8)$$

applying equation (6). Equation (8) can also account for stock liquidity responses to monetary policy shock with a lag (Goyenko and Ukhov 2009), since the shock first influences short-term bond liquidity and through which it transfers to stock liquidity. The Taylor rule model can also be written as

$$IL_{t+1} = c + d(\omega + \omega_\pi \pi_t + \omega_y y_t + \eta_t) + u_{t+1}$$

if we use equation (7).

Therefore, the first set of testable null hypotheses is whether the coefficients on inflation and output gap are smaller or equal to zero, since according to the model, the increase of Taylor rule fundamentals should raise the federal funds rate, and drive up stock illiquidity.

An increase in the interest rate (or Taylor rule fundamentals) tightens the market maker's capital constraint. This would then result in higher commonality in liquidity, measured by the covariance of individual stock liquidity and the common factor of liquidity which is usually stock market liquidity (Brunnermeier and Pedersen 2009; and Coughenour and Saad 2004). The second set of testable hypothesis is whether the federal fund rate and Taylor rule fundamentals are the determinants of commonality in liquidity.

$$IL_{i,t} = c + d \times IL_{m,t} + w \times IL_{m,t} \times i_t + u_t$$

where $d > 0$, according to Hameed, Kang, and Viswanathan (2010) and Chordia, Roll, and Subrahmanyam (2000). Substituting i_t with equation (5),

$$IL_{i,t} = c + d \times IL_{m,t} + w \times IL_{m,t} \times [(1-\rho)(\mu + \lambda \pi_t + \gamma y_t) + \rho i_{t-1} + v_t] + u_t$$

The second testable null hypothesis is that the coefficients before interaction term of market liquidity with inflation and output gap are smaller or equal to zero (the opposite sign with coefficient of common factor). In this case, the increase in of Taylor rule fundamentals raises the federal funds rate, which drives up commonality in stock liquidity.

Koch, Ruenzi and Starks (2010) explain commonality in liquidity from the demand side. They identify mutual funds as a group of intuitional investors who demand liquidity of stocks at the same time due to shocks in net inflow, net outflow or information. These shocks create a sudden demand for stock liquidity by mutual funds. Since they simultaneously buy or sell a certain group of stocks, the correlated trading of mutual funds can force the relevant stock liquidity to co-move with each other. In order to link our Taylor rule model with the commonality in liquidity, we utilize the "Fed model" where stocks and bonds compete for space in a mutual fund's portfolio. In equilibrium, the yield of the stock market is positively linear correlated with the yield of the bonds.

$$E(\frac{e_t}{p_t})^* = \alpha_d + \beta_d \times lty_t$$

where $\beta_d > 0$, lty is the long term yield of the bond; $\frac{e_t}{p_t}$, the earnings price ratio, is the yield of the stocks. We substitute the long term yield with the summation of the term spread and federal funds rate. Assuming exogenous stock yield for monetary policy shocks, a positive shock to the federal funds rate would increase the attractiveness of bonds. The correlated trading of mutual funds should be less severe and decrease the commonality in liquidity. This shock to the federal funds rate can be driven by shocks to the Taylor rule fundamentals. Therefore, an increase in inflation or output gap is equivalent to an elevated federal funds rate and lower commonality in liquidity. $IL_{mutual,t}$ is the liquidity of the portfolio which is highly held by mutual fund. Thus,

$$IL_{i,t} = c_m + d_m \times IL_{mutual,t} + w_m \times IL_{mutual,t} \times i_t + u_t$$

where $d_m > 0$. Substituting i_t with equation (5)

$$IL_{i,t} = c_m + d_m \times IL_{mutual,t} + w_m \times IL_{mutual,t} \times [(1-\rho)(\mu + \lambda\pi_t + \gamma y_t) + \rho i_{t-1} + v_t] + u_t$$

The null hypothesis becomes that coefficients on interaction term of liquidity of stocks highly held by mutual fund with inflation and output gap are greater or equal to zero (the same sign with coefficient of common factor). The upsurge in the Taylor rule fundamentals raises federal funds rate. Then the increased federal funds rate diminishes commonality in liquidity from the demand side.

3. Data

We utilize monthly data spanning November, 1965 to November, 2008 for the macroeconomics variables. The period when the Federal Reserve uses Taylor rule or Federal Reserve's behavior can be explained by Taylor rule is a debated issue. Orphanides (2003) shows that using real time data, the U.S. monetary policy can be described by Taylor rule since 1951 Treasury-Federal Reserve Accord. According to Glarida, Gali and Gertler (2000) and Rudebusch (2006), the monetary policy during Greenspan's era can be empirically explained by Taylor rule. The discretion Greenspan used can fit into the forward-looking Taylor rule category where Greenspan uses forecast of Taylor rule fundamentals for preemption (Orphanides 2003). Real output, inflation, federal funds rate (FFR) and the unemployment rate of real-time data for the U.S. is taken from the Philadelphia Fed Real-Time Database for Macroeconomists. We use the seasonally adjusted industrial production index as a proxy for U.S. output since GDP data are available only at the quarterly frequency. We use the GDP Deflator to measure inflation, calculated as a 12-month difference in the log of the price levels measured by GDP Deflator. The estimated output gap depends on the measure of potential output. We use the most commonly used detrending technique where the output gap is constructed by taking the residuals from an OLS regression of the log of real output, y_t on a constant term and a linear time trend, $X = [1, t]$. The detrending method decomposes the log of real output, y_t , measured by the real GDP, into a trend component, T_t , and a cycle component, c_t :

$$y_t = T_t + c_t$$

The reason why we use linear output gap (quadratic output gap gives similar result) rather than output gap based Hodrick-Prescott (HP) Filter or Baxter-King (BK) Filter, is that HP filter is not available until 1981, and BK Filter is not available until 1999. Linear output gap was the leading method for Federal Reserve to evaluate output gap in 1970s. Furthermore, according to Nikolsko-Rzhevskyy and Papell (2009), the real time output gap from linear trend is closer to the output gap implied by Okun's Law than the output gap based on HP filter and Baxter-King (BK) Filter in 1970s.

Alternatively, the difference between the unemployment rate and the natural rate of unemployment (cyclical unemployment) can measure the output gap. We use only real time unemployment rate as in Blinder and Reis (2005) to analyze the effect of Taylor rule fundamental on stock liquidity, when we assume the natural rate of unemployment is constant over time. Since the accurate way to estimate the natural rate of unemployment appears about 1997 by Staiger, Stock and Watson, in the real time when policymakers made their decisions about monetary policy, the information of estimated natural rate of unemployment is not available to them. Furthermore, natural rate of unemployment is relatively stable over time compared with real unemployment rate.

All the real time data in month t reflect values for month t-1. The descriptive statistics for our monthly variables are in Table 1.1. Inflation, the linear output gap, unemployment rate, and federal funds rate are all in percentages. During this period, the average inflation rate is about 3.85% for each month and the linear output gap is about -4.24%. The unemployment rate is 5.87% and the average of federal funds rate is 6.39%.

In order to assess stock liquidity, we apply the following four estimates.

1. Amihud Ratio: the liquidity ratio, $L_{id} = \frac{|r_{id}|}{dv_{id}}$ is proposed by Amihud (2002) makes use of the information within changes in the stock price and trading volume, as a proxy for the stock illiquidity. Intuitively, it evaluates the price impact of a unit order flow. L_{id} is calculated as the ratio of absolute change of price to the dollar trading volume for stock i at day d. In an illiquid market, the change of price is larger for a certain amount of order flow. A rise in L_{id} indicates higher illiquidity. The monthly liquidity ratios we use are the daily average of the liquidity ratio for each stock. The data is from November, 1965 to November, 2008. The market liquidity is equal-weighted average of Amihud ratio for individual stock.

2. Return reversal (Pastor) as defined by Pastor and Stambaugh (2003) measures liquidity using the daily ordinary least squares estimates of $rrev_{id}$

$$r_{i,d+1}^{e} = \alpha_i + \beta_i r_{i,d} + rrev_{id} sign(r_{i,d}^{e}) dv_{id} + \varepsilon_{i,d+1}$$

here $r_{i,d}$ is the return of stock i at day d . $r_{i,d}^{e}$ is the return of stock i at day d in excess of market returns for that day. Intuitively, it is the change of price for stock i at day d that cannot be justified by market return. $sign(r_{i,d}^{e})dv_{id}$ is the sign of $r_{i,d}^{e}$ times dollar trading volume for stock i on day d . $rrev_{id}$ measures the future return of a stock that cannot be explained by the current return and market returns. It adjusts for the dollar trading volume. When the liquidity falls, the absolute value of the excess return from order flows becomes larger due to a greater impact of order flows on stock price. Usually $rrev_{id}$ is negative, which means a reversal of stock return. The monthly $rrev_{id}$ we are using is the average of the daily estimates. The data from November, 1965 to November, 2008 is taken from Lubos Pastor's website. The market liquidity is equal-weighted average of $rrev_{id}$ for individual stocks. In order to address non-stationarity, they scale the market $rrev_{d}$ by $\frac{m_t}{m_1}$, where m_t is the total dollar value of stocks at the end of month of $t-1$ and m_1 as the total dollar value of stocks for August 1962.

3. $Ctaq$ is the trade-weighted average of effective costs of all trade for each stock. Effective cost is defined as the log difference between the transaction price and the quote midpoint from TAQ data set. The market effective cost sample includes 150 stock from Nasdaq and 150 stocks from

NYSE/AMEX. The stocks are randomly drawn from each portfolio based on market capitalization and the portfolio is rebalanced each year. Market illiquidity would then be the cross-sectional equal-weighted average of effective costs of individual stocks for a given month. The monthly data from January, 1993 to December, 2005 is taken from Joel Hasbrouck's website.

4. Z is the statistical common factor of effective cost for 150 stocks from NYSE/AMEX (before 1985), 150 stocks from Nasdaq and 150 stocks from NYSE/AMEX (after 1985). These stocks are also randomly drawn from each portfolio based on market capitalization and the portfolio is rebalanced each year. Hasbrouck (2009) extended the Roll model of effective costs by adding excess market return in the linear model. The effective cost of each stock is estimated by the Gibbs sampler using CRSP data. Z is then estimated from a latent common factor model using effective cost from each above mentioned stock. We use Z in order to determine whether Taylor rule fundamentals are related to common factors of stock liquidity. The monthly data from November, 1965 to December, 2005 is also from Joel Hasbrouck's website.

5. The theory based liquidity measure (Chordia, Huh, and Subrahmanyam 2009) is the structural estimate of Kyle's (1985) lambda scaled by the current price. In month t for each stock, it is defined as

$$\frac{\lambda_t}{p_t} = \frac{N_t^{\,0.5} std\,(R_t)}{(N_t + 1) std\,(z_{t-1})}$$

where $std(R_t)$ is the standard deviation of the stock's return. To estimate it, we exploit daily returns to calculate the standard deviation of monthly returns. $std(z_{t-1})$ is the standard deviation of the uninformed order flow. If we assume normally distributed uninformed trading orders with zero mean, then $std(z_{t-1})$ is the proportion to the expected absolute value of order flow. Therefore, we use average trading volume to approximate it. N_t is the number of informed traders, which can be estimated by the number of analysts following a stock plus one (to avoid a zero dominator). Since there are many extreme observations in the sample, the data is square rooted. The data is from January, 1972 through December, 2002. Market illiquidity is the cross-sectional equal-weighted average of liquidity of individual stocks in a certain month. On average we have 2094.2 stocks in each month, with a minimum of 1837 and a maximum of 2338.

The descriptive statistics for different measures of market liquidity are in Table 1.1. The Amihud ratio is extremely small, since there is a large difference in magnitudes between changing stock prices and dollar trading volume. The average liquidity measure by Pastor and Stambaugh (2003) is -0.033, indicating a reversal in stock return. The magnitude of $Ctaq$, Z and the square root of our theory based liquidity measure are at conventional levels.

Mutual fund ownership (MFO) for an individual stock is calculated as the ratio of shares of the stock held by all the mutual funds to all shares outstanding. The liquidity of a portfolio highly owned by a mutual fund (MLIQU) is calculated as the top quarter of equal-weighted average of liquidity in individual stocks that are owned by mutual funds. On average, the portfolio includes about 298 stocks each month. This sample includes January, 1980 to December, 2002.

In table 1.2, we show that the contemporary correlations between different variables. Amihud ratio, $Ctaq$, Z and theory based liquidity measure are all positively correlated. The correlation between the Amihud ratio and theory based liquidity measure is as high as 0.83. The correlation between Amihud ratio and $Ctaq$ is as high as 0.87. The reason why liquidity as measured by Pastor is negatively correlated with other liquidity measures is that most of the observations in Pastor are negative. The federal funds rate is positively correlated with all illiquidity measures (except Pastor's), since the growth of the federal funds rate indicates a tight funding constraint for market makers and low liquidity in the stock market. Inflation and linear output gap are also positively correlated with stock market illiquidity, which directly follows from the Taylor rule. Finally, linear output gap and unemployment rate are negatively correlated, and most of the macro variables are highly correlated with the expected sign.

4 Empirical Results

4.1 Taylor rule and stock market liquidity

We calculate the market liquidity by taking equal-weighted average of liquidity for individual stocks. In order to test if there is a unit root in the time series, we utilize the Philips-Perron test, augmented Dickey-Fuller test and Dickey-Fuller test with generalized least-squares regression. We find that inflation, the unemployment rate and federal funds rate, and theory based market liquidity cannot reject the unit root hypothesis at conventional level. Therefore, we took differences for each of these variables which insured stationarity. The result using levels are qualitatively similar and available upon request.

In table 1.3, we run the predictive regression with the theory based liquidity measure as the dependent variable and Taylor rule fundamentals as independent variables. In order to insure that any effect is truly from Taylor rule fundamentals on stock liquidity, we lag the Taylor rule fundamentals. In table 1.3, when the linear output gap increases by 1% (unemployment rate goes down by 1%), the future market illiquidity goes up by 0.23% (by 4.6%). If inflation increases by 1%, the future market illiquidity increases by 3.5% (linear output gap), or 4.3% (output gap defined by the unemployment rate). The result is statistically and economically significant. High linear output gap and inflation compel the Federal Reserve to increase the federal funds rate, which tightens the market makers' financial constraint. It then reduces market makers' incentive to provide liquidity, which cuts down the liquidity in the whole stock market. A rise in the unemployment rate pressures the Federal Reserve to cut the federal funds rate in order to stimulate the economy. This frees the market makers from their funding constraint and improves stock market liquidity. If we impose a partial adjustment assumption, past federal funds rate correlates positively with stock market liquidity. The marginal effect is about 2.7% for various output gap measurements. When the past federal funds rate increases by 1%, the future stock market illiquidity increases by 2.7%, since the Federal Reserve cannot adjust federal funds rate so quickly and constraining market maker funding. The adjusted R-squared can be as high as 5.4%, which indicates that about 5.4% of the variability in stock market liquidity can be explained by Taylor rule fundamentals. The overall strong effect of Taylor rule fundamentals on stock market liquidity can also be confirmed by F-statistics, which tests null hypothesis that all of the coefficients of Taylor rule fundamentals jointly equal zero.

The result for unemployment rate is different from the result found by Næs, Skjeltorp, Ødegaard (2010). In their paper, they treat stock market liquidity as the leading indicator for the economy (unemployment rate). Using quarterly data, they conclude that increases in illiquidity raises the unemployment rate. Taylor rule fundamentals such as inflation, linear output gap and unemployment rate have two roles. Firstly, they can identify the position of the economy in the business cycle (Næs, Skjeltorp, Ødegaard 2010). Secondly, they are used as an indicator in Taylor rule for Federal Reserve to form monetary policy which dampens the business cycle and stabilizes the economy. Given these two channels for Taylor rule fundamentals to influence stock liquidity, opposite conclusions may arise from monetary policy and business cycle perspectives. Therefore, we would like to decide to what extent inflation and output gap influence stock market liquidity through Taylor rule channel.

In order to test whether Taylor rule fundamentals affect stock liquidity only through federal funds rate as shown in equation (1) and the Taylor rule itself (equations 3 or 5), we adopt the similar methodology as used by Hansen and Singleton (1983) and Hall (1988) who test the validity of the Consumption Capital Asset Pricing Model (CCAPM). In the linear framework, we use lag of inflation, linear output gap, and unemployment rate and twice lagged the federal funds rate (The result is similar when using first lag of federal funds rate) as instrumental variables for the current federal funds rate. These variables are good candidates for instrumental variables since lagged macroeconomic variables are predetermined and Taylor rule fundamentals are correlated with the federal funds rate. The result is similar, if we utilize lag of federal funds rate as endogenous variable and 2nd lag of inflation, linear output gap, unemployment rate, and second or third lag of federal funds rate as instrumental variables.

We use control function approach to do the test. In the first stage, we regress the federal funds rate on lagged Taylor rule fundamentals. Then, we regress stock liquidity on the fitted federal funds rate from the first stage to acquire the residual which is the part of illiquidity that cannot be explained by fitted federal funds rate. Finally, we want to test the null hypothesis that the lagged Taylor rule fundamentals cannot predict residuals from the second stage, which is equivalent to saying that the information available in the Taylor rule fundamentals at time t is not able to predict stock liquidity at time t+1 after accounting for the extent to which they predicts federal funds rate. Rejection of the null suggests that the Taylor rule fundamental's relationship with liquidity is through not only the federal funds rate but also from other channels. Our statistics are similar to Basmann's statistics (Basmann 1960) (Sargan (1958)'s statistics give similar results), if we apply Chi-square statistics to test the null in the last OLS regression. In this section, we did not use difference variables, since nonstationary will only affect t-statistics and inference in OLS regression. We just detrend illiquidity. The results are in the tables 4 and 5.

With linear output gap and inflation in the first stage, the R-squared is 0.48 for the model with no smoothing (Table 1.4). The signs of estimated coefficient are as expected (equation 3). Using Basmann and Sargan statistics, the null hypothesis that Taylor rule fundamentals' relationship with liquidity is through the federal funds rate only cannot be rejected. Appling unemployment rate and inflation in the first stage, the R-squared is as 0.46 for the model with no smoothing. In this case, the null hypothesis that Taylor rule fundamentals link with liquidity through only federal funds rate can be rejected at 1% level. We suspect that it is unemployment rate that predicts the residual, which means it affects stock liquidity not only through the federal funds rate, but also through other channels (for example, business cycle channel). The assertion is confirmed by C statistics (distance difference statistics) reported in table 1.5. In the first stage, we regress the federal funds rate on the lag of linear output gap, unemployment rate and inflation. The unemployment rate becomes redundant after including linear output gap, since we cannot reject redundancy by Breusch et al. (1999)'s redundancy statistic (the p-value for the statistics is 0.961). The C statistics which tests whether the unemployment rate can predict residual is as high as 41.7. Thus, we can reject that unemployment rate is uncorrelated with the residual at 1% level. After excluding the lagged unemployment rate, lagged inflation and linear output gap is unable to predict the residual.

When considering a model with smoothing (equation (5)), as shown in table 1.4, Taylor rule fundamentals are still good predictors, with a high R-squared in the first stage and expected signs for each estimated coefficient. Using Basmann and Sargan statistics, the null hypothesis can be rejected at 1% level. Thus in this case the Taylor rule fundamentals are not related to liquidity only through the federal funds rate. We test whether the lagged federal funds rate is the predictor for residuals with C statistics, reported in table 1.5. In the first stage, we regress the federal funds rate on lagged linear output gap and inflation and 2^{nd} lag of federal funds rate. The 2^{nd} lag of federal funds rate is not redundant even after including linear output gap (for the Breusch et al. (1999) redundancy statistics, p-value is 0.00). The C statistics to test the predictability of 2^{nd} lag of federal funds rate for residual is as high as 98.3, which rejects that the 2^{nd} lag of federal funds rate is uncorrelated with the residual at 1% level.

In summary, the find that the linear output gap and inflation influence stock liquidity only through the federal funds rate according to Taylor rule, while unemployment rate and lagged federal funds rate can impact stock liquidity through other channels (could be from business cycle channel). Therefore, we would expect when using monthly data, as in our paper, we can focus our analysis more on the monetary policy perspective, which is relatively faster and more effective within a short time interval. With longer time interval data (such as quarterly), the unemployment rate would reflect information of the business cycle (the second potential channel) more than information from monetary policy. According to Næs, Skjeltorp, Ødegaard (2010), liquidity is a leading indicator of the economy, and the reduction in liquidity indicates an upsurge in future unemployment rate, since a liquid stock market encourages people to invest in long term projects (there are several other explanations). Using quarterly data, we observe a positive relationship between contemporary unemployment rate and stock illiquidity (the coefficient is 0.041 and significant at the 8% level). When using lagged illiquidity as in Næs, Skjeltorp, Ødegaard (2010), the result is qualitatively similar. However, the results for inflation (the coefficient is 0.081 and significant at 1% level) and linear output gap (the coefficient is 0.015 and significant at 1% level) are similar to the results from monthly data. From this evidence, we can conclude that the effect of Taylor rule on stock market liquidity is strong.

In order to check if the result is stable in subperiods, we graph coefficients from recursive regressions of stock market liquidity on Taylor rule fundamentals with no smoothing (figure 1.1) and with smoothing (figure 1.2) starting from the middle of the sample (August, 1987). From figure 1.1 and 1.2, the coefficient for the linear output gap is fairly stable over time and above zero both in the model with no smoothing and with smoothing. For the unemployment rate, the coefficients are below zero both in the model with smoothing and no smoothing. Coefficients for inflation are similar when using different measurements of output gap and similar when using model with and with no smoothing. Finally, the coefficients of the lagged federal funds rate are always greater than zero no matter what output gap measurements used. Thus the effect of Taylor rule fundamentals is stable over time: expansions in inflation and output gap indicate higher future stock illiquidity.

4.2 The effect of Taylor rule fundamentals on liquidity of individual stocks

From the previous sections, we find that Taylor rule fundamentals can influence stock market liquidity. The increase in the output gap and inflation can decrease stock market liquidity. In this section, we test whether the Taylor rule has a similar effect on the liquidity of individual stocks.

In panel A of table 1.6, the estimated coefficients of the linear output gap and inflation have positive signs, indicating that the liquidity for individual stocks on average increases when linear output gap and inflation increases. The panel data model indicates that mean of the coefficients are significant mostly at the 1% level, when we utilize fixed-effects models (within regression estimator) and random-effects models with the generalized least squares (GLS) estimator and apply the assumption that the disturbance term of illiquidity is first-order autoregressive. In order to account for cross sectional dependence of liquidity in different stocks, we report Driscoll-Kraay (1998) standard errors. We assume that the disturbance term is heteroskedastic and autocorrelated (maximum 8 lags for autocorrelation). Even so, the average effect of the linear output gap on the individual stock liquidity is still significant at the 5% level. When the federal funds rate is increased by the Taylor rule, the market maker has less incentive and ability to provide liquidity for individual stocks. Moreover, in the regression of 5416 stocks, more than half have positive coefficients for inflation (50.28%) and linear output gap (66.53%) with median coefficients of 0.00018 and 0.00038 respectively. There are 8.90% stocks whose liquidity is significantly positive correlated with inflation and 2.44% stocks whose liquidity is significantly positive correlated with the linear output gap. Results including partial adjustment of the federal funds rate are similar.

When we use the unemployment rate to measure output gap (panel B of table 1.6), more than half of 5416 stocks have a positive coefficient for inflation (53.82%) and a negative coefficient on unemployment rate (68.17%). Here the median of the coefficients are 0.0015 and -0.014 respectively. The liquidity of 10.95% stocks is significantly and positively correlated with inflation and the liquidity of 16.10% stocks is significantly negatively correlated with unemployment rate. The panel data models indicate that the mean of the coefficients are significant at 1% level using a fixed-effects model (within regression estimator) and random-effects models with a GLS estimator and assuming disturbance term of illiquidity as first-order autoregressive. In order to account for cross sectional dependence of liquidity in different stocks, we report Driscoll-Kraay (1998) standard errors. We assume the disturbance term is heteroskedastic and autocorrelated (maximum 8 lags for autocorrelation). The average effect of inflation and unemployment rate on individual stock liquidity is till significant at 5% level. Our result with the partial adjustment of federal funds rate is similar. The overall effect of Taylor rule fundamentals on stock liquidity can also be confirmed by P-value, which tests null hypothesis that all of the coefficients of Taylor rule fundamentals jointly equal zero. From table 1.6, we conclude that an expansion in linear output gap (or a drop in the unemployment rate) and increase in inflation can drive up illiquidity of individual stocks for different Taylor rule specifications.

4.3 Other measurements of liquidity, market capitalization ranked, liquidity ranked portfolio

Using other liquidity measures such as $Ctaq$, Pastor and Amihud ratio, we confirm our results for market liquidity in previous sections in table 1.7. In addition, we regress our Taylor rule fundamentals on the common factor of illiquidity (Z). In this section, we use levels of Taylor rule fundamentals and levels of liquidity. Since the time periods are different for different liquidity measures, the results for the unit root test for inflation, unemployment rate and federal funds rate changes over time. Additionally, the unit root test for the liquidity level can always reject the non-stationary assumption for different liquidity measures and the common factor of liquidity: $Ctaq$, Amihud Ratio, Pastor and Z at the 1% level. We detrend $Ctaq$, Amihud Ratio, and Z. Pastor is not detrended, since the linear trend is not obvious at the 5% level for Pastor. In table 1.7, for different measures of liquidity (except Pastor), elevated inflation or output gaps indicate higher illiquidity at the monthly horizon. The highest adjusted R-squared is 13%, which indicates about 13% of the variability of stock market liquidity can be explained by Taylor rule fundamentals. For Pastor, since most of the observations are below zero, we can see the signs are negative (positive) for inflation and output gap (unemployment rate). Furthermore, when we regress our Taylor rule fundamentals on the common factor of illiquidity (Z), inflation is positively correlated with the common factor of stock liquidity, while unemployment rate is negatively correlated with the common factor. The overall effect of Taylor rule fundamentals on stock market liquidity (or the common factor of stock illiquidity) can also be confirmed by F-statistics that test null hypothesis that all of the coefficients of Taylor rule fundamentals jointly equal zero.

From previous sections, we can find that Taylor rule fundamentals influence stock liquidity at market and individual levels. We want to investigate whether this relationship holds for stocks with different characteristics, and whether stocks with different characteristics have different response to Taylor rule fundamental changes. We first rank stocks by market capitalization at the end of previous year, and group stocks for the current year and calculate the equal-weighted average of liquidity of stocks in the portfolio (size 1 includes the stocks with lowest market capitalization). We rebalance the portfolio every year. In order to take into account cross portfolio correlation of liquidity, we use the Seemingly Unrelated Regression (SUR) Model (The result from equation by equation regressions is similar). In table 1.8, with the same independent variables across equations, the coefficients monotonically decrease from the portfolio of small stocks to large stocks. For small stocks, the Taylor rule fundamentals have a larger effect on illiquidity than large stocks (higher correlation between Taylor rule fundamentals and illiquidity in small stocks). 1% growth of inflation decreases liquidity for the smallest stocks by 23%, while decreasing liquidity for the largest stocks by 0.14%. Similar results can be seen for the linear output gap (marginal effect of 1% growth of linear output gap is 2.2% for the smallest stocks and 0.064% for the largest stocks) and unemployment rate (marginal effect for 1% rise in unemployment rate is -21% for the smallest stocks and -0.36% for the largest stocks). In addition, we test whether the coefficients of linear output gap, unemployment rate and inflation jointly equal zero with Chi-squared statistics. We can always reject it at 1% level. This result indicates that when the output gap and inflation increases, the funding liquidity for the market maker tightens. It decreases liquidity for the portfolio formed by market capitalization. The effect for small stocks is bigger than large stocks, indicating that when facing a financial constraint, market makers try to provide liquidity for large stocks. It is a case of flight to quality. The result is qualitatively similar when using the Taylor rule model with smoothing.

We also form a portfolio for individual stock illiquidity. We first rank stocks by detrended Amihud ratio from the end of the previous year. Then stocks are grouped for the current year and equal-weighted in the portfolio (illiquidity 1 includes the highest illiquid stock). In order to take into account cross-portfolio correlation, we use the Seemingly Unrelated Regression (SUR) Model. For illiquid stocks, the Taylor rule fundamentals have a greater effect on liquidity in the sense that the coefficients are larger. For example a 1% increase in inflation diminishes liquidity for the most illiquid stocks by 24%, while it only decreases liquidity for the most liquid stocks by 0.08%. Similar results can be seen for linear output gap (marginal effect for 1% expansion in linear output gap is from 2% for the most illiquid stocks to 0.056% for the most liquid stocks) and unemployment rate (marginal effect for 1% increase in unemployment rate is from -21% for the most illiquid stocks to -0.29% for the most liquid stocks). In addition, we test whether the coefficients of linear output gap, unemployment rate and inflation are jointly zero. Our Chi-squared statistics allow us to reject it at 1% level. These results indicate that when output gap and inflation increase, the funding liquidity for market maker tightens: liquidity decreases for a portfolio formed by illiquidity. The effect for illiquid stocks is greater than liquid stocks, indicating that when facing financial constraints, market makers try to provide liquidity for more liquid stocks. It confirms the “flight to liquidity” phenomenon. When the federal funds rate is raised by an output gap or inflation, the funding constraint tightens. It forces the market makers to provide liquidity to highly liquid stocks, which makes illiquid stocks suffer more. The result is qualitatively similar when we use the Taylor rule model with smoothing.

4.4 Taylor rule and commonality in liquidity: from the demand and supply side

Brunnermeier and Pedersen (2009) and Coughenour and Saad (2004) find that from the liquidity supply side, when an increase in the federal funds rate tightens a market makers funding constraint, commonality in stock liquidity intensifies. If we connect it with the Taylor rule, growth in the output gap and inflation should augment the commonality in liquidity. We generate an interaction variable for market liquidity and inflation and output gap to check how Taylor rule fundamentals influence commonality in liquidity when using market liquidity as the common factor for individual stock liquidity. The market liquidity for each stock is formed by equal-weighted averages of liquidity for all stocks(excluding the liquidity of that specific stock). We apply differences for every variable in the panel data, since there might be a unit root. For individual stocks, since the time interval is different from each stock, we did not test the unit root. Therefore, we use levels of the data. The liquidity series for all stocks are detrended.

Table 1.10 shows that liquidity of individual stock co-moves with market liquidity, which confirms the finding by Chordia, Roll, and Subrahmanyam (2000). The coefficients of interaction terms of linear output gap, inflation and market liquidity have the same signs as market illiquidity, which indicates that the commonality of liquidity goes up (the covariance of individual stock liquidity and market liquidity goes up), when linear output gap and inflation increase. When the federal funds rate is driven up by the Taylor rule, the funding constraint for market makers tightens. It means higher commonality in liquidity. As we can see from the table, in the regression of 5416 stocks, over half have positive coefficients for the inflation interaction term (53.51%) and linear output gap interaction term (55.89%). The median of coefficients are 0.0045 and 0.0039 respectively. 30.32% of stocks' co-movement with market liquidity is significantly affected by inflation and 29.41% of stocks' co-movement with market liquidity is significantly influenced by the linear output gap. The panel data model indicates that means of the coefficients are significant mostly at 1% level, with the fixed-effects models (using the within regression estimator) and random-effects models with the GLS estimator. Moreover, when we assume the disturbance term of illiquidity is first-order autoregressive, the result is even stronger. In order to account for the cross sectional dependence of liquidity in different stocks, we report Driscoll-Kraay (1998) standard errors. We assume the disturbance term is heteroskedastic and autocorrelated (a maximum of 8 lags for autocorrelation). Even so, the average effect of inflation on the commonality in liquidity is still significant at 1% level.

When we use the unemployment rate to measure output gap, in the regression of 5416 stocks, more than half of them have positive coefficient for inflation interaction term (52.05%) and negative coefficient for unemployment rate interaction term(57.77%), with the median of coefficients 0.0030 and -0.016 respectively. 29.39% of stocks' co-movement with market liquidity is significantly affected by inflation and 32.05% of stocks' co-movement with market liquidity is significantly influenced by the unemployment rate. The panel data model indicates that the mean of the coefficients are significant mostly at 1% level, when we apply fixed-effects models (using the within regression estimator), random-effects models using the GLS estimator. Furthermore, when we assume the disturbance term of illiquidity is first-order autoregressive, the result is once again even stronger. In order to account for the cross sectional dependence of liquidity in different stocks, we report Driscoll-Kraay (1998) standard errors. We assume the disturbance term is heteroskedastic and autocorrelated (maximum 8 lags for autocorrelation). The average effect of inflation on the commonality is still significant at 1% level. Our result with the assumption of partial adjustment of federal funds rate is similar. From table 1.10, we can conclude that an increase in the linear output gap (or a reduction in the unemployment rate) and expansion of inflation can boost commonality in liquidity in the stock market for different Taylor rule specifications.

According to Koch, Ruenzi and Starks (2010), commonality in liquidity can also be driven by the demand side. We use the liquidity of stocks highly owned by mutual fund as the common factor.

We rank all the stocks held by mutual funds by the mutual fund ownership. This is calculated by the ratio of shares of the stock held by all the mutual funds to all shares outstanding. The top 25% of stocks held by mutual fund are used to form the portfolio every quarter. On average, the portfolio includes about 298 stocks each year. The sample is from January, 1980 to December, 2002. Using equal-weighted averages, we calculate the liquidity for the mutual fund highly owned portfolio. Mutual funds tend to buy and sell the stocks owned by them together because of shocks to net inflow, net outflow or information. This correlated trading by mutual funds forces the relevant stock liquidity to co-move with each other. According to the “Fed model”, when stocks and bonds compete for space in a mutual fund portfolio, an upsurge in the federal funds rate renders bonds more attractive. The correlated trading of mutual funds in the stock market must be less severe, decreasing the commonality in liquidity. Shocks to the federal funds rate is driven by shocks in inflation and output gap, according to Taylor rule. Therefore, when inflation or output gap goes up, the federal funds rate increases and commonality in liquidity declines, if Taylor rule has the dominant effect.

However, inflation and output gap also act as business cycle indicators. For example, an increase in the unemployment rate indicates that the economy is in the trough, demand for stock decrease due to the wealth effect. Depleted wealth during the trough of the business cycle forces people to invest less in the stock market and spend a greater proportion of their income on consumption. Therefore, we can argue in this case that growing inflation and output gap indicates an elevated demand for stock, higher correlated trading and greater commonality in liquidity from the demand side. The final effect depends on the relative importance of the two opposite effects.

The table 1.11 reports the effect of the federal funds rate on commonality in liquidity from the demand and supply side. From the supply side, a rise in the federal funds rate tightens a market makers' budget constraint, which generates more commonality in liquidity in the sense that the coefficient of the common factor (market liquidity) increases from 0.88 to 0.8827(0.88+0.0027), if federal funds rate rises by 1% with the random effect model and applying the assumption that the disturbance term of illiquidity is first-order autoregressive disturbance term (Table 1.11, Panel A). The result is similar when using other econometrics models.

Panel B in table 1.11 reveals the effect of federal funds rate on commonality in liquidity from the demand side. According to the "Fed model", an increase in the federal funds rate decreases the demand of a stock, which lessens the commonality in liquidity from the demand side. For example, a 1% upsurge in the federal funds rate reduces the commonality in liquidity on average by -0.047 (from 2.22) using random effect model and applying the assumption that the disturbance term of illiquidity is first-order autoregressive. The result is similar when using other econometrics models.

When we use Taylor rule fundamentals such as inflation and output gap as indicators for commonality in liquidity from the demand side (table 1.12), we see that an expansion in inflation and output gap actually increases the commonality in liquidity, which contradicts the "Fed model". For example, when we use unemployment rate as a measure of output gap, a 1% increase in the inflation intensifies the commonality in liquidity by 0.055 (random effect model with GLS estimator). In a regression of 4816 stocks, more than half have a positive coefficient for the inflation interaction term (50.79%) and a negative coefficient for the unemployment rate interaction term (52.18%). The median of coefficients are 0.0028 and -0.0061 respectively. 27.68% of stocks' co-movement with liquidity from highly mutual fund owned stock is significantly affected by inflation. 26.04% of stocks' co-movement with liquidity from highly mutual fund owned stock is significantly influenced by the unemployment rate. The panel data model indicates that the mean of the coefficients are significant at the 1% level with the fixed-effects models (within regression estimator) and random-effects models (GLS estimator). In addition, when we apply a first-order autoregressive disturbance term, the results are qualitatively similar. We also find similar results when using a linear output gap. From table 1.12, we can conclude that an increase in linear output gap (fall in unemployment rate) and expansion in inflation can drive up commonality in liquidity in the stock market. Increasing inflation and output gap often indicates that the economy is in a peek and the representative consumer then invests more money in the stock market in order to smooth consumption, which augments the demand for the stock and increases the commonality in liquidity from the demand side. The effect overweighs the effect of inflation and output gap for monetary policy.

In summary, Taylor rule fundamentals affect commonality in liquidity mainly from the liquidity supply side. An increase in inflation and output gap tightens market makers' financial constraints and enhances commonality in liquidity. From the demand side, the effect of the Taylor rule is not as strong as the wealth effect.

5 Conclusion

In this paper, we link stock liquidity and commonality in liquidity with macroeconomic variables via the Taylor rule, the monetary policy rule that Federal Reserve applies to determine federal funds rate. From the liquidity supply side, we conclude that increases in inflation and output gap decrease stock liquidity at both the market and individual stock level. Inflation and the linear output gap influence stock liquidity only through the federal funds rate. This result is robust to various econometrics models, time periods and measures of stock liquidity. Using a portfolio formed by market capitalization and stock liquidity, we find the effect of Taylor rule fundamentals on stock liquidity is bigger for stocks with low market capitalization and low liquidity, which provides evidence on “flight to quality” and “flight to liquidity”: when market maker faces financial constraint, she tends to provide liquidity to stocks with large market capitalization, and high liquidity.

We also find that contemporaneous Taylor rule fundamentals affect commonality of liquidity from the supply side of liquidity. When Taylor rule fundamentals indicate a tighter monetary policy, we find that commonality in liquidity in the stock market increases. These results are robust to different measurements of output gap and specifications of Taylor rule models. From the demand side of liquidity, although an increase in the federal funds rate lessens the commonality in liquidity due to the “Fed model”, we find the effect of Taylor rule fundamentals contradicts the “Fed model”. We find an increase in inflation and output gap augments commonality in liquidity. This can be understood that a representative consumer invests more money in the stock market in order to smooth their consumption when business cycles are at the peak which is indicated by high inflation and high output gap. The demand for stock and the commonality in liquidity from the demand side thus increases. The effect overweighs the effect of inflation and output gap as Taylor rule fundamentals for monetary policy.

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Figure 1.1 The Dynamics of Inflation, Output Gap coefficients from the Taylor Rule Model with no Smoothing (Linear Output Gap and Unemployment rate)

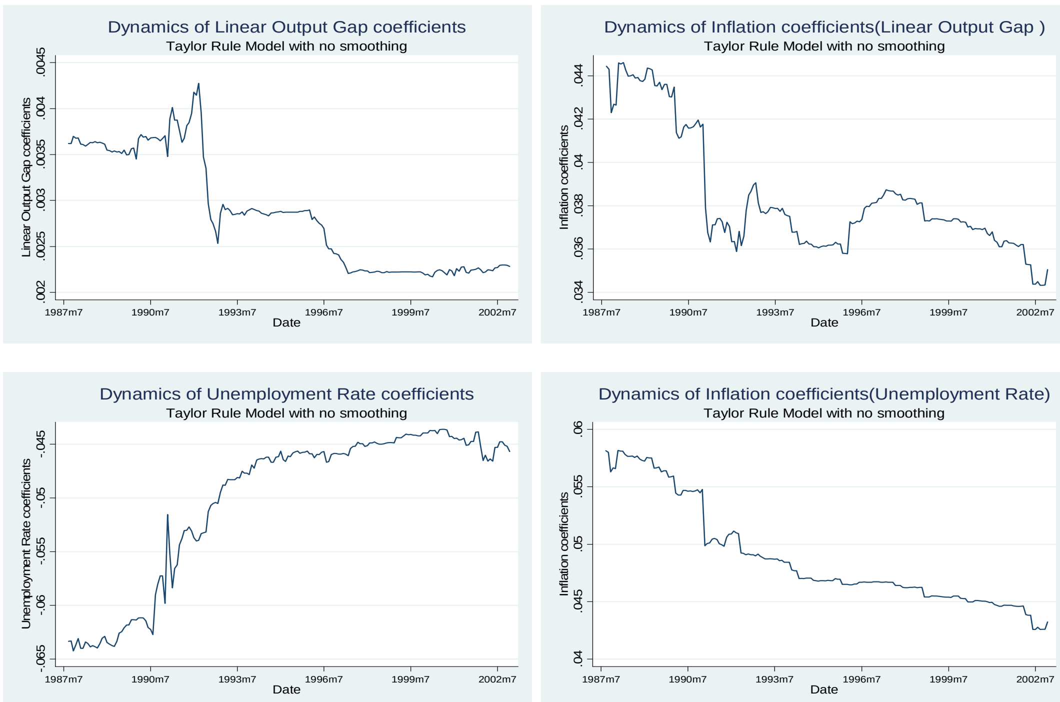

Figure 1.2 The Dynamics of Inflation, Output Gap and past federal funds rate coefficients from the Taylor Rule Model with Smoothing (Linear Output Gap and Unemployment rate)

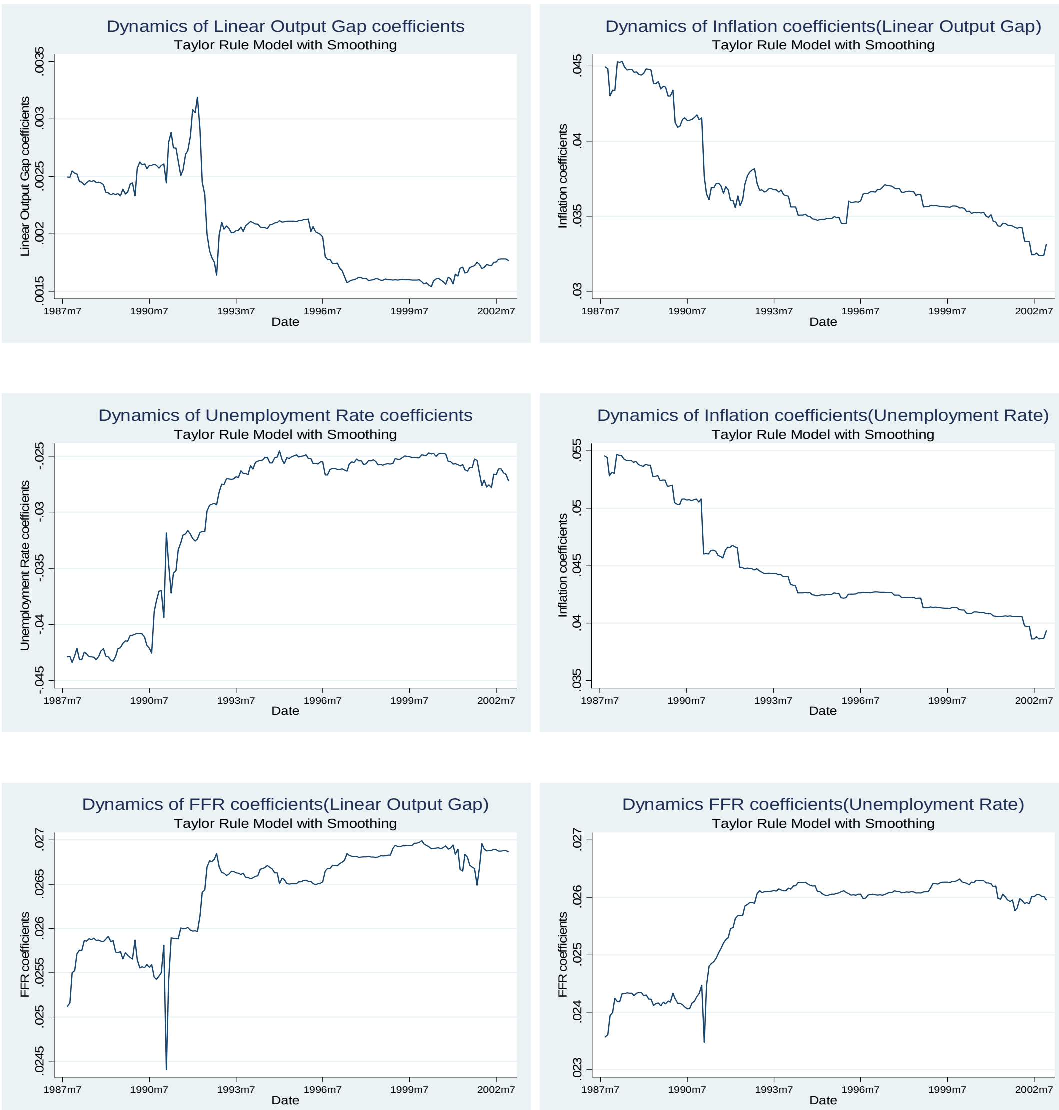

Table 1.1: Descriptive Statistics for Monthly Variables

Variable	Mean	Std Dev	Median	Skewness	Kurtosis
Inflation	3.85	2.29	3.14	1.21	3.73
Linear Gap	-4.24	4.15	-4.48	-0.045	3.32
Unemployment rate	5.87	1.49	5.7	0.72	3.45
FFR	6.39	3.32	5.56	1.12	5.00
Amihud Ratio	4.46e-07	4.65e-07	2.63e-07	1.73	5.84
Pastor	-0.033	0.064	-0.023	-1.51	9.16
Ctaq	0.0097	0.0036	0.0099	-0.32	1.94
Z	0.44	0.26	0.38	1.66	6.43
TBLM	0.64	0.41	0.51	1.97	7.01
MFO	0.11	0.12	0.067	1.62	6.19
MLIQU	0.14	0.069	0.15	0.35	2.43

Notes: Real output, inflation, the federal funds rate (FFR) and the unemployment rate are real-time data from the Philadelphia Fed Real-Time Database for Macroeconomists. We use the seasonally adjusted industrial production index as a proxy for U.S. output. Inflation is calculated as a 12-month difference in the log of the price level measured by GDP Deflator. Linear Gap is linearly detrended output gap. Amihud Ratio: the liquidity ratio, $L_{id} = \frac{|r_{id}|}{dv_{id}}$ is proposed by Amihud (2002) to exploit information both about change of stock price and trading volume, as a proxy for the stock illiquidity. The market liquidity is the equal-weighted average of the Amihud ratio for individual stocks. Return reversal (Pastor) measures liquidity using the daily ordinary least squares estimates of $rrev_{id}$ based on the equation $r^e_{i,d+1} = \alpha_i + \beta_i r_{i,d} + rrev_{id}\, sign(r^e_{i,d}) dv_{id} + \varepsilon_{i,d+1}$. The market liquidity is the equal-weighted average of $rrev_{id}$ for individual stocks. $Ctaq$ is the trade-weighted average of effective cost of all trade for each stock. Effective cost is defined as the log difference between the transaction price and quote midpoint from the TAQ data set. Market illiquidity is the cross-sectional equal-weighted average of effective cost of individual stocks at a certain month. Z is the statistical common factor of effective cost of 150 stocks from the NYSE/AMEX (before 1985), 150 stock from Nasdaq and 150 stocks from NYSE/AMEX(after 1985). Theory based liquidity measure (TBLM) by Chordia, Huh, and Subrahmanyam (2009) is the structural estimate of the Kyle lambda scaled by the current price. In month t, it is defined as $\frac{\lambda_t}{p_t} = \frac{N_t^{0.5}\, std(R_t)}{(N_t + 1)\, std(z_{t-1})}$. Since there are many extreme observations in the sample, the square root is used. Market TBLM is the cross-sectional equal-weighted average of liquidity of individual stocks in a certain month. Mutual fund ownership (MFO) for individual stock is calculated as the ratio of shares of the stock held by all the mutual funds to all shares outstanding. When we calculate the statistics for MFO, we exclude stocks not held by mutual fund. Liquidity of the portfolio which is highly owned by mutual fund (MLIQU) is calculated as equal-weighted average of liquidity of individual stocks which are highly owned by mutual fund (top 25%).

Table 1.2: Correlation between different variables

Variable	Inflation	Linear Gap	Unemployment rate	FFR	Amihud Ratio	Pastor	$Ctaq$	Z	TBLM
Inflation	1								
Linear Gap	0.0651	1							
U-rate	0.4229	-0.6177	1						
FFR	0.7044	0.1037	0.2781	1					
Amihud Ratio	0.5811	0.4240	0.0012	0.3377	1				
Pastor	-0.1210	-0.1426	0.0709	-0.0771	-0.3066	1			
$Ctaq$	0.1401	-0.4447	0.1887	0.5590	0.8701	0.0860	1		
Z	0.2556	0.1013	-0.0277	0.1398	0.3064	-0.3136	0.3659	1	
TBLM	0.6451	0.2194	0.1790	0.1165	0.8310	-0.2270	0.1763	0.3471	1

Notes: Real output, inflation, federal funds rate (FFR) and unemployment rate of real-time data for the U.S. is from the Philadelphia Fed Real-Time Database for Macroeconomists. We use the seasonally adjusted industrial production index as a proxy for U.S. output. Inflation is calculated as a 12-month difference in the log of the price level measured by GDP Deflator. Linear Gap is linearly detrended output gap. Amihud Ratio: the liquidity ratio, $L_{id} = \frac{|r_{id}|}{dv_{id}}$ is proposed by Amihud (2002) to exploit the information both about change of stock price and trading volume, as a proxy for the stock illiquidity. The market liquidity is equal-weighted average of Amihud ratio for individual stock. Return reversal (Pastor) measures liquidity using the daily ordinary least squares estimates of $rrev_{id}$ based on equation $r^{e}_{i,d+1} = \alpha_i + \beta_i r_{i,d} + rrev_{id} sign(r^{e}_{i,d}) dv_{id} + \varepsilon_{i,d+1}$. The market liquidity is equal-weighted average of $rrev_{id}$ for individual stock. $Ctaq$ is the trade-weighted average of effective cost of all trade for each stock. Effective cost is defined as the log difference between transaction price and quote midpoint from TAQ data set. Market illiquidity is the cross-sectional equal-weighted average of effective cost of individual stocks at a certain month. Z is the statistical common factor of effective cost of 150 stock from NYSE/AMEX (before 1985), 150 stock from Nasdaq and 150 stocks from NYSE/AMEX(after 1985). Theory based liquidity measure(TBLM) by Chordia, Huh, and Subrahmanyam (2009) is the structural estimate of Kyle lambda scaled by current price. In month t, it is defined as $\frac{\lambda_t}{p_t} = \frac{N_t^{0.5} std(R_t)}{(N_t+1) std(z_{t-1})}$. Since there are many extreme observations in the sample, TBLM is taken square root. Market TBLM is the cross-sectional equal-weighted average of liquidity of individual stocks in a certain month.

Table 1.3: Taylor rule and market liquidity

Theory based liquidity measure				
	Linear Gap		Unemployment rate	
Inflation	0.035 (2.09)**	0.033 (2.01)**	0.043 (2.66)***	0.039 (2.45)***
Output Gap	0.0023 (1.67)**	0.0018 (1.31)*	-0.046 (-1.98)**	-0.027 (-1.16)
Lagged FFR	-	0.027 (3.76)***	-	0.026 (3.56)***
Adj-R-sq	0.020	0.054	0.0226	0.053
F-Statistic	4.69***	8.01***	5.28***	7.88***

Notes: the dependent variable is the theory based liquidity measure. Independent variables include Taylor rule fundamentals. With the assumption of partial adjustment for federal funds rate, we include lagged federal funds rate. F-statistics is to test null hypothesis that all of the coefficients of Taylor rule fundamentals jointly equal zero. T statistics are in parentheses. They are testing one side null hypothesis whether coefficients of inflation and linear output gap are smaller or equal to zero (for unemployment rate they are testing one side null hypothesis whether the coefficient is greater or equal to zero). One asterisk indicates significance at the 10% level; two asterisks at the 5% level; three asterisks at the 1% level.

Table 1.4 Linking of Taylor rule fundamentals to stock market liquidity

First stage regression				
	Linear Gap		Unemployment rate	
Inflation(L)	0.86 (17.22)***	0.070 (2.26)**	0.94 (16.62)***	0.092 (2.73)***
Output Gap(L)	0.15 (4.31)***	0.045 (2.79)***	-0.17 (-1.75)**	-0.082 (-1.85)**
FFR(L2)	-	0.90 (37.52)***	-	0.91 (38.26)***
Adj-R-sq	0.48	0.89	0.46	0.89
F-Statistic	172.24***	1025.68***	157.91***	1012.19 ***
Sargan	0.122	98.42***	22.96***	137.37***
Basmann	0.121	132.64***	24.27***	216.12***

Notes: The table tests whether Taylor rule fundamentals influence stock liquidity through federal funds rate only as shown in equation (1) and Taylor rule with and with no smoothing. In the first stage, we regress federal funds rate on lagged Taylor rule fundamentals. Then, we regress stock liquidity on the fitted federal funds rate from the first stage to acquire the residual. Finally, we test the null hypothesis that the lagged Taylor rule fundamentals cannot predict the residual from the second stage. The statistics are Basmann's statistics (Basmann 1960) and Sargan (1958)'s statistics. We use one side test for t-statistics. One asterisk indicates significance at the 10% level; two asterisks at the 5% level; three asterisks at the 1% level.

Table 1.5 Endogeneity of unemployment rate and federal funds rate

First stage regression		
	Unemployment Rate(L)	federal funds rate(L2)
Inflation(L)	0.83	0.070
	(13.42)***	(2.26)***
Output Gap(L)	0.17	0.045
	(4.05)***	(2.79)***
U-rate(L) /FFR(L2)	0.12	0.90
	(0.98)	(37.52)***
Adj-R-sq	0.48	0.89
F-Statistic	115.13***	1025.68***
Sargan	41.8***	98.42***
Basmann	46.6***	132.64***
C statistics	41.7***	98.3***

Notes: The table tests whether unemployment rate and lagged federal funds rate connect with stock liquidity not only through federal funds rate but also through other channels(for example, business cycle channel). Basmann's statistics (Basmann 1960), Sargan (1958)'s statistics and C statistics (distance difference statistics) are used. In the first stage, we regress federal funds rate on linear output gap, unemployment rate and inflation. Then we use C statistics tests whether the unemployment rate and lagged federal funds rate can predict residual. We use one side test for t-statistics. One asterisk indicates significance at the 10% level; two asterisks at the 5% level; three asterisks at the 1% level.

Table 1.6 Taylor rule and liquidity of individual stocks

A: Theory based liquidity measure(Linear Output Gap)										
	FE(within)		RE(GLS)		AR(1) FE(within)		AR(1) RE		Percentage/ Median	
Inflation t D.K. sd	0.035 11.97*** 1.56*	0.034 11.75*** 1.49*	0.035 12.11*** 1.64*	0.034 11.83*** 1.53*	0.033 10.43***	0.033 10.43***	0.033 10.55***	0.033 10.48***	Positive Significant at 5%	50.28 8.90
Linear t D.K. sd	0.0020 7.94*** 2.02**	0.0013 5.30*** 1.41*	0.0020 8.28*** 1.70**	0.0014 5.85*** 1.26	0.0014 3.28***	0.00055 1.29*	0.0013 3.29***	0.00072 1.80**	Positive Significant at 5%	66.53 2.44
L.FFR t D.K. sd	-	0.028 21.95*** 3.44***	-	0.027 21.81*** 3.75***	-	0.024 14.93***	-	0.024 14.95***	-	-
Adj-R-sq P-value	0.0004 0.00	0.001 0.00	0.0004 0.00	0.001 0.00	0.0004 0.00	0.001 0.00	0.0004 0.00	0.001 0.00	Inflation Output gap	0.00018 0.00038
B: Theory based liquidity measure(Unemployment Rate)										
	FE		RE(GLS)		AR(1) FE		AR(1) RE		Percentage/ Median	
Inflation t D.K. sd	0.042 14.97*** 1.81**	0.039 13.90*** 1.69**	0.043 15.22*** 1.93**	0.039 14.15*** 1.76**	0.035 11.13***	0.034 10.82***	0.035 11.28***	0.034 10.96***	Positive Significant at 5%	53.82 10.95
U-rate t D.K. sd	-0.052 -12.78*** -1.80**	-0.033 -8.03*** -1.25	-0.051 -12.77*** -1.73**	-0.033 -8.03*** -1.20	-0.050 -10.84***	-0.042 -9.05***	-0.049 -10.83 ***	-0.042 -9.14***	Negative Significant at 5%	68.17 16.10
L.FFR t D.K. sd	-	0.026 20.20*** 3.34***	-	0.026 20.15*** 3.58***	-	0.022 13.92***	-	0.022 13.99***	-	-
Adj-R-sq P-value	0.0005 0.00	0.0011 0.00	0.0005 0.00	0.0011 0.00	0.0005 0.00	0.001 0.00	0.0005 0.00	0.001 0.00	Inflation Output gap	0.0015 -0.014

Notes: On the left part of the table, we use fixed-effects models (within regression estimator) and random-effects models using the GLS estimator. We assume that the disturbance term of illiquidity is first-order autoregressive. In order to account for the cross sectional dependence of liquidity in different stocks, we report Driscoll-Kraay (1998) standard errors. We assume the disturbance term is heteroskedastic and autocorrelated (maximum 8 lags for autocorrelation). On the right part of the table, we regress individual stock liquidity for 5416 stocks on Taylor rule fundamentals and report the percentage of positive and significant estimated coefficients(negative and significant coefficients for unemployment rate). The median of the coefficients for Taylor rule fundamentals are in the right corner. P-value is the probability to reject joint hypothesis that all of the coefficients of Taylor rule fundamentals equal zero. T statistics are in the parentheses. They are testing one side null hypothesis whether coefficients of inflation and linear output gap are smaller or equal to zero (for unemployment rate they are testing one side null hypothesis whether the coefficient is greater or equal to zero). One asterisk indicates significance at the 10% level; two asterisks at the 5% level; three asterisks at the 1% level.

Table 1.7 Taylor rule and market liquidity: different measures

A: Linear Output Gap								
	Z		*Ctaq*		Pastor		Amihud ratio	
Inflation	0.015	0.014	-0.00013	-0.00015	-0.0029	-0.0036	3.02e-08	5.07e-08
t	2.95***	2.06**	-0.57	-0.67	-2.39 ***	-2.08 **	5.28***	6.34 ***
Linear	-0.00082	-0.00095	0.00011	0.00012	-0.0021	-0.0022	6.00e-09	6.97e-09
t	-0.30	-0.34	3.12 ***	3.66 ***	-3.20 ***	-3.32 ***	1.90**	2.22 **
Lagged	-	0.00038	-	0.00023	-	0.00073	-	-2.05e-08
FFR		0.08		3.84 ***		0.61		-3.67 ***
Adj-R-sq	0.0138	0.0120	0.0529	0.1297	0.0283	0.0279	0.0567	0.0791
F-statistics	4.35**	2.94**	5.30***	8.60***	8.50 ***	5.92 ***	16.47***	15.71***
B: Unemployment Rate								
	Z		*Ctaq*		Pastor		Amihud ratio	
Inflation	0.020	0.020	0.000023	-0.000096	-0.0049	-0.0054	4.55e-08	6.57e-08
t	3.74***	2.75 ***	0.10	-0.39	-3.68 ***	-3.00 ***	7.41***	7.99 ***
U-rate	-0.021	-0.021	-0.00044	-0.00024	0.0064	0.0065	-5.27e-08	-5.33e-08
t	-2.53 ***	-2.51***	-3.17***	-1.33 *	3.13 ***	3.17 ***	-5.59***	-5.73***
Lagged	-	0.00016	-	0.00014	-	0.00053	-	-1.99e-08
FFR		0.03		1.73 **		0.44		-3.67***
Adj-R-sq	0.0266	0.0246	0.0547	0.0629	0.0275	0.0261	0.1046	0.1262
F-statistics	7.57***	5.03***	5.45***	4.43***	8.29 ***	5.60 ***	31.08***	25.76***

Notes: Dependent variables include Z , $Ctaq$, Pastor and Amihud ratio. Independent variables include Taylor rule fundamentals. With the assumption of partial adjustment for federal funds rate, we include lagged federal funds rate. F-statistics is to test null hypothesis that all of the coefficients of Taylor rule fundamentals jointly equals zero. T statistics are reported for each variable. They are testing one side null hypothesis whether coefficients of inflation and linear output gap are smaller or equal to zero (for unemployment rate they are testing one side null hypothesis whether the coefficient is smaller than zero). One asterisk indicates significance at the 10% level; two asterisks at the 5% level; three asterisks at the 1% level.

Table 1.8 Portfolio formed by market capitalization

Amihud liquidity ratio (Linear Output Gap/unemployment rate)										
	Size 1(small)		Size 2		Size 3		Size 4		Size 5	
Inflation t	0.17 6.00***	0.23 7.47***	0.11 5.42***	0.15 7.01***	0.064 4.72***	0.095 6.50***	0.044 5.12 ***	0.066 7.17***	0.030 5.13***	0.047 7.40***
Output Gap t	0.022 1.37*	-0.21 -4.37***	0.013 1.15	-0.15 -4.54***	0.011 1.43*	-0.11 -4.81***	0.0069 1.45*	-0.077 -5.46 ***	0.0057 1.74**	-0.057 -5.90***
Adj-R-sq Chi2-statistics	0.0705 39.11***	0.1003 57.54 ***	0.0578 31.66***	0.0918 52.13 ***	0.0468 25.32***	0.0841 47.40 ***	0.0539 29.41 ***	0.1020 58.61 ***	0.0560 30.61***	0.1104 64.06***

	Size 6		Size 7		Size 8		Size 9		Size 10	
Inflation t	0.019 4.95***	0.03 7.54***	0.0054 2.33***	0.016 6.57***	0.0016 1.36 *	0.0075 6.00***	0.00036 0.70	0.0034 6.39***	0.00028 1.42*	0.0014 6.72 ***
Output Gap t	0.0046 2.21 **	-0.040 -6.51***	0.0059 4.68***	-0.035 -9.52 ***	0.0037 5.50 ***	-0.020 -10.25***	0.0019 6.58***	-0.010 -12.44***	0.00064 5.73***	-0.0036 -11.69***
Adj-R-sq Chi2-statistics	0.0565 30.89 ***	0.1198 70.24 ***	0.0529 28.83***	0.1602 98.40 ***	0.0605 33.23***	0.1736 108.41 ***	0.0795 44.59***	0.2326 156.37 ***	0.0653 36.07***	0.2138 140.35***

Notes: Dependent variables are Amihud ratios of different portfolios. Independent variables include Taylor rule fundamentals. We form a portfolio by market capitalization at the end of previous year, and group stocks for the current year. We then calculate the equal-weighted average of liquidity of stocks in the portfolio (size 1 includes the stocks with lowest market capitalization). The portfolio is rebalanced every year. In order to take into account cross portfolio correlation of liquidity, we apply a Seemingly Unrelated Regression (SUR) Model. Chi-square statistics is to test null hypothesis that all of the coefficients of Taylor rule fundamentals jointly equals zero. T statistics are reported for each variable. They are testing one side null hypothesis whether coefficients of inflation and linear output gap are smaller or equal to zero (for unemployment rate they are testing one side null hypothesis whether the coefficient is smaller than zero).One asterisk indicates significance at the 10% level; two asterisks at the 5% level; three asterisks at the 1% level.

Table 1.9 Portfolio formed by liquidity

Amihud liquidity ratio (Linear Output Gap/unemployment rate)										
	Illiquidity1(highest)		Illiquidity2		Illiquidity 3		Illiquidity 4		Illiquidity 5	
Inflation t	0.18 6.12 ***	0.24 7.57***	0.10 5.09 ***	0.15 6.77 ***	0.070 5.28 ***	0.10 7.19***	0.042 4.69 ***	0.067 6.99***	0.025 4.33 ***	0.042 6.86***
Output Gap t	0.020 1.26	-0.21 -4.35***	0.015 1.39 *	-0.15 -4.66 ***	0.011 1.46 *	-0.11 -5.17 ***	0.010 2.00 **	-0.087 -5.87 ***	0.0074 2.29 **	-0.060 -6.29***
Adj-R-sq Chi2-statisitics	0.0723 40.21 ***	0.1023 58.83***	0.0530 28.89 ***	0.0879 49.72***	0.0569 31.13 ***	0.0997 57.16 ***	0.0503 27.31 ***	0.1029 59.16 ***	0.0468 25.34 ***	0.1057 60.98***

	Illiquidity 6		Illiquidity 7		Illiquidity 8		Illiquidity 9		Illiquidity 10	
Inflation t	0.014 3.76 ***	0.025 6.58 ***	0.0058 2.69 ***	0.014 6.07***	0.0014 1.31 *	0.0063 5.64***	0.00079 1.68 **	0. 0030 6.23***	-0.000073 -0.47 *	0.00080 5.12***
Output Gap t	0.0054 2.70 ***	-0.040 -6.81***	0.0044 3.63 ***	-0.027 -7.79***	0.0029 4.96 ***	-0.016 -9.61***	0.0013 4.98 ***	-0.0075 -10.12 ***	0.00056 6.52 ***	-0.0029 -12.20 ***
Adj-R-sq Chi2-statisitics	0.0423 22.80 ***	0.1089 63.08 ***	0.0405 21.76 ***	0.1194 69.99***	0.0502 27.26 ***	0.1560 95.39***	0.0529 28.83 ***	0.1718 107.06 ***	0.0762 42.56 ***	0.2238 148.79 ***

Notes: Dependent variables include the Amihud ratio of different portfolio. Independent variables include Taylor rule fundamentals. We form portfolio by liquidity of stocks at the end of previous year, and group stocks for the current year. We then calculate the equal-weighted average of liquidity of stocks in the portfolio (illiquidity 1 includes the highest illiquid stocks). We rebalance the portfolio every year. In order to taking into account for cross portfolio correlation of liquidity, we apply a Seemingly Unrelated Regression (SUR) Model. Chi-square statistics is to test null hypothesis that all of the coefficients of Taylor rule fundamentals jointly equals zero. T statistics are reported for each variable. They are testing one side null hypothesis whether coefficients of inflation and linear output gap are smaller or equal to zero (for unemployment rate they are testing one side null hypothesis whether the coefficient is smaller than zero).One asterisk indicates significance at the 10% level; two asterisks at the 5% level; three asterisks at the 1% level.

Table 1.10 Taylor rule and commonality in liquidity from supply side

A: Theory based liquidity measure(Linear Output Gap)						
	FE(within)	RE(GLS)	AR(1) FE(within)	AR(1) RE	Percentage/ Median	
Market liquidity	0.86	0.86	0.83	0.83	Positive	70.83
t	54.79 ***	55.04***	48.30 ***	48.77 ***	Significant	45.77
D.K. sd	16.30***	16.96***			at 5%	
Inflation	0.010	0.010	0.013	0.013	Positive	53.51
t	5.13***	5.16 ***	5.90***	5.87 ***	Significant	30.32
D.K. sd	2.33***	2.53***			at 5%	
Linear	0.0028	0.0027	0.0035	0.0035	Positive	55.98
t	2.49***	2.43***	2.89***	2.90***	Significant	29.41
D.K. sd	1.28	1.15			at 5%	
Adj-R-sq	0.0138	0.0138	0.0138	0.0138	Market	0.25
P-value	0.00	0.00	0.00	0.00	Inflation	0.0045
					Output gap	0.0039
B: Theory based liquidity measure(Unemployment Rate)						
	FE	RE(GLS)	AR(1) FE	AR(1) RE	Percentage/ Median	
Market liquidity	0.90	0.90	0.87	0.88	Positive	70.37
t	34.72 ***	34.94***	28.30 ***	28.63***	Significant	43.17
D.K. sd	26.56***	27.38***			at 5%	
Inflation	0.010	0.010	0.013	0.013	Positive	52.05
t	4.99***	5.06***	5.61 ***	5.63***	Significant	29.39
D.K. sd	2.20**	2.39 ***			at 5%	
U-rate	-0.0065	-0.0067	-0.0081	-0.0085	Negative	57.77
t	-1.82**	-1.89**	-1.85**	-1.94**	Significant	32.05
D.K. sd	-1.09	-1.14			at 5%	
Adj-R-sq	0.0138	0.0138	0.0138	0.0138	Market	0.38
P-value	0.00	0.00	0.00	0.00	Inflation	0.0030
					Output gap	-0.016

Notes: On the left part of the table, we utilize fixed-effects models (within regression estimator) and random-effects models using the GLS estimator (applying the assumption that the disturbance term of illiquidity is first-order autoregressive). In order to account for the cross sectional dependence of liquidity in different stocks, we report Driscoll-Kraay (1998) standard errors. We assume the disturbance term is heteroskedastic and autocorrelated (with a maximum 8 lags for autocorrelation). On the right part of the table, we regress individual stock liquidity for 5416 stocks on market liquidity, an interaction term of linear output gap, inflation, unemployment rate and market liquidity. We report the percentage of positive and significant coefficients (negative and significant coefficients for unemployment rate). The median of the coefficients for each regressor are in the right corner. P-value is the probability to reject joint hypothesis that all of the coefficients of independent variables equal zero. T statistics are reported for each variable. They are testing one side null hypothesis whether coefficients of inflation and linear output gap are smaller or equal to zero (for unemployment rate they are testing one side null hypothesis whether the coefficient is greater or equal to zero). One asterisk indicates significance at the 10% level; two asterisks at the 5% level; three asterisks at the 1% level.

Table 1.11 Federal funds rate and commonality in liquidity from supply side and demand side

A: Theory based liquidity measure(supply)						
	FE(within)	RE(GLS)	AR(1) FE(within)	AR(1) RE	Percentage/ Median	
Market liquidity	0. 91	0.91	0.88	0.88	Positive	67.10
t	66.53 ***	66.90 ***	53.82***	54.24***	Significant at 5%	44.05
D.K. sd	20.30***	20.07***				
FFR	0.0011	0.0010	0.0026	0.0027	Positive	56.07
t	0.72	0.70	1.40*	1.45*	Significant at 5%	32.33
D.K. sd	0.59	0.56				
Adj-R-sq	0.0138	0.0138	0.0138	0.0138	Market	0.16
P-value	0.00	0.00	0.00	0.00	FFR	0.0054
B: Theory based liquidity measure(demand)						
	FE	RE(GLS)	AR(1) FE	AR(1) RE	Percentage/ Median	
MLIQU	2.26	2.26	2.21	2.22	Positive	69.58
t	32.73***	32.94***	28.54***	28.88***	Significant at 5%	46.72
D.K. sd	6.23***	5.67***				
FFR	-0.047	-0.048	-0.047	-0.047	Negative	47.86
t	-7.85***	-7.91***	-6.62***	-6.65***	Significant at 5%	25.21
D.K. sd	-3.17***	-2.84***				
Adj-R-sq	0.0025	0.0025	0.0025	0.0025	Market	0.52
P-value	0.00	0.00	0.00	0.00	FFR	0.0046

Notes: On the left part of the table, we utilize fixed-effects models (within regression estimator) and random-effects models using the GLS estimator and apply the assumption that disturbance term of illiquidity is first-order autoregressive. In order to account for the cross sectional dependence of liquidity in different stocks, we report Driscoll-Kraay (1998) standard errors. We assume the disturbance term is heteroskedastic and autocorrelated (with a maximum 8 lags for autocorrelation). On the right part of the table, we regress individual stock liquidity for 5416 stocks on market liquidity, an interaction term of federal funds rate and market liquidity in the analysis from the liquidity supply side. We regress individual stock liquidity for 4816 stocks on liquidity of highly mutual fund owned stocks, an interaction term of federal funds rate and liquidity of highly mutual fund owned stocks in the analysis from the liquidity demand side. We report the percentage of positive and significant coefficients (negative and significant coefficients for interaction term of federal funds rate and liquidity of highly mutual fund owned stock). The median of the coefficients for each regressor are in the right corner. P-value is the probability to reject joint hypothesis that all of the coefficients of independent variables equal zero. T statistics are reported for each variable. They are testing one side null hypothesis whether coefficients of market liquidity, interaction term of federal funds rate and market liquidity are smaller or equal to zero from liquidity supply side. They are testing one side null hypothesis whether coefficients of liquidity of highly mutual fund owned stocks are smaller or equal to zero and interaction term of federal funds rate and liquidity of highly mutual fund owned stocks are greater or equal to zero from liquidity demand side. One asterisk indicates significance at the 10% level; two asterisks at the 5% level; three asterisks at the 1% level. Liquidity of the portfolio which is highly owned by mutual fund (MLIQU) is calculated as equal-weighted average of liquidity of individual stocks which are highly owned by mutual fund (top 25%).

Table 1.12 Taylor rule and commonality in liquidity from demand side

A: Theory based liquidity measure(Linear Output Gap)						
	FE(within)	RE(GLS)	AR(1) FE(within)	AR(1) RE	Percentage/ Median	
MLIQU	1.63	1.63	1.79	1.79	Positive	65.34
t	14.55***	14.59***	14.72***	14.87***	Significant	42.40
D.K. sd	3.72***	3.51***			at 5%	
Inflation	0.054	0.056	0.040	0.041	Positive	50.71
t	2.91***	3.02***	1.94**	2.02***	Significant	28.82
D.K. sd	0.89	0.87			at 5%	
Linear	-0.0037	0.0027	0.0035	0.017	Positive	48.57
t	-0.53	2.43***	2.30***	2.28***	Significant	22.51
D.K. sd	-0.16	-0.19			at 5%	
Adj-R-sq	0.0024	0.0024	0.0024	0.0024	Market	0.53
					Inflation	0.0025
P-value	0.00	0.00	0.00	0.00	Output gap	-0.0024
B: Theory based liquidity measure(Unemployment Rate)						
	FE	RE(GLS)	AR(1) FE	AR(1) RE	Percentage/ Median	
MLIQU	1.81	1.82	2.53	2.54	Positive	63.97
t	9.62***	9.75***	11.82***	12.02***	Significant	41.45
D.K. sd	2.13***	2.14***			at 5%	
Inflation	0.054	0.055	0.053	0.053	Positive	50.79
t	2.93***	3.04***	2.60***	2.67***	Significant	27.68
D.K. sd	0.94	0.90			at 5%	
U-rate	-0.024	-0.026	-0.14	-0.14	Negative	52.18
t	-0.93	-1.03	-4.72***	-4.82***	Significant	26.04
D.K. sd	-0.24	-0.29			at 5%	
Adj-R-sq	0.0024	0.0024	0.0024	0.0024	Market	0.63
					Inflation	0.0028
P-value	0.00	0.00	0.00	0.00	Output gap	-0.0061

Notes: On the left part of the table, we utilize fixed-effects models (within regression estimator) and random-effects models using the GLS estimator and apply the assumption that disturbance term of illiquidity is first-order autoregressive. In order to account for the cross sectional dependence of liquidity in different stocks, we report Driscoll-Kraay (1998) standard errors. We assume disturbance terms are heteroskedastic and autocorrelated (a maximum of 8 lags for autocorrelation). On the right part of the table, we regress individual stock liquidity for 4816 stocks on liquidity from highly mutual fund owned stocks, interaction term of linear output gap, inflation, unemployment rate and liquidity from highly mutual fund owned stocks. We report the percentage of positive and significant coefficients (negative and significant coefficients for unemployment rate). The median of the coefficients for each regressor are in the right corner. P-value is the probability to reject joint hypothesis that all of the coefficients of independent variables equal zero. T statistics are reported for each variable. They are testing one side null hypothesis whether coefficients of inflation and linear output gap are smaller or equal to zero (for unemployment rate they are testing one side null hypothesis whether the coefficient is greater or equal to zero). One asterisk indicates significance at the 10% level; two asterisks at the 5% level; three asterisks at the 1% level. Liquidity of the portfolio which is highly owned by mutual fund (MLIQU) is calculated as equal-weighted average of liquidity of individual stocks which are highly owned by mutual fund (top 25%).

Chapter2

Stock Return Predictability and the Taylor Rule

Lei Jiang
Tanya Molodtsova

Abstract

The paper uses real-time data to show that inflation and output gap, the variables that typically enter Taylor rules for interest rate setting, can provide evidence of out-of-sample predictability for stock returns from 1969 to 2008. In addition to out-of-sample tests that are based on mean squared prediction error comparisons, we test for the dependence of stock returns on Taylor rule predictors using the information about the whole distribution. The evidence is robust to using various measures of output gap and window sizes. Investor can time the market using Taylor rule fundamentals and generate higher utility.

Keywords: Stock return predictability, Taylor rules, real-time data

JEL Classification: G12, G17

1. Introduction

The literature on stock return predictability is far from being consistent. Although some studies have found evidence of out-of-sample predictability with business condition variables (Fama and French, 1989), monetary policy variables (Patelis,1998), valuation ratios and risk factors, these findings are not robust to sample period and estimation methodology. In a recent comprehensive study, Goyal and Welch (2008) conclude that none of the conventional macroeconomic or financial variables can predict excess returns in-sample or out-of-sample in the last 30 years.

Although it is commonly accepted that monetary policy decisions affect private-sector decision-making, there is a disconnect between most research on stock return predictability and the literature on monetary policy evaluation, which is based on some variant of the Taylor (1993) rule. Studying the links between monetary policy and asset prices is important for both a practitioner and a policymaker. From an investor’s point of view, understanding these links is important to gauge empirical asset pricing. Bernanke and Kuttner (2005), for example, argue that “The most direct and immediate effects of monetary policy actions, such as changes in the federal funds rate, are on the financial markets by affecting asset prices and returns, policymakers try to modify economic behavior in ways that will help to achieve their ultimate objectives.” Thus, studying the links between monetary policy and asset prices is crucial for policymakers to understand the monetary policy transmission mechanism.

Several recent papers connect literature on asset prices with the literature on Taylor-type monetary policy rules. Engel and West (2005) use the Taylor rule model as an example of a present value model where asset prices approach a random walk as the discount factor approaches one. Engel and West (2006), Mark (2009), Engel, Mark, and West (2007), Molodtsova and Papell (2009), and Molodtsova, Nikolsko-Rzhevskyy, and Papell (2008, 2009) examine the empirical performance of Taylor-rule based exchange rate models either in-sample or out-of-sample and find that Taylor rule fundamentals, such as inflation and output gap, have a potential for explaining exchange rate behavior.

In this paper, we use real-time data from 1970 to 2008 to examine in-sample and out-of-sample predictability of monthly and quarterly stock returns with Taylor rule fundamentals. The starting point of our analysis is the “Fed model” of stock return predictability used, for example, in Lander, Orphanides and Douvogiannis (1997). The model relates stock returns to long term yields. Despite its satisfactory in-sample and out-of-sample performance, the Fed model does not reflect how the monetary policy is conducted or evaluated. We augment the model by substituting the Taylor rule fundamentals for the U.S. Federal Funds rate.

There are a number of different specifications that we consider. Starting with Taylor (1993), the interest rate reaction function where the nominal interest rate responds to the difference between inflation and its target, the output gap, the equilibrium real interest rate, and (sometimes) the lagged interest rate and the real exchange rate, has become the standard method for evaluating monetary policy.[1] Following Clarida, Gali, and Gertler (1998) (CGG thereafter), it has become common practice to assume partial adjustment of interest rate to its target within a period. To incorporate gradual adjustment of the Federal Funds rate to its target, we include lagged interest rate in the model in addition to inflation and the output gap. Alternatively, we can derive a model with no smoothing that does not include the lagged interest rate.

Economic theory suggests several reasons why monetary policy should play an important role in determining stock returns. Since stock prices are determined in a forward-looking manner, monetary policy is likely to influence stock prices through the interest rate (discount) channel, and indirectly through its influence on market participants’ expectations of the future economic activity, which has an effect on the determinants of dividends and the stock return premium.

[1] Asso, Kahn, and Leeson (2007) examine the intellectual history of the Taylor rule and its influence on macroeconomic research and monetary policy.

Changes in the federal funds rate are thought to lead to changes in the value of market portfolios ("wealth effect") and the cost of capital ("credit channel"). Although a number of studies have documented the interaction between monetary policy and stock returns either in a VAR framework or using event study methodology, relatively few papers to date have attempted to provide an explanation for the stock market's reaction to monetary policy.[2]

Although, it makes sense to evaluate stock return models in-sample and out-of sample using real-time data, which were available to market participants when they made their decisions, most of the previous literature used revised data on macroeconomic variables. We fill this gap by using real time data on inflation and output gap to precisely mimic the decision making process of investors in the stock market.

Although, the evidence of stock return predictability with different measures of monetary policy is far from being consistent, most existing studies find the interest rates to be reliable predictors of stock returns. At the same time, the out-of-sample performance of other macroeconomic variables, such as inflation and measures of economic activity, is relatively less stellar. In a recent study, Cooper and Priestley (2008) demonstrate that the output gap is a reliable predictor of stock returns.

The estimated output gap depends on the measure of potential output. We implement the most commonly used detrending techniques that differ in their definition of potential output. The output gap is calculated as percentage deviations of actual output from a linear time trend, a quadratic time trend, a Hodrick-Prescott (1997) (HP) trend and Baxter-King (BK) Filter adjusted

[2] Patelis (1997), Thorbecke (1997), Goto and Valkanov (2002) use a VAR-based methods to study stock returns response to changes in either federal funds rates, inflation or federal funds futures. Boyd et al. (2001) focus on the stock market's response to employment news, and find that stock prices rise when there is bad labor market news during expansions, and fall during contractions. Bernanke and Kuttner (2005) study the impact of monetary policy surprises on stock prices, and find that a 25-basis-point cut in the federal funds rate is associated with a one percent increase in broad stock indexes. Crowder (2006) estimates the response of stock returns to innovations in the federal funds rate in a SVAR model that either includes or excludes price index. He finds positive shocks in FFR leads to immediate declines in S&P 500 returns, and increases in price index lead to higher FFR and lower stock returns. Rigobon and Sack (2004) estimate the response of daily stock returns to changes in FFR in a GARCH model. D'Amico and Farka (2003) study the response to changes in federal funds futures on FOMC meeting days. Both papers conclude that monetary tightening leads to declines in equity returns.

for the end-of sample uncertainty using a version of Watson (2007) correction method[3]. Because the estimation of a trend requires both past and future data, it is difficult to accurately estimate its values at the beginning and the end of the sample. The end-of-sample uncertainty is particularly relevant for real-time analysis, since the end-of-sample observations are those that we are interested in the most. Alternatively, following Blinder and Reis (2005), the difference between the natural rate of unemployment and the unemployment rate can replace the output gap.

Inoue and Kilian (2004) argue that in-sample predictability does not necessarily mean out-of sample predictability, and vice versa. Thus, to measure the links between Taylor rule fundamentals and stock returns, we first examine the in-sample performance of the models using standard measures, such as t-statistics, F-statistics, R-squared, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Then, we compare the out-of-sample performance of the Taylor rule models to the performance of the constant return model and the long term yield model, also known as the Fed model. The out-of-sample predictability of the models is evaluated using the out-of-sample R-squared, defined as one minus the ratio of the mean squared prediction errors (MSPE) from the two models, and three other test statistics described below.

We compare the mean squared prediction errors (MSPE) from the two models using the test of Diebold and Mariano (1995) and West (1996) (DMW test). While the DMW test statistic is appropriate for non-nested models, when comparing the MSPE's of two nested models, the use of standard normal critical values with DMW test usually results in very poorly sized tests, with far too few rejections of the null.[4] McCracken (2007) tabulated asymptotical critical values that can be used for 1-step ahead forecast comparisons using DMW test.

[3] While Watson (2007) proposes to deal with the end-of-sample uncertainty by augmenting the series of GDP with 600 forecasts and backcasts from an AR (6) model before applying the filter, we are forecasting 12 periods ahead using AR(4) model.

[4] McCracken (2007) shows that using standard normal critical values for the DMW statistic results in severely undersized tests, with tests of nominal 0.10 size generally having actual size less than 0.02.

In addition to DMW test, we use the CW test that was recently proposed by Clark and West (2006, 2007) for comparing predictive ability of the two nested models. The simulations in Clark and West (2006) suggest that the inference made using asymptotically normal critical values results in properly-sized tests. We bootstrap the critical value for CW test using the algorithm described in section four. Using the data for the U.S. from 1970 to 2008, we find evidence of stock return predictability with Taylor rule fundamentals, which is robust to using various measures of economic activity and different window sizes. This indicates that investors can time the market using available information and generate economically and statistically significant profit.

Both DMW and CW test statistics are based on mean squared error comparisons and ignore the information about the higher moments of the distribution. In order to avoid this limitation, we use the Matusita-Bhattacharya-Hellinger measure of dependence between stock returns and monetary policy variables, which is used in Maasoumi and Racine (2002).

These three testing procedures are not equivalent to each other. While rejecting the null hypothesis based on the DMW statistic indicates that the richer model has more forecasting ability in the sense that it has lower MSPE, rejecting the null based on CW statistics indicates that a linear combination of the two models contains more information useful for predicting stock returns than the simpler model. Rogoff and Stavrakeva (2008) and provide more details on the importance of this distinction. Rejection of the dependence test based on the Matusita-Bhattacharya-Hellinger test indicates that the stock return depends on the predictors in the Taylor rule model. We find strong evidence of out-of-sample predictability, forecasting ability and dependence based on all three statistics with Taylor Rule fundamentals. The evidence of predictability improves toward the end of the sample when the U.S. monetary policy is generally characterized by the Taylor rule.

A number of papers examine how a surprise increase in the Federal Funds rate affects stock returns. Bernanke and Kuttner (2005) find that a 25-basis-point cut in the federal funds rate is associated with a one percent increase in broad stock indexes. We extend the question by looking at the effect of Taylor rule fundamentals, the determinants of federal fund rate, on stock return. We find that an increase in U.S. inflation leads to a decrease in forecasted stock returns in the whole sample. This finding provides evidence to support inflation illusion hypothesis in Campbell and Vuolteenaho (2004). The predictability of stock returns in a Taylor rule model comes from the fact that the Federal Reserve responds to inflation by increasing Federal Funds rate. This increases the gap between long term yield and earnings growth. In addition, the portfolio rebalance by stock market participants generates the negative relationship between inflation and forecasted returns.

The output gap coefficient follows the same pattern regardless of how the potential output is calculated. It starts near zero, falls sharply around 1991, and stays negative for whole sample. Since most of the empirical evidence is consistent with the hypothesis that the Fed adopted some variant of the Taylor rule starting in the mid-1980s, our findings indicate that an increase output gap caused forecasted decrease in stock returns starting at the point when most of the observations in the forecasting regression were from periods where U.S. monetary policy is generally characterized by a Taylor rule. We find that the evidence of out-of-sample predictability is stronger in the model with no smoothing.

The rest of the paper is organized as follows. Section 2 introduces the stock return model which motivates our empirical research. In section 3, we describe the data. Section 4 describes the how the out-of-sample test statistics are constructed and the inference is made. In section 5, we the results of in-sample and out-of-sample tests are discussed. Section 6 concludes.

2 .Stock Return Model

The starting point for our analysis is the so-called “Fed model”, where stocks and bonds are competing for the space in a representative investor’s portfolio. Exogenous risk premium on stocks versus bonds and exogenous growth of the earnings are assumed. The yield of stock market index is positively correlated with yield of bond in the equilibrium. Otherwise, investor will switch to investing in a high yielding asset (Campbell and Vuolteenaho (2004)).

$$E\left(\frac{e_t}{p_t}\right)^* = \alpha + \beta \times lty_t \qquad (1)$$

where $\beta > 0$, lty is the long term yield of a bond; and $\frac{e_t}{p_t}$ is the earnings price ratio is yield of a stock.

The shock to the long term yield generates a change in equilibrium earnings price ratio. Given exogenous earnings of the stock, the stock price must change to adjust earnings price ratio to the equilibrium. According to Lander, Orphanides and Douvogiannis (1997), investors’ adjustment of portfolio between stock and bond moves the stock price. The change of stock price or stock return (if we do not consider dividend) will be correlated with the deviation and equilibrium earnings price ratio.

$$r_{t+1} = \alpha_1 + \beta_1\left[\frac{e_t}{p_t} - E\left(\frac{e_t}{p_t}\right)^*\right] + \varepsilon_t \qquad (2)$$

where $\beta_1 > 0$. Substituting equation (1) into equation (2), yields

$$r_{t+1} = \alpha_1 - \alpha\beta_1 + \beta_1\frac{e_t}{p_t} - \beta_1\beta \times lty_t + \varepsilon_t \qquad (3)$$

We refer to equation (3) as the long term yield model thereafter. According to the pure expectation theory, long term interest rate depends on the expected short-term interest rate, and we can substitute long term yield by the summation of term spread and federal fund rate (Campbell, 1987 and Fama and French, 1989).

$$r_{t+1} = \alpha_1 - \alpha\beta_1 + \beta_1 \frac{e_t}{p_t} - \beta_1\beta \times (term_t + i_t) + \varepsilon_t \qquad (4)$$

where i_t is federal funds rate, the interest rate on loans from banks with excess reserves to banks with insufficient reserves.

Following Taylor (1993), the central bank sets the federal funds rate in response to inflation gap and output gap

$$i_t^* = \pi_t + \phi(\pi_t - \pi^*) + \gamma y_t + r^* \qquad (5)$$

where i_t^* is the target level of the federal funds rate, π_t is the inflation rate, π^* is inflation target, y_t is the output gap, defined as percent deviation of actual output from an estimate of its potential level, and r^* is the equilibrium level of the real interest rate. $\phi > 0$ and $\gamma > 0$, since in order to stabilize the economy, central bank raises federal fund rate when inflation and/or output is above the target.

We can combine π^* and r^* in equation (3) into a constant term, $\mu = r^* - \phi\pi^*$. Short term nominal interest rate target follows the equation:

$$i_t^* = \mu + \lambda\pi_t + \gamma y_t \qquad (6)$$

where $\lambda = 1 + \phi$.

Following Clarida, Gali and Gertler (1998), we allow for the possibility that the interest rate adjusts gradually to achieve its target level:

$$i_t = (1-\rho)i_t^* + \rho i_{t-1} + v_t \qquad (7)$$

where $0 \le \rho < 1$. Substituting equation (6) into (7), gives the following equation,

$$i_t = (1-\rho)(\mu + \lambda\pi_t + \gamma y_t) + \rho i_{t-1} + v_t \qquad (8)$$

To derive the Taylor-rule-based forecasting equation for stock returns, we substitute equation (8) into equation (4).

$$r_{t+1} = \omega + \omega_d \frac{e_t}{p_t} + \omega_t Term + \omega_\pi \pi_t + \omega_y y_t + \omega_i i_{t-1} + \eta_t \qquad (9)$$

where $\omega_d = \beta_1 > 0$, $\omega_t = -\beta_1\beta < 0$, $\omega_\pi = -\beta_1\beta \times (1-\rho)\lambda < 0$, $\omega_y = -\beta_1\beta \times (1-\rho)\gamma < 0$, and $\omega_i = -\beta_1\beta \times \rho < 0$.

Although term spread appears in equation (9), it actually does not play an important role in explaining stock return variation. The coefficient on term spread is never significantly different from zero no matter what measure of the output gap is used, and whether we include lagged interest rate or not. This result is also robust to different data frequency and different time periods. Therefore, the predictability of stock return comes only from Taylor rule fundamentals.

If the interest rate adjusts to its target level within the period, the Taylor Rule model without smoothing is as follows:

$$r_{t+1} = \omega + \omega_d \frac{e_t}{p_t} + \omega_t Term + \omega_\pi \pi_t + \omega_y y_t + \eta_t \qquad (10)$$

If inflation exceeds its target (positive inflation gap) and/or real output is higher than its potential (positive output gap), the Federal Reserve uses open market operations or other monetary policies to reduce money supply and increase federal fund rate in order to stabilize the economy. The increase in federal fund rate reduces output gap and decreases inflation through interest effect. At the same time, the raise in federal fund rate pushes the implicit equilibrium yield in the stock market up, and generates a deviation between observed and equilibrium yield.

In the next period, stock prices should decrease to make the yield go back to equilibrium, which generates a negative price change or negative return.

3. Data

We use monthly and quarterly data from October 1969 to November 2008. Stock return is continuously compounded return of S&P 500 index including dividends taken from the Center for Research in Security Prices (CRSP). Long term yield of government bond, S&P500 index at the end of each month and moving sum of 12 month earnings on S&P 500 index are taken from Amit Goyal's website.[5] Term spread is the difference between long term yield and the federal funds rate. Earnings Price Ratio is the ratio of earnings and S&P500 Index.

The real-time real GDP, inflation, and unemployment rate is from the Philadelphia Fed Real-Time Database for Macroeconomists. We use GDP Deflator to measure inflation. Inflation is calculated as a 12-month (or 4-quarter) difference in the log of the price level measured by GDP Deflator. The federal funds rate (FFR) is taken from the Federal Reserve Bank of Saint Louis database.

The estimated output gap depends on the measure of potential output. We use the most commonly used detrending techniques that differ in the definition of potential output. Potential output is estimated as percentage deviations of actual output from a linear time trend, a quadratic time trend, a Hodrick-Prescott (1997) (HP) trend, and Baxter and King (1999) (BK) trend. All of these detrending methods decompose the log of real output, y_t , measured by the real GDP, into a trend component, T_t , and a cycle component, c_t :

$$y_t = T_t + c_t$$

[5] http://www.goizueta.emory.edu/faculty/AmitGoyal/

We use four main detrending methods to estimate the output gap:

1. Linear Time Trend. The output gap is constructed by taking the residuals from an OLS regression of the log of real output, y_t , on a constant term and a linear time trend, X= {1 t}.

2. Quadratic Time Trend. The output gap is constructed by taking the residuals from an OLS regression of the log of real output, y_t , on a constant term and a quadratic time trend, X= {1 t t^2}.

3. Hodrick-Prescott (HP) Filter. One of the most popular detrending techniques is suggested by Hodrick and Prescott (1997). A time series, y_t , is decomposed into a trend component, T_t , and a cycle component, c_t . The output gap is calculated by minimizing the loss-function,

$$L = \arg\ \min \sum_{t=1}^{T} \left(y_t - T_t\right)^2 + \lambda \sum_{t=2}^{T-1} \left[\left(T_{t+1} - T_t\right) - \left(T_t - T_{t-1}\right)\right]$$

The smoothness parameter, λ, punishes the variability in the trend component. Increase in the value of λ makes the trend component smoother, and the trend component becomes a linear trend as λ approaches to infinity. Following the convention, we choose λ = 1600 to detrend quarterly series, and λ = 14400 for monthly series. To take care of the end-of-sample distortions created by the filter, we apply the technique advised by Watson (2007) by using AR (8) model to forecast and backcast the log of GDP 12-periods ahead before applying the filter.

4. Baxter-King (BK) Filter. Baxter and King (1999) proposed a filter that admits frequency components between 6 and 32 quarters in a time series. The BK filter is a symmetric filter and is subject to the end-of-sample problem that becomes even more severe with real-time data, when no future data is available and the focus is on the last available observation in each period. We apply the same method proposed by Watson (2007) to get an estimate of output gaps at the end of the sample.

Alternatively, as in Blinder and Reis (2005), the difference between the natural rate of unemployment and the unemployment rate can replace the output gap. The descriptive statistics for the variables used are shown in Table 2.1.

4. Model Comparisons

4.1 Out-of Sample Tests Based on MSPE Comparisons

The central question in this paper is whether Taylor rule variables can provide evidence of out-of-sample predictability for stock returns. Before addressing this issue, we need to summarize some econometric results.

Following much of the literature on stock return predictability, we are interested in comparing the mean square prediction errors from two nested models. The benchmark model is constant return model, while the alternative is a linear model.

Model 1: $y_t = \delta + \varepsilon_t$

Model 2: $y_t = X_t^{'}\beta + \varepsilon_t$, where $E_{t+1}(\varepsilon_t) = 0$

The simplest statistic commonly used in the literature to compare the out-of-sample performance of the two models is out-of-sample R^2, which is defined as

$$OOS - R^2 = 1 - \frac{MSPE_2}{MSPE_1} \qquad (14)$$

where $MSPE_1$ and $MSPE_2$ are mean squared prediction errors from the constant return model and the alternative linear model, respectively. Therefore, the out-of-sample R^2 approaches to one, when the MSPE of the alternative model is much smaller than that of the null model, which indicates the evidence in favor of the alternative model.

To formally test the null hypothesis that the two MSPEs are equal against the alternative that the MSPE of model 2 is smaller than the MSPE of model 1, we use the procedure introduced by Diebold and Mariano (1995) and West (1996) that uses sample MSPEs to construct a t-type statistic, which is assumed to be asymptotically normal. To construct the DMW statistic, let

$$\hat{f}_t = \hat{e}_{1,t}^2 - \hat{e}_{2,t}^2 \qquad \text{and} \qquad \bar{f} = P^{-1} \sum_{t=T-P+1}^{T} \hat{f}_{t+1} = \hat{\sigma}_1^2 - \hat{\sigma}_2^2$$

where $\hat{e}_{1,t}$ and $\hat{e}_{2,t}$ are the sample forecast errors from the models 1 and 2, respectively. Then, the DMW test statistic is computed as follows,

$$DMW = \frac{\bar{f}}{\sqrt{P^{-1}\hat{V}}}, \qquad \text{where} \qquad \hat{V} = P^{-1} \sum_{t=T-P+1}^{T} (\hat{f}_{t+1} - \bar{f})^2$$

Suppose we have a sample of T+1 observations. The last P observations are used for predictions. The first prediction is made for the observation R+1, the next for R+2, …, and the final for T+1. We have T+1=R+P, where R is the size of rolling window, and P the total number of forecasts. To generate prediction for period t=R, R+1, …, T, we use only the information available prior to t.

McCracken (2007), among others, shows that application of the DMW statistic with standard normal critical values to nested models results in severely undersized tests, which in our case would lead to far too few rejections of the null hypothesis of no predictability. Clark and West (2006) demonstrate analytically that the asymptotic distributions of sample and population difference between the two MSPEs are not identical, namely the sample difference between the two MSPEs is biased downward from zero under the null. In order to test for predictability, we construct the adjusted test statistic as described in Clark and West (2006) by adjusting the sample MSPE from the alternative model by the amount of the bias. This adjusted CW test statistic is asymptotically standard normal.

It is important to understand the distinction between predictability and forecasting ability. We use the term "predictability" as a shorthand for "out-of-sample predictability" in the sense used by Clark and West (2006, 2007), rejecting the null of a zero slope in the predictive regression in favor of the alternative of a nonzero slope. The CW methodology tests whether the regression coefficient in the linear model is zero rather than whether the sample MSPE from the model-based forecast is smaller than the sample MSPE from the random walk forecast.

Rogoff and Stavrakeva (2008) argue that predictive models are not robust to different window sizes. We report the results using 7 different P/R ratios (0.4, 0.6, 0.8, 1, 1.4, 2 and 3), which corresponds to 7 different window sizes. With monthly data, this translates into a regressions with 334-, 293-, 260-, 234-, 195-, 156- and 117-month rolling windows starting in February 1970. With quarterly data, the sizes of the rolling windows are 112, 98, 87, 78, 65, 52, 39 quarters starting in the 2nd quarter of 1970. The predictions start around 1998, 1994, 1991, 1989, 1986, 1983 and 1980 respectively.

Because our sample size is relatively small and independent variables are serially correlated, we cannot rely inference on the asymptotic critical value provided by McCracken (2004) or Clark and McCracken(2001). Therefore, we bootstrap critical values using procedure, which is motivated by Mark (1995), Kilian(1999) and Rapach and Wohar(2006).

4.2 Tests Based on Matusita-Bhattacharya-Hellinger Measure of Dependence

In addition to the DMW and CW statistics, we use the normalization of the Matusita-Bhattacharya-Hellinger measure of dependence to test for nonlinear "affinity" between stock return and out-of-sample prediction based on Taylor rule model.

The test statistic is calculated using the formula:

$$S_\rho = \frac{1}{2}\int_{-\infty}^{\infty}\int \left(f_{r,\hat{r}}^{\frac{1}{2}} - f_r^{\frac{1}{2}} f_{\hat{r}}^{\frac{1}{2}} \right)^2 dr d\hat{r}$$

where $f_{r,\hat{r}}$ is the joint density of stock return and predicted return. f_r is the marginal density of stock return and $f_{\hat{r}}$ is the marginal density of predicted return. S_ρ is normalized between zero and one. Lower value of S_ρ indicates weaker dependence of stock return on the predictors.

S_ρ uses the information of the whole distribution instead of just first two moments to test the dependence rather than correlation. The null hypothesis is independence. The insignificant S_ρ means the failure of the model rather than just no correlation, which indicates that no significant information about stock return distribution is contained Taylor rule fundamentals.

Following Maasoumi and Racine (2002), we use kernel density estimator for the density of the marginal and joint distributions of real and predicted return. The kernel function is the second order Gaussian kernel. The bandwidth is selected via likelihood cross-validation. In order to calculate the critical values, we bootstrap under the null of independence. The result shows that stock returns are dependent on the Taylor rule fundamentals in many cases. We can use the predictors in the Taylor rule model to predict stock return.

In order to see if Taylor rule fundamentals contain more information than the long term yield, we also compare Taylor rule model with the model using only long term yield in equation (3) by out-of-sample R^2 and the DMW statistic.

4.3. Certainty Equivalence Tests

In order to see if the trading strategy based on Taylor rule model can generate higher utility than the strategies based on constant return model or long term yield model, we follow Ferreira and Santa-Clara (2010) to compare the certainty equivalence based on different models. Suppose that the utility function of a single period representative investor, $U(W_{t+1})$, is strictly increasing and twice differentiable, and W_{t+1} is the wealth level at time t+1. Since $E_tU(W_{t+1})$ =

U(CE), where CE stands for the certainty equivalence, maximizing expected utility is equivalent to maximizing the certainty equivalence with strictly increasing utility function.

$$CE = E_t(W_{t+1}) - \frac{\gamma}{2} Var_t(W_{t+1})$$

which is derived from Taylor approximation. We assume the initial wealth is 1 and coefficient of relative risk aversion equals γ.

Investor can invest in stock and in a risk free asset. Therefore,

$$W_{t+1} = w_t R_{t+1} + (1 - w_t) RF_{t+1},$$

where w_t is the weight to invest in stock. R_{t+1} is stock return and RF_{t+1} is return on risk free asset at time t+1, which is known at time t.

In order to find the weight of the optimal portfolio for the investor, we can maximize certainty equivalence. The optimal weight, $w_t = \dfrac{E_t R_{t+1} - RF_{t+1}}{\gamma Var_t(R_{t+1})}$, can be empirically estimated by $w_t = \dfrac{\hat{R}_{t+1} - RF_{t+1}}{\gamma \hat{Var}(R_{t+1})}$, where $\hat{R}_{t+1}$ is the predicted value from rolling regressions using constant return model, Long term yield model, and the Taylor rule model, $\hat{Var}(R_{t+1})$ is the estimated variance of stock return, and γ can take on the value of 1, 2, or 3. After the portfolio weight is determined, the return can be calculated, and the certainty equivalence can be estimated for each model.

5. Empirical Results

5.1 In-Sample Estimation Results

Panels A and B of Table 2.2 report OLS regression results for the Taylor rule model using monthly and quarterly data, respectively. Although we substitute long term yield by Taylor rule fundamentals and term spread, the coefficient for term spread is consistently insignificantly different from zero. We only report the coefficient and standard errors for the Taylor rule fundamentals. The model with lagged interest rate, we included the first lag of federal fund rate in addition to inflation and output gap. The adjusted R-squared and F-statistics are reported in the last two rows of each panel. Standard error is in the parenthesis. The results in panel A indicate that inflation is negatively correlated with stock returns, and all the coefficients are statistically different from zero at 5% level. Most of the output gap measures are also significantly different from zero (except for unemployment rate) with negative signs. The results confirm our prediction that when inflation and output gap go up, the forecasted stock market return goes down. F-statistics also rejects that Taylor rule fundamentals cannot be used to predict stock return. The adjusted R-squared indicates that using the Taylor rule model, we can explain 4% of variation in stock returns with monthly real-time data.

Taylor-rule based models that include lagged interest rates have almost the same adjusted R-squared. Furthermore, the t-statistics of lagged federal fund rate is not statistically different from zero, although the sign is negative as predicted. Partial adjustment model is not better than the model with no smoothing. Quarterly data generates similar results, with a much stronger in-sample fit than monthly data. 14% of variation in stock returns can be predicted by Taylor rule model with quarterly real-time data.

In Table 2.3, we further compare the Taylor rule model with the long term yield model by looking at adjusted R-squared, Akaike's Information Criterion (AIC) and Bayesian information Criterion (BIC). Most of the AIC and BIC in Taylor rule model are lower than those in the long term yield model. Besides, all the adjusted R-squared from Taylor rule model either with smoothing or without smoothing are much higher than from the long term yield model. The result is robust to different data frequency. The evidence indicates that although long term yield is more directly connected with stock return, the Taylor rule fundamentals include more predictive information than long term yield.[6]

The in-sample analysis also provides evidence for inflation illusion hypothesis. If the correlation between inflation and stock yield does not exist, it is an evidence in favor of claim by Asness (2003) that inflation increases both nominal interest rate and divided growth at the same level and the effect of inflation on yield of the stock should be zero. If there is the positive relationship between inflation and future stock yield, according to Campbell and Vuolteenaho (2004), there are three potential explanations: 1. inflation only drives down the real dividend growth. 2. inflation only drives up the risk premium. The third explanation is from a behavioral bias perspective: inflation illusion makes stock market participants fail to see that the inflation increases nominal dividend growth. Rather, bond market investors increase nominal bond yield. Campbell and Vuolteenaho (2004) regress dividend yield' components on inflation and provide evidence to support inflation illusion.

Our paper provides evidence to support inflation illusion argument by directly testing the predictive relationship between inflation and stock return. Positive correlation between inflation and stock yield is equivalent to negative correlation between inflation and stock return. The existence of negative relationship between inflation and future stock return verifies inflation drives up long term yield more than growth of the earnings, which means the under reaction to the inflation shock of stock market relatively to bond market (inflation illusion). As we can see, in Table 2.2, inflation is negatively correlated with stock return, the result is robust to different data frequency and the use of different output gap measures of output gap. The result does not change if the model with smoothing is used.

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[6] In unreported table, we use monthly and quarterly data to estimate the equation (9) and (10) without the term spread. The results provide evidence in support of the Taylor rule model based on lower AIC and BIC.

Figure 2.1 shows the dynamics of inflation coefficients for the model without smoothing with P/R ratios equal to 1. The observed pattern also confirms the negative relationship is consistent over time.[7] Both in-sample and out-of-sample evidence provides support for inflation illusion argument.

5.2 Out-of-Sample Model Comparisons

As we know, strong in-sample performance does not necessarily indicate good out-of-sample performance of the model. Moreover, we want to see whether an investor can use the information available to her at a given time to predict stock return. First, compare constant return model and Taylor rule model out-of-sample. Unlike most of the previous studies in which revised data of macroeconomic variables was used, we use real time data of inflation and output gap, because revised data are in fact not available when investors make their out of sample predictions.

Tables 4 and 5 report the results for 1-month ahead and 1-quarter ahead out-of-sample tests for Taylor-rule based models with and without interest rate smoothing using different measures of economic activity and different window sizes. DMW is a test for equal predictive accuracy of Taylor rule model and constant return model. S_ρ is a test for dependence of stock return on Taylor rule fundamentals. CW is a test for predictability of the Taylor rule fundamentals. R^2 is out-of-sample R-squared. Critical values are obtained using bootstrap.

Three observations can be made based on these results. First, the evidence of stock return predictability is stronger without smoothing than with smoothing in the test based on first two moments, i.e. the DMW, CW, and the OOS R^2, but it is stronger with smoothing than without it based on the dependence test. Second, the evidence of predictability is stronger with monthly data than with quarterly data. Third, the evidence of stock return predictability improves toward the end of the sample when the U.S. monetary policy is generally characterized by a Taylor rule. All

[7] In an unreported table, we also regress long term yield and growth of earnings on inflation. Inflation drives higher long term yield, while inflation is insignificantly affect earnings growth.

statistics are much stronger for the window sizes with P/R ratios of 1.4 and 1, which produce the first forecasts for May 1986 and August 1989. Using quarterly data, we obtain similar but slightly weaker result.

We have presented evidence that, using both Taylor rule model specifications, the constant return (no predictability) null hypothesis can be consistently rejected. Moreover, the equal MSPE hypothesis can be consistently rejected in favor of the alternative hypothesis of out-of-sample forecasting ability for the S&P 500 returns with Taylor rule fundamentals. Independence of stock return on predictors is usually rejected. The specifications include inflation and either linear, quadratic, HP filtered, BK filtered output gap, or the unemployment rate in the forecasting regression. It is clear that the information about future return contains in Taylor rule model is much higher than the information contained only in past return.

Since Taylor rule model was derived from the model with only long term yield, it is not clear whether Taylor rule fundamentals include more information than long term yield which is more directly connected with stock return. Table 2.6 addresses this question by reporting DMW and out of sample R-square statistics, when comparing the Taylor rule model with the Long term yield model. DMW is a test for equal predictive accuracy of Taylor rule model. R2 is out-of-sample R-squared. Since the models are non-nested, we use standard normal critical values for inference.

Taylor rule model outperforms long term yield models. The results are as follows. First, the evidence of stock return predictability is stronger without smoothing than with it. Second, the evidence of predictability is stronger with monthly data than with quarterly data. Third, the evidence of stock return predictability improves toward the end of the sample when the U.S. monetary policy is generally characterized by a Taylor rule. All statistics are much stronger from the window sizes with P/R ratios of 1, which produce the first forecasts for August 1989. We can also see similar results in quarterly data.

Figure 2.1 shows the dynamics of inflation and output gap coefficients from monthly and quarterly Taylor Rule model. We use output gap constructed by linear trend. We estimate rolling regressions with roughly a 20-year window with P/R ratios of 1. An increase in U.S. inflation leads to a decrease in forecasted stock returns during the whole sample. The output gap coefficient follows the same pattern regardless of how potential output is calculated.[8] It falls sharply around 1991, and stays negative for rest of the sample. The empirical evidence is consistent with the hypothesis that the Federal Reserve adopted some variant of the Taylor rule starting in the mid-1980s. Our findings indicate that an increase in inflation and output gap causes forecasted decrease in stock returns starting at the point when U.S. monetary policy is generally characterized by a Taylor rule.

Table 2.7 reports the estimated certainty equivalence in percentages for different models and different risk aversion factors. Panels A and B show certainty equivalence in percentages for Taylor rule models with and without smoothing, respectively. Panel C and D report certainty equivalence in percentages for constant return model and long term yield model, respectively. The results show that Taylor rule models generate higher certainty equivalence than constant return model and long term yield model. The result is robust to the use of different output gap measures and different data frequency.

6. Conclusions

This paper connects monetary policy variables to stock returns via the Taylor (1993) rule. Using real time quarterly and monthly data, we find un-sample and out-of sample predictability and interdependence of stock returns with Taylor rule fundamentals between 1969 and 2008.

DMW and CW test statistics provide strong evidence that the Taylor rule models have higher forecasting ability and contains more information useful to predict stock returns than

[8] Although we do not report these results, the plots are very similar when using various measures of economic activity.

constant return model. Dependence test of stock return on Taylor rule predictors using the information of the whole distribution also confirms that Taylor rule fundamentals are good predictors. That Taylor model has more forecasting ability than long term yield model is confirmed by DMW and out of sample R-square, although according to the model, long term yield has a closer connection with stock return. The predictability of Taylor rule fundamentals is robust to different measures of output gap and different window size in recent 30 years. Taylor rule model can generate higher utility for investors with a strictly increasing and twice differentiable utility function. Forecasting ability is stronger in no smoothing model and there is evidence in favor of inflation illusion of stock market participants. The evidence of predictability improves toward the end of the sample when the U.S. monetary policy is generally characterized by a Taylor rule.

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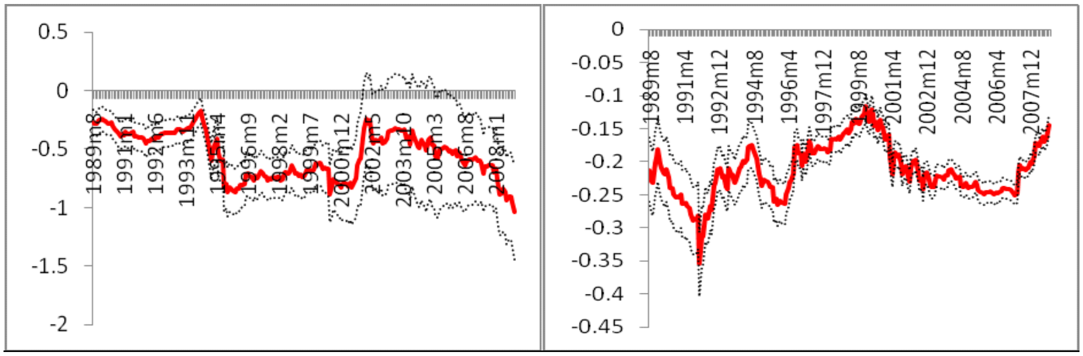
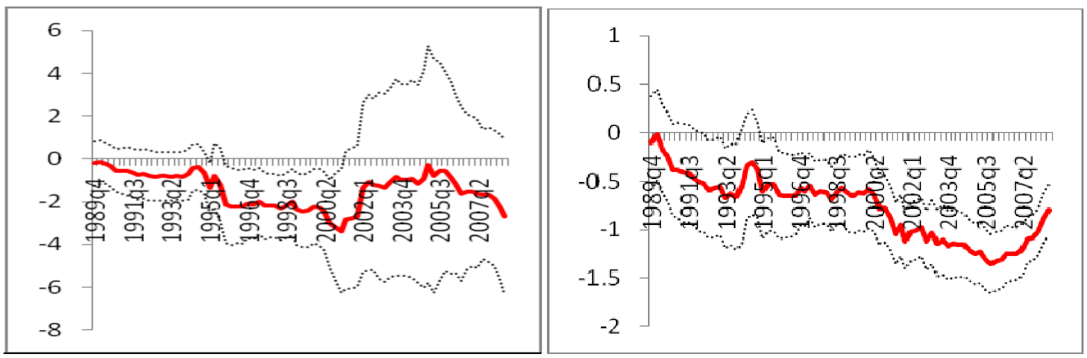


Inflation Coefficient Output Gap Coefficient

A. Monthly Data



Inflation Coefficient Output Gap Coefficient

B. Quarterly Data

Figure 2.1. The Dynamics of Inflation and Output Gap Coefficients from the Taylor Rule Model with Smoothing and Linear Output Gap, P/R =1(the confidence interval is at 5% level)

Table 2.1: Descriptive Statistics for Monthly Variables

Variable	Mean	Std Dev	Min	Max
Return	0.88	4.45	-21.58	16.81
Inflation	3.91	2.40	0.75	11.32
Linear Gap	-5.07	3.43	-15.05	2.58
Quadratic Gap	0.08	3.03	-10.42	6.26
HP-Watson Gap	-0.54	1.31	-5.55	1.71
Unemployment	6.10	1.39	3.50	10.80
BK-Watson	-0.53	1.24	-5.83	1.83
FFR	6.48	3.44	0.97	19.10
LTY	7.70	2.34	4.29	14.82
S&P500 Index	522.48	473.85	63.54	1549.38
Earnings (12 month)	26.08	19.29	5.13	84.95
Term Spread	1.23	2.01	-6.97	4.41
Earnings Price Ratio	0.07	0.03	0.02	0.15

Notes: Return is S&P 500 index continuously compounded return including dividends from February 1970 to November 2008 from CRSP. Linear Gap is linearly detrended output gap. Quadratic Gap is quadraticlly detrended output gap. HP-Watson Gap is output gap detrended using Hodrick-Prescott (HP) Filter with Watson (2007) adjustment. Unemployment is unemployment from the Philadelphia Fed Real-Time Database for Macroeconomists. BK-Watson Gap is the output gap calculated using Baxter-King (BK) Filter with Watson (2007) adjustment. LTY is long term yield on government bond. S&P500 Index is the index at the end of each month. Earnings is the moving sum of 12 month earnings on S&P 500 index. Long term yield, S&P500 Index, and Earnings, are taken from Amit Goyal's website. Term Spread is the difference between long term yield and federal fund rate. Earnings Price Ratio is the ratio of earnings and S&P500 Index. The data are in percentages.

Table 2.2: In-Sample Estimation Results: Model with Taylor Rule Variables

	Linear Gap		Quadratic Gap		HP Filter Gap		BK Filter Gap		Unemployment	
A: Monthly Data										
Inflation	- 0.40	-0.40	-0.57	-0.58	-1.03	-1.09	-0.99	-1.04	-0.36	-0.36
	(0.17)	(0.17)	(0.23)	(0.23)	(0.25)	(0.26)	(0.24)	(0.25)	(0.18)	(0.18)
Output Gap	-0.16	-0.18	-0.16	-0.16	-0.86	-0.93	-0.88	-0.95	0.00	0.01
	(0.07)	(0.07)	(0.11)	(0.11)	(0.24)	(0.25)	(0.24)	(0.25)	(0.23)	(0.27)
Lagged FFR	-	-0.10	-	-0..03	-	-0.13	-	- 0.13	-	-0.01
		(0.13)		(0.12)		(0.13)		(0.13)		(0.15)
Adj-R-sq	0.03	0.03	0.02	0.02	0.04	0.04	0.04	0.04	0.02	0.02
F-Statistic	4.69	3.88	3.71	2.98	6.49	5.41	6.61	5.51	3.22	2.57
B: Quarterly Data										
	Linear Gap		Quadratic Gap		HP Filter Gap		BK Filter Gap		Unemployment	
Inflation	- 1.07	-1.09	-1.78	-1.77	-3.21	-3.20	-3.15	-3.13	-0.92	-0.87
	(0.53)	(0.53)	(0.73)	(0.73)	(0.81)	(0.81)	(0.77)	(0.77)	(0.57)	(0.58)
Output Gap	-0.68	-0.65	-0.64	-0.60	-2.92	-2.87	-3.09	-3.04	0.18	-0.30
	(0.26)	(0.27)	(0.36)	(0.36)	(0.77)	(0.80)	(0.78)	(0.80)	(0.75)	(0.87)
Lagged FFR	-	0.13	-	-0.29	-	0.10	-	0.10	-	0.44
		(0.35)		(0.34)		(0.34)		(0.33)		(0.40)
Adj-R-sq	0.09	0.08	0.07	0.07	0.13	0.13	0.14	0.13	0.05	0.05
F-Statistic	4.76	3.81	3.81	3.18	6.76	5.39	7.19	5.74	2.94	2.60

Notes: This table reports OLS regression using the Taylor rule model with monthly data (Panel A) and quarterly data (Panel B). We only report coefficients and standard errors for Taylor rule fundamentals, since the coefficient on the term spread is always insignificantly different from zero. Linear Gap is linearly detrended output gap. Quadratic Gap is quadraticlly detrended output gap. HP-Watson Gap is output gap detrended using Hodrick-Prescott (HP) Filter with Watson (2007) adjustment. Unemployment is unemployment from the Philadelphia Fed Real-Time Database for Macroeconomists. BK-Watson Gap is the output gap calculated using Baxter-King (BK) Filter with Watson (2007) adjustment. In the models with smoothing, we include the first lag of federal fund rate. The adjusted R-square and F-statistics are reported in the last two rows of each panel. The models are estimated using the data from Febuary1970 to November 2008. Standard errors are reported in the parenthesis.

Table 2.3: In-Sample Estimation Results: Taylor Rule models vs. Long Term Yield Model

	Taylor rule model w/o smoothing		**Taylor rule model w/ smoothing**		**Long term yield Model**	
	AIC	BIC	AIC	BIC	AIC	BIC
A. Monthly Data						
Linear Gap	2705.15	2725.87	2706.48	2731.35	2715.50	2727.95
Quadratic Gap	2708.94	2729.66	2710.87	2735.73	-	-
HP (Watson)	2698.20	2718.92	2699.09	2723.95	-	-
BK (Watson)	2697.73	2718.45	2698.62	2723.49	-	-
Unemployment	2710.87	2731.58	2712.86	2737.73	-	-
B. Quarterly Data						
Linear Gap	1077.82	1093.01	1079.69	1097.91	1089.02	1098.14
Quadratic Gap	1081.36	1096.55	1082.63	1100.85	-	-
HP (Watson)	1070.66	1085.85	1072.57	1090.80	-	-
BK (Watson)	1069.17	1084.35	1071.07	1089.29	-	-
Unemployment	1084.66	1099.85	1085.38	1103.60	-	-

Notes: This table reports the Akaike's information criterion (AIC) and Bayesian information criterion (BIC) from the Taylor rule model and the Long term yield model with monthly (Panel A) and quarterly data (Panel B). Taylor rule models are estimated using linear time trend output gap, quadratic time trend output gap, Hodrick-Prescott (HP) Filter with Watson (2007) adjustment, Baxter-King (BK) Filter with Watson (2007) adjustment, and unemployment rate from the Philadelphia Fed Real-Time Database for Macroeconomists. The Long term yield model is the model with long term yield.

Table 2.4: One-Month-Ahead Forecasts: Taylor Rule Models vs. Constant Return Model

	w/o smoothing				w/ smoothing			
	DMW	S_p	CW	R^2	DMW	S_p	CW	R^2
				P/R=3				
Linear Gap	-1.33*	0.0062	1.21*	-0.04**	-2.35	0.0060**	0.33	-0.07
Quadratic Gap	-0.83**	0.0062	1.53**	-0.02***	-1.83	0.0138***	0.58	-0.05*
HP (Watson)	-0.08***	0.0074	2.59***	-0.00***	-1.28*	0.0046	1.53*	-0.04**
BK (Watson)	-0.00***	0.0062	2.62***	-0.00***	-1.22*	0.0053*	1.63*	-0.03**
Unemployment	-2.31	0.0040	-0.02	-0.07	-3.12	0.0053	-0.31	-0.11
				P/R=2				
Linear Gap	0.02***	0.0143***	2.11***	0.00***	-0.46**	0.0210***	1.86**	-0.01**
Quadratic Gap	-0.36**	0.0119**	1.62**	-0.01**	-0.81**	0.0154***	1.29*	-0.03*
HP (Watson)	0.25***	0.0103***	2.34**	0.01***	-0.07***	0.0117**	2.06**	-0.00***
BK (Watson)	0.27***	0.0112	2.34**	0.01***	-0.12**	0.0147***	2.08**	-0.00**
Unemployment	-0.09*	0.0084	1.44*	-0.00***	-0.78**	0.0118***	0.95	-0.02**
				P/R=1.4				
Linear Gap	0.99***	0.0153	2.80***	0.03***	0.79***	0.0189***	2.80***	0.02***
Quadratic Gap	0.52***	0.0114	2.24**	0.01***	0.80***	0.0131*	2.51***	0.02***
HP (Watson)	1.25***	0.0098	2.94***	0.03***	1.18***	0.0133**	2.96***	0.04***
BK (Watson)	1.30***	0.0102	3.06***	0.03***	1.23***	0.0150	3.12***	0.04***
Unemployment	0.84***	0.0104	2.21***	0.02***	1.03***	0.0115**	2.44***	0.02***
				P/R=1.0				
Linear Gap	1.51***	0.0204***	3.27***	0.05***	1.56***	0.0241***	3.57***	0.05***
Quadratic Gap	1.25***	0.0116	2.69***	0.03***	1.57***	0.0137***	3.27***	0.04***
HP (Watson)	1.91***	0.0131*	3.38***	0.05***	1.79***	0.0228**	3.57***	0.05***
BK (Watson)	1.77***	0.0110*	3.31***	0.05***	1.58***	0.0115**	3.52***	0.05***
Unemployment	2.06***	0.0196**	3.04***	0.04***	2.13***	0.0181***	3.45***	0.05***
				P/R=0.8				
Linear Gap	1.67***	0.0142	3.03***	0.05***	1.17***	0.0169*	2.85***	0.04***
Quadratic Gap	0.92***	0.0095	1.99**	0.02***	0.08*	0.0221***	1.87**	0.00*
HP (Watson)	1.32***	0.0105	2.55***	0.04***	0.99***	0.0116*	2.50***	0.03***
BK (Watson)	1.27***	0.0112	2.52***	0.04***	0.78**	0.0106*	2.38**	0.03**
Unemployment	1.95***	0.0143**	2.66***	0.04***	0.78***	0.0171***	2.22***	0.02***
				P/R=0.6				
Linear Gap	1.51***	0.0323*	2.76***	0.06***	1.13***	0.0274*	2.61***	0.04***
Quadratic Gap	0.91**	0.0141	1.75**	0.02**	-0.20	0.0187**	1.24	-0.00
HP (Watson)	1.32***	0.0181	2.39***	0.04***	0.84**	0.0169*	2.23**	0.03**
BK (Watson)	1.26***	0.0096	2.40***	0.04***	0.74**	0.0163**	2.20**	0.03**
Unemployment	1.16***	0.0160**	1.90**	0.03**	0.01*	0.0231	1.27*	0.00*
				P/R=0.4				
Linear Gap	1.56***	0.0179	2.61***	0.06***	1.48***	0.0234**	2.50***	0.06***
Quadratic Gap	1.54***	0.0238	2.20***	0.04***	1.14**	0.0369*	1.88**	0.03**
HP (Watson)	1.46***	0.0633	2.30***	0.05***	1.17**	0.0268	2.09**	0.04**
BK (Watson)	1.28**	0.0188	2.18**	0.04***	1.02**	0.0148	1.97**	0.03**
Unemployment	1.74***	0.0265***	2.28***	0.04***	1.40***	0.0233***	1.94**	0.03**

Notes: DMW is a test for equal predictive accuracy of Taylor rule model and constant return model. S_p is a test for dependence of stock return on Taylor rule fundamentals. *CW* is a test for predictability of the Taylor rule fundamentals. R^2 is out-of-sample R-squared. Critical values are from bootstrap. *P/R* includes 3, 2, 1.4, 1, 0.8, 0.6, 0.4. One asterisk indicates significance at the 10% level; two asterisks at the 5% level; three asterisks at the 1% level.

Table 2.5: One-Quarter-Ahead Forecasts: Taylor Rule Model vs. Constant Return Model

	w/o smoothing				w/ smoothing			
	DMW	S_p	CW	R^2	DMW	S_p	CW	R^2
				P/R=3				
Linear Gap	-1.20*	0.0088	1.47*	-0.13*	-1.79	0.0094*	1.56*	-0.21
Quadratic Gap	-1.43	0.0070	1.37	-0.15	-2.06	0.0064	1.44	-0.24
HP (Watson)	-0.74*	0.0064	2.12*	-0.07*	-1.97	0.0150	1.75	-0.22
BK (Watson)	-0.80	0.0041	1.89	-0.07*	-2.00	0.0180	1.66	-0.22
Unemployment	-2.43	0.0043	0.13	-0.22	-2.48	0.0052	-0.50	-0.26
				P/R=2				
Linear Gap	-0.52*	0.0171**	1.45*	-0.06	-0.89	0.0232**	1.06	-0.11
Quadratic Gap	-0.72	0.0136*	1.18	-0.09	-1.14	0.0214***	0.85	-0.14
HP (Watson)	-0.32*	0.0101	1.70	-0.03*	-0.71	0.0114*	1.31	-0.07
BK (Watson)	-0.40	0.0102	1.48	-0.04	-0.83	0.0134*	1.11	-0.08
Unemployment	-0.92	0.0132	0.55	-0.08	-1.62	0.0168***	-0.09	-0.16
				P/R=1.4				
Linear Gap	0.54**	0.0169	1.97**	0.07***	0.42**	0.0253**	1.81*	0.05***
Quadratic Gap	0.20**	0.0139	1.68*	0.02**	0.23**	0.0171	1.65*	0.02**
HP (Watson)	0.70**	0.0181	2.26**	0.06**	0.47**	0.0097	2.13*	0.04**
BK (Watson)	0.70**	0.0118	2.17*	0.06**	0.48**	0.0168	2.06	0.04**
Unemployment	0.22**	0.0167*	1.43	0.02**	0.03*	0.0126	1.12	0.00*
				P/R=1.0				
Linear Gap	1.00***	0.0280**	2.17**	0.13***	0.87***	0.0065	2.17**	0.11***
Quadratic Gap	0.54**	0.0151	1.81*	0.06**	0.31*	0.0147	1.91**	0.03**
HP (Watson)	1.00**	0.0122	2.31**	0.09***	0.52**	0.0160*	2.28**	0.05**
BK (Watson)	0.96**	0.0085	2.23*	0.09**	0.44*	0.0143	2.20*	0.04*
Unemployment	1.07***	0.0146	1.90*	0.08***	0.86**	0.0177*	2.02*	0.07**
				P/R=0.8				
Linear Gap	1.18***	0.0248*	2.22**	0.14***	0.76**	0.0184	1.91**	0.09**
Quadratic Gap	0.69**	0.0154	1.69*	0.06**	-0.26	0.0174	1.29	-0.03
HP (Watson)	0.61*	0.0112	1.80	0.06*	0.24	0.0116	1.51*	0.02
BK (Watson)	0.71*	0.0114	1.80*	0.07*	0.21	0.0120	1.46	0.02
Unemployment	1.47***	0.0139	2.13**	0.10***	0.46*	0.0191	1.63	0.03*
				P/R=0.6				
Linear Gap	1.07**	0.0333	2.00**	0.13***	0.74**	0.0367	1.70*	0.09**
Quadratic Gap	0.37	0.0115	1.12	0.03*	-0.24	0.0154	0.69	-0.02
HP (Watson)	0.65*	0.0075	1.55	0.06*	0.79*	0.0077	1.35	0.03
BK (Watson)	0.67	0.0066	1.58	0.06*	0.38	0.0086	1.35	0.04
Unemployment	0.24	0.0104	0.91	0.02	-0.23	0.0133	0.51	-0.02
				P/R=0.4				
Linear Gap	1.25**	0.0361**	2.13**	0.16***	1.18**	0.0264*	2.06**	0.15***
Quadratic Gap	1.18**	0.0144	1.83**	0.11**	1.03**	0.0138	1.69*	0.10**
HP (Watson)	1.29**	0.0131	1.99*	0.12**	1.25**	0.0112	1.95*	0.11**
BK (Watson)	1.06*	0.0106	1.78	0.11**	1.01*	0.0093	1.75	0.10**
Unemployment	1.30**	0.0127	1.84**	0.09**	1.08*	0.0110	1.58	0.08*

Notes: DMW is a test for equal predictive accuracy of Taylor rule model and constant return model. S_p is a test for dependence of stock return on Taylor rule fundamentals. *CW* is a test for predictability of the Taylor rule fundamentals. R^2 is out-of-sample R-squared. Critical values are from bootstrap. *P/R* includes 3, 2, 1.4, 1, 0.8, 0.6, 0.4. One asterisk indicates significance at the 10% level; two asterisks at the 5% level; three asterisks at the 1% level.

Table 2.6: One-Period-Ahead Forecasts: Taylor Rule Model vs. Long Term Yield Model

	1-Month Ahead Forecasts				1-Quarter Ahead Forecasts			
	w/o smoothing		*w/ smoothing*		*w/o smoothing*		*w/ smoothing*	
	DMW	R^2	DMW	R^2	DMW	R^2	DMW	R^2
P/R=3								
Linear Gap	-0.49	-0.01	-1.54	-0.04	-0.47	-0.04	-1.17	-0.12
Quadratic Gap	0.06	0.00	-1.03	-0.03	-0.67	-0.06	-1.43	-0.15
HP (Watson)	0.65	0.02	-0.48	-0.01	0.13	0.01	-1.17	-0.13
BK (Watson)	0.72	0.02	-0.40	-0.01	0.08	0.01	-1.20	-0.13
Unemployment	-1.66	-0.04	-2.75	-0.08	-1.61	-0.13	-1.73	-0.16
P/R=2								
Linear Gap	-0.15	-0.00	-0.75	-0.02	-0.34	-0.03	-0.83	-0.08
Quadratic Gap	-0.63	-0.02	-1.23	-0.03	-0.62	-0.05	-1.18	-0.10
HP (Watson)	0.12	0.00	-0.28	-0.01	0.00	0.00	-0.48	-0.04
BK (Watson)	0.14	0.00	-0.34	-0.01	-0.09	-0.01	-0.63	-0.05
Unemployment	-0.35	-0.01	-1.33	-0.03	-0.82	-0.05	-1.71	-0.12
P/R=1.4								
Linear Gap	0.17	0.00	-0.03	-0.00	0.32	0.03	0.15	0.01
Quadratic Gap	-0.44	0.01	-0.17	-0.00	-0.12	-0.01	-0.12	-0.01
HP (Watson)	0.40	0.01	0.45	0.01	0.36	0.03	0.08	0.01
BK (Watson)	0.41	0.01	0.47	0.01	0.35	0.03	0.09	0.01
Unemployment	-0.33	-0.01	-0.14	-0.00	-0.25	-0.02	-0.57	-0.03
P/R=1.0								
Linear Gap	1.18	0.04	1.36^{*}	0.04	1.32^{*}	0.13	1.29^{*}	0.11
Quadratic Gap	0.78	0.02	1.50^{*}	0.03	0.79	0.07	0.57	0.04
HP (Watson)	1.40^{*}	0.04	1.50^{*}	0.04	1.19	0.10	0.72	0.06
BK (Watson)	1.25	0.04	1.28	0.04	1.11	0.10	0.60	0.05
Unemployment	1.47^{*}	0.03	2.23^{**}	0.04	1.40^{*}	0.09	1.43^{*}	0.07
P/R=0.8								
Linear Gap	1.95^{**}	0.07	1.74^{**}	0.06	1.89^{**}	0.19	1.56^{*}	0.15
Quadratic Gap	1.53^{*}	0.04	0.98	0.02	1.57^{*}	0.13	0.57	0.04
HP (Watson)	1.79^{**}	0.05	1.68^{**}	0.05	1.38^{*}	0.12	1.05	0.09
BK (Watson)	1.66^{**}	0.05	1.37^{*}	0.04	1.42^{*}	0.13	0.97	0.09
Unemployment	2.30^{**}	0.05	1.95^{**}	0.04	2.46^{***}	0.16	1.76^{**}	0.10
P/R=0.6								
Linear Gap	2.37^{***}	0.09	2.17^{**}	0.07	2.01^{**}	0.20	1.69^{**}	0.16
Quadratic Gap	2.29^{**}	0.05	1.38^{*}	0.03	1.64^{*}	0.11	0.91	0.06
HP (Watson)	2.36^{***}	0.07	1.94^{**}	0.06	1.83^{**}	0.13	1.54^{*}	0.11
BK (Watson)	2.20^{**}	0.07	1.76^{**}	0.06	1.73^{**}	0.13	1.44^{*}	0.11
Unemployment	2.58^{***}	0.06	1.78^{**}	0.03	1.70^{**}	0.09	1.21	0.06
P/R=0.4								
Linear Gap	1.77^{**}	0.06	1.72^{**}	0.06	1.40^{*}	0.15	1.33^{*}	0.14
Quadratic Gap	1.79^{**}	0.04	1.39^{*}	0.03	1.36^{*}	0.09	1.19	0.08
HP (Watson)	1.55^{*}	0.05	1.23	0.04	1.25	0.10	1.21	0.10
BK (Watson)	1.37^{*}	0.04	1.09	0.04	0.99	0.09	0.95	0.08
Unemployment	1.94^{**}	0.04	1.68^{**}	0.03	1.45^{*}	0.08	1.20	0.06

Notes: DMW is test for equal predictive accuracy of Taylor rule model and Long term yield model. R^2 is out-of-sample R-square. DMW critical values are 1.28 at 10%, 1.645 at 5% and 2.325 at 1%. *P/R* includes 3, 2, 1.4, 1, 0.8, 0.6, 0.4. One asterisk indicates significance at the 10% level; two asterisks at the 5% level; three asterisks at the 1% level.

Table 2.7: Certainty Equivalence Comparisons

	Panel A: Taylor Rule Model w/o smoothing			Panel B: Taylor Rule Model w/ smoothing		
	γ=1	γ=2	γ=3	γ=1	γ=2	γ=3
Monthly						
Linear Gap	0.324	0.302	0.288	0.329	0.305	0.290
Quadratic Gap	0.305	0.293	0.283	0.307	0.295	0.284
HP (Watson)	0.315	0.298	0.286	0.318	0.299	0.287
BK (Watson)	0.314	0.297	0.285	0.316	0.298	0.286
Unemployment	0.309	0.296	0.285	0.309	0.296	0.285
Quarterly						
Linear Gap	0.901	0.784	0.687	0.898	0.784	0.689
Quadratic Gap	0.883	0.784	0.695	0.878	0.785	0.697
HP (Watson)	0.888	0.783	0.691	0.885	0.783	0.692
BK (Watson)	0.881	0.776	0.684	0.877	0.775	0.684
Unemployment	0.879	0.786	0.698	0.876	0.786	0.699
	Panel C: Constant Return Model			Panel D: Long term yield Model		
	γ=1	γ=2	γ=3	γ=1	γ=2	γ=3
Monthly	0.288	0.284	0.276	0.302	0.292	0.283
Quarterly	0.827	0.752	0.670	0.851	0.768	0.684

Notes: This table reports certainty equivalence in percentages for different models and values of risk aversion factor, γ. The data are at monthly and quarterly frequency. Panels A and B report certainty equivalence in percentages for Taylor rule models with and without smoothing using different measures of the output gap. Panels C and D include certainty equivalence in percentages for the constant return and Long term yield models. P/R ratio is 0.6.

Chapter 3

Order imbalance, liquidity and market efficiency: evidence from the Chinese stock market

By Lei Jiang

Abstract

In this paper, we use data from Chinese stock market to quantify the amount of time it takes for the market to converge to efficiency. Our results indicate that order imbalance may predict returns when there is no designated market maker. Including a variable for the direction of trade in Chinese stock market, we find that it takes longer for information regarding order imbalance to be incorporated into stock prices in China than in the U.S.. With information on past returns and order imbalance, we find it takes between 15 minutes to 30 minutes to converge to efficiency in the Chinese stock market. The process of converging to efficiency depends highly on liquidity and insider information.

Keywords: order imbalance, market efficiency, liquidity

JEL Classification: G12, G14

How efficient stock prices are generated, what process or pathway the stock market takes before it converges to efficiency, and what factors affect those processes are interesting topics in financial economics. In this paper, we use information on the order imbalance of individual stocks and past returns as predictors to evaluate the speed in which it takes to converge to efficiency in the Chinese stock market. We calculate the actual speed for the market to incorporate information. This by itself is important to further understand the Chinese stock market. As to the best of our knowledge, no such information has been released. After comparing my results to the U.S. market, we find that that liquidity of stocks affects the process of convergence.

Campbell *et al.* (1999) argue that the first order return autocorrelation declines with trading volume. This implies that there exists predictive information in trading volume and stock returns. Order imbalance from traders (from either a liquidity trader or insider) or the inventory of a market maker should be more informative than trading volume, since order imbalance not only includes information on trading volume, but also includes information on the trading direction. Order imbalance is defined as the difference between the volume of buyer initiated trade and seller initiated trade. It can affect stock returns according to the following two groups of models: inventory adjustment behavior by the market maker and arbitrage orders from an insider.

In the first model, according to Chordia and Subrahmanyam (2004), investors continue inputting orders from one direction, say from buy orders, and the market maker accumulates inventory from the opposite side, since she is now lacking this certain stock. Since the market maker is risk averse, when she reaches her initial optimal portfolio, any deviation from the optimal point gives her an incentive to raise both the bid and ask price that she enters into the trading system. This will increase costs to the buyer as well as profits for the seller. Then she can induce even more sell orders and prevent further buy orders, to eliminate her negative inventory. Therefore, in the short run, negative inventory could predict higher transaction prices in the future and higher returns. In a contrasting model, Back and Baruch (2004) argue that arbitrage orders by an insider can also predict stock returns. In an asymmetric information model, the order input by a liquidity trader should be symmetric on both sides: the volume of sell orders should be approximately equal to the volume of buy orders. Then if there is an order imbalance in a certain period, it would be due to insiders' orders, since the insider has more information than both the liquidity trader and uninformed market maker. Consequently, the market maker's negative inventory indicates net buy orders made by an insider, which should predict higher stock price in the future and thus higher stock returns. In this second class of models, the predictive relationship between order imbalance and stock returns exists when there is asymmetric information. Since both of effects exist within stock market at the same time and both effects predict that positive inventory means lower returns in the future, it is difficult to disentangle the two effects.

In the short run, when we make an assumption of constant stock returns, the predictability of stock returns indicates a form of inefficiency. Thus investors can take advantage of inefficiency and arbitrage. This arbitrage behavior can make the predictability disappear, and thus achieve market efficiency. How long this process actually takes to converge the stock market to efficiency can be used to evaluate the market. Generally speaking, the quicker information is incorporated into stock prices, the more efficient is the market. In the paper, we would like to evaluate the efficiency of the Chinese stock market with information on order imbalance and past returns.

The Chinese stock market has its own unique microstructure. First, there is no designated market maker, as in the NYSE (specialist) or NASDAQ(market maker). Hence, everyone who provides liquidity can be seen as a market maker in the market. We test the predictability of order imbalance in the Chinese market by randomly selecting 20 out of 900 stocks from the Shanghai Stock Exchange in 2006. My results indicate that Chinese traders' propensity to act as a market maker is high, since future return can be predicted by order imbalance. This result is robust to various econometrics models.

The Chinese stock market is also unique because the direction of trade is publicly available information released by the exchange at the moment of trade. This can therefore be observed by every participant in the market. In contrast, in the U.S., this information was kept in the books which then can be accessed only by specialists or at most guessed by very sophisticated floor traders. According to Chorida et al. (2002), this could be seen as private information. From this perspective, the predictability of stock returns in the U.S. would be a violation of strong form efficiency (Fama 1970, 1991). However, the predictability of stock returns in China only reflects the failure of a semi-strong form efficiency. Generally speaking, achieving a strong form of efficiency should be harder than a semi-strong form. Therefore, it should take more time. However, our results indicate that in China, it takes 15 to 30 minutes to converge to efficiency which is substantially slower than the 5 to 10 minutes needed in the U.S.A.(Chordia *et al.*, 2005). This result brings to question what factors might affect the time to converge to efficiency.

From inventory effect models, liquidity in the market should be one of the factors that affect the time to convergence. When the market is liquid, the market maker can adjust their inventory in a relatively short time, sophisticated investors can also use the information of past return quickly. This would decrease the predictability of order imbalance and past returns. This result is confirmed by our evidence: the predictability of order imbalance and past returns is stronger when liquidity decreases. GJR-GARCH(1,1) and fixed-effects models (using the within regression estimator) are used to evaluate stock returns. My results provide evidence for the predictability of order imbalance and past returns on future returns using a more accurate model. Hamilton (2010) points out an error in not implementing a GARCH model for stock returns whose conditional variance follows GARCH process. Even if one's interest is in only the conditional mean, OLS may still lead to over rejection of a true null hypothesis. Furthermore, the null is asymptotically rejected with probability one. Inference about parameters in the mean equation by OLS can be largely affected by high-variance outliers.

The paper is organized as follows. In section one, we briefly review previous research that leads to our empirical research. In section two, we describe the data set to use in the paper. In section three, we provide evidence about how long to take to converge to weak form efficiency in Chinese stock market. In section four, we test the predictability of order imbalance on stock return. In section five, we evaluate how liquidity affects the speed to converge to efficiency. Section six concludes.

1 Related Literature

Inventory models analyze the stock market from the perspective of a market makers' inventory control effect in the short run. Amihud and Mendelson's model (1980) allows ask and bid prices to change along with order imbalance. They conclude that when a dealer has an optimal inventory position in which she would like to maintain, a positive order imbalance induces the market maker to lower both bid and ask prices. A negative order imbalance may raise both bid and ask price to induce future sales. This Bid-ask spread widens when order imbalance increases. Chordia and Subrahmanyam (2004) provide the first empirical evidence on the effect of order imbalance on stock return from an inventory effect in U.S. stock market. In their three period model, which includes uncertain stock prices, there is no insider in the market. There are two types of liquidity traders who adjust their portfolio due to some exogenous liquidity reasons. Because of price concessions for block trades, those liquidity traders have the incentive to place relatively small orders sequentially, which generates a positive autocorrelation of the order. Since the competitive market maker is risk averse, she clears the market by taking the opposite position in order to gain a liquidity fee. Furthermore, she has an initial optimal portfolio to maintain. Hence, when she inputs the bid and ask price, her strategy is to decrease any deviation from the optimal level. The authors solved the market makers' maximization problem and conclude that there is a correlation between order imbalance and stock returns. They claim the association comes from the autocorrelation of exogenous orders.

There is another set of theoretical papers which argue that the predictability of order imbalance on stock return comes from insider information. Kyle (1985) solves a partially revealing equilibrium model and argues that the prices set by market makers depend on the summation of orders from the insider and the liquidity trader, the variances of the fundamental value and liquidity trader's order. Because the existence of order imbalance is due to insider information about the overvaluation or undervaluation of stocks, the market maker can set up prices to protect herself from losing too much to the insider and profit from the liquidity trader. Equilibrium prices partially reveal the insider information and insiders are awarded by her information. Therefore, the correlation between return and order imbalance can be observed. Easley and O'Hara(1987) argue that the identity of an insider can be revealed by trade size. Large trade sizes increase the probability of being an insider's order. Risk neutral insiders when behaving competitively have the incentive to trade with relatively large orders in the pooling and separating equilibriums. Hasbrouck (1991) provides empirical evidence to measure the information content of stock trades in the NYSE. In his vector autoregressive (VAR) model, he supports the argument that large orders involve more information in the sense that it has a large price impact. Easley and O'Hara(1991) address the effect of order types on market volatility, and they conclude that the uncertainty in order helps to reduce the volatility of prices.

2 Data

In this paper, we utilize tick-by-tick data for every securities transaction made in the Shanghai and Shenzhen Stock Exchange in 2006. This data is from the Hao Cheng Asset Management Limited. The data set contains information on the exact time of transaction, the transaction price (in RMB), the trading volume (in round lots which equals a 100 shares), three limit buy orders with prices and order sizes, three limit sell orders with prices and order sizes, and the trading direction variable for each transaction. Unlike the U.S. market, where trading direction variable is publically unavailable, studies utilizing Chinese stock markets do not have to use Lee and Ready's (1991) algorithm to infer trading directions. It is publically available. We can calculate the inventory (negative order imbalance) for a specific stock by taking the difference between the volume of buyer-initiated trade and seller-initiated trade.

Daily transaction data from Jan. 4th, 2000 to May 14th, 2008 from the Shanghai Securities Composite Index and Shenzhen Stock Exchange Component Index is from CCERDATA and includes 2180 trading days. The Shanghai (securities) Composite Index has been declared by the Shanghai Stock Exchange since July 15th, 1991. It uses equal weighted average prices of all the stocks traded in Shanghai and reflects the price and value of the stock market. Shenzhen Stock Exchange Component Index declared by the Shenzhen Stock exchange since January 23th, 1995, uses weighted average prices of 40 representative stocks traded in Shenzhen and reflects the general stock market situation.

The descriptive statistics of daily stock return in percentage in the two markets are calculated using adjusted closing prices of the index. The statistics of daily return in Shanghai and Shenzhen are reported in Table 3.1.

The negative sample skewnesses within the Shanghai and Shenzhen indices indicate an asymmetric distribution of stock return. A high kurtosis indicates a fatter tail than a standard normal distribution. Results from the Jarque-Bera (J.B.) test confirm that the sample does not come from a normal distribution at the 5% level. The Kolmogorov-Smirnov(K-S) statistic is 0.0373, and the asymptotic P-value equals 0.101. Therefore we can confirm that the sample of stock returns in the Shanghai Stock Exchange and Shenzhen Stock Exchange are drawn from the same continuous distribution at the 5% level. In order to infer statistical properties of return, one can analyze either one. I also graph daily stock returns in percentages for the Shanghai Securities Composite Index and Shenzhen stock Exchange Component Index (they are available upon request). My figures and table 3.1 indicate the presence of a fat tail and clustered volatility. Thus simple OLS Standard errors cannot be used. A common error made by financial research papers arises when authors do not utilize a GARCH model for stock return when the main research question is on the mean equation. According to Hamilton (2010), hypothesis tests for parameters at the conditional mean of the model would be invalid without the use of a GARCH model, since the type one error goes to one as the fourth moment approaches infinity. Furthermore, both White and Newey-West standard errors would be still problematic in a simple linear model. Therefore, a GARCH model is a good candidate for predicting stock returns in the Chinese stock market.

3 Weak form efficiency in Chinese stock market

Using daily return data, we check the autocorrelation of stock return lags up to 9 periods with the autocorrelation function (ACF) and partial autocorrelation function (PACF). The results indicate that there is no autocorrelation with 95 percent confidence. This further indicates that lag terms should not be included in the mean function at the daily level (specific results are available upon request). Investors cannot predict the stock return by past returns at the daily horizon. Moreover, we check the autocorrelation of the squared stock returns up to 9 periods by ACF and PACF. These results indicate that there are autocorrelations in the squared returns and they can be captured by a GARCH model. Then we perform the Ljung-Box Q test to verify serial correlation. The Q statistic equals 15.23 with a critical value of 18.31. Hence, we cannot reject the null hypothesis that there is no serial correlation in the stock return up to 10 lags at the 5% level. However for the squared return series, we reject the null hypothesis, since the Q statistic equals 94.05. This confirms the results from the ACF. We also perform the Lagrange Multiplier test for the ARCH effect. The null hypothesis is conditional homoscedasticity of return sequence up to 10 lags. In our case, the ARCH statistic equals 63.620 which is much greater than the critical value

18.307. Therefore, we can reject the null hypothesis at the 5% level. I conclude that the GARCH specification is a good way appropriate to describe the volatility of Chinese stock returns.

Since there is no prior on which GARCH model fits the Chinese data best, we estimate and select the model according to Likelihood ratio test, Akaike information criteria (AIC) and Bayesian information criteria(BIC). Using the returns from the Shanghai Securities Composite Index, I estimate the GARCH(1,1) model with AR(4) for the stock index returns in the mean function. The results are in table 3.2. The t-statistic of the lagged returns indicates that there is no autocorrelation in the mean function, and thus the Chinese stock market satisfies the weak form efficiency at the daily horizon.

To verify whether the Chinese stock market satisfies the semi-strong form efficiency, we consider the day-of-the-week effect on stock returns. We use Monday as a reference category, and create 4 dummy variables to capture the effects of a given weekday. We can see from table 3.2 that there are day-of-the-week effects in the stock returns within the Chinese market. The t-statistic for the constant becomes significant after including the weekdays (from 1.13 to 2.34), which indicates that on Monday, the return of the index is 0.16% higher than on other weekdays. Since Monday reflects returns for three days (Saturday, Sunday and Monday), it should have a higher return given the greater risk exposure. In addition, the coefficient before the Wednesday dummy is negative and statistically significant. Consequently, compared with other weekdays, the Wednesday return is 0.11% lower. This confirms findings by Nippani and Pennathur (2004). We then conduct a likelihood ratio test for the hypothesis that the restricted model is true: one should not include weekday effect variables in the mean function. After the test, we can reject the null hypothesis at 5% level, since the statistic is 11.74(critical value 9.49). Finally, we use the Akaike information criteria(AIC) and Bayesian information criteria(BIC) to compare the unrestricted model with restricted model. The AIC is in favor of an unrestricted model, but the BIC is in favor of a restricted model, since the BIC imposes more penalties on the additional parameters. Thus, we further justify the use of GJR-GARCH (1,1)-t through t statistics, the likelihood ratio test, AIC and the BIC[9], since there is clear leverage effect in the stock market(the result is available upon request).

From the analysis above, we conclude that the stock market return in China at a daily horizon satisfies the weak form efficiency. This would indicate that past prices and returns cannot predict future returns. An obvious day-of-week effect in Chinese stock market therefore rejects semi-strong form efficiency at the daily horizon.

Since the above evidence indicates that it takes no more than 4 hours to incorporate past return information into stock prices (Chinese stock market trades 4 hours a day), using intraday data, we can identify the speed to converge to weak form efficiency with a GJR-GARCH (1,1)-t model.

Table 3.3 uses past returns to predict future returns using data at 10, 15 and 30 minute intervals. We notice the joint-hypothesis problem: market efficiency cannot be tested without the assumption of an equilibrium model. In our test, we use a “constant return” asset-pricing model

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[9] Note: Leverage effect which is first documented by Black(1976) indicates that bad news decreases return next period and make debt to equity ratio increase, which increases the volatility next period. This asymmetric effect can be captured by GJR-GARCH(1,1) which was introduced by Glosten, Jagannathan and Runkle(1993).

by claiming that the returns in a short interval is constant. Hence, our joint null hypothesis is constant return and market efficiency. The rejection can be explained by rejecting either constant return or inefficiency. However, since our time interval is fairly small, constant return is a good assumption which is also used by many papers in microstructure. Therefore, a rejection would question the efficient market hypothesis during that specific time interval. At the 10 minute interval, an investor can predict future returns by the lagged returns, which violates the weak form efficiency. The time for investors to absorb price information about the fundamental value is more than 10 minutes. It also violates the weak form efficiency in stock market at the 15 minute interval. In contrast, at the 30 minute interval, the serial dependence in stock returns disappears, which satisfies the weak form efficiency. Hence, the actual time to converge to efficiency is somewhere between 15 and 30 minutes. In order to check the robustness of this result over different subperiods, we divide the sample into two subsamples to see whether it takes the same amount of time for information of the historical stock price to be incorporated into the future stock return. It turns out that our result is robust for different subsamples. Compared to the convergence time in the U.S. market, which was less than 5 minutes in 2002(Chordia et al., 2005), the Chinese stock market takes much more time to incorporate past return information.

4 Predictability of Order Imbalance on Stock Return

In this section, we attempt to utilize order imbalance information to forecast future returns. The microstructure in the Chinese stock market is different from the U.S. in the sense that there is neither a designated market maker nor specialist to provide liquidity in the market. However, the inventory effect theory may still be valid, if who want to gain the liquidity fee and trade for reasons other than insider information and liquidity can be seen as market makers. The econometrics model I use in the following analyses are GJR-GARCH(1,1), GJR-GARCH(1,1) with firm dummies, and fixed-effects models (using the within regression estimator). Any predicative relationship can be interpreted as a violation of the efficient market hypothesis if equilibrium asset pricing model has constant returns.

The stocks ID numbers are from SH600000 to SH600995 in the Shanghai stock market. Several stocks were barred from trading by the China Securities Regulatory Commission after their initial public offering. Therefore, the actual number of stocks may be smaller than 996. Since there is no such measurement as portfolio order imbalance, we have to calculate order imbalances for each individual stock. Given the large amount of data and the similarity between Chinese stocks, we randomly draw 20 stocks to serve as a proxy of market portfolio. The descriptive statistics for this sample of 20 stocks is reported for each time interval: 10 minutes, 15 minutes, 30 minutes, and 60 minutes in Table 3.4.

We run regressions for each time interval: 10 minutes, 15 minutes, 30 minutes and 60 minutes. In the regressions, we use the GARCH-GJR model for volatility and use returns as the dependent variable and lagged order imbalance as the independent variable in the mean equation. The results are shown in Table 3.5.

Table 3.5 reports the results for averages of the parameter estimates of these 20 stocks utilizing a GARCH-GJR model and Maximum likelihood estimation. The average t-statistic across different the stocks are in parentheses. The dependent variable is current returns. At the 10 minute interval, the t statistics is -12.78. Consequently, we can conclude that even if there is no designated market maker, order imbalance can still predict future returns, due to the trades made by those imaginary market makers. In an unreported test, we can see that the GARCH effect in the model above is fairly significant. At 15 minutes, we find a similar result. But at the 30 and 60 minute intervals, the predicative relationship between lagged order imbalance and returns disappears. Hence, we cannot reject the null hypothesis that the market is efficient during the last two time intervals. As time interval becomes wider, market makers have more time to adjust their inventory back to an optimal level. After her inventory is optimized, the predictability should also disappear, since she does not want to induce further orders by setting inducing prices. Therefore, at these time intervals, the market satisfies semi-strong form efficiency. The time it takes is on average more than 15 minutes but less than 30 minutes for the Chinese stock market.

In order to see whether the result is subject to model specification, we do the following two robustness checks. Firstly, we use dummy variables for each stock to capture the individual effect for those stocks. Secondly, I utilize panel data analysis with a fixed-effects model (the within regression estimator).

The different econometrics models generate similar results, which confirm the predictive relationship between lagged order imbalance and stock return. The coefficient for order imbalance or inventory is negative which is consistent with either the inventory model or the asymmetric information model. In the inventory model, when the market maker accumulates a positive inventory, which is equivalent to saying she bought too much, she lowers the price in the market. This decreases the profit of the potential seller and the cost to potential buyer. There will be more buy orders than sell order from liquidity traders, which can help the market maker eliminate the positive inventory. Since she lowers prices in the future, the return in the future should be lower. Consequently, positive inventory predicts negative return. The asymmetric information model argues that the reason why the market maker accumulates positive inventory is because a trader who has advantageous information keep selling. The reason why they continue to sell is because they know that currently the stock is overvalued. Hence, in the future, stock price tends to decrease and thereby reflect the fundamental value. That is also why positive inventory indicates lower future return.

Compared with the convergence time in the U.S. market which is between 5 and 10 minutes in 2002(Chordia et al., 2005), the convergence time in China is a bit longer. When we consider the microstructure, the result is even more interesting. In the U.S.A., information of a market maker's inventory is private information. During trading, the information is recorded by market makers or specialists in the market. Other people cannot access the information. Very sophisticated floor traders may be able to guess the number with error and make some arbitrage decisions in reaction. However, the story is different in China. Accurate trading direction information is declared by the stock exchanges and it can be accessed by all the participants in market. People do not have to spend time inferring or guessing the trading direction of a specific transaction. Investors can easily calculate order imbalance using trading volume and trading direction information. Therefore, ceteris paribus, one should expect that the Chinese stock market achieves efficiency quicker than the U.S. stock market, at least in the perspective of order imbalance. According to Fama(1970, 1991), to achieve semi-strong form efficiency is also easier than strong form efficiency. However, the evidence contradicts to this predication. In China, it actually takes longer to achieve efficiency than in the U.S.

Before we further explore the factors that affect market efficiency, we want to test the predictability of order imbalance on stock return using another specification of return: AR(1). We would like to test whether the predictive relation between lagged order imbalance and return still exists. As one can see from Table 3.6, for both GARCH-GJR and GARCH-GJR with firm dummies models, the predictability still exist, although it becomes a little bit weaker. Here, one can say nothing about market efficiency. We do not intend to test efficient market hypothesis, since AR(1) stock return is not a valid market equilibrium model in the short run. This test is purely to confirm the predictability of order imbalance.

5 The effect of Liquidity on Predictability

In the above sections, we provide evidence that past stock return and order imbalance can be used as predictors of future stock returns in the Chinese stock market for short time intervals. If one believes that the equilibrium asset pricing model is equivalent to the constant return models over short time periods (in our case 10 minutes, 15 minutes and so on), those results indicate that on average, market efficiency can be achieved between 15 and 30 minutes for Chinese stocks. During that time, the value of the information is identified and arbitrage orders are placed in the market to generate new equilibrium price. But what factors actually affect the process? From inventory effect models, one can predict that liquidity in the market should be one factor. When the market is liquid, the market maker can adjust their inventory in relatively short time frames, and thus decrease the predictability of order imbalance. With return information, arbitrageurs can earn a profit by taking the advantage of information with relatively low cost in a liquid market. This would in turn drive stock price to the level justified by the information within short time frames.

Liquidity is a complex concept. There are many liquidity measurements available from different perspectives. Early researches attach liquidity to market structure and exogenous transaction costs. From the perspective of the risk faced by market makers, sources of illiquidity can come from inventory risk and asymmetric information (Stoll (1978), Ho and Stoll (1981), Ho and Stoll (1983), Glosten and Milgrom(1985)). More recent studies focus on the effect of funding liquidity and the financial constraint faced by market makers on stock liquidity. Brunnermeier and Pedersen(2009) provide a theoretical model to link asset liquidity to the funding availability of market makers, which depends on capital and marginal requirement. Hameed *et al.* (2010) argue that stock market return has a reverse effect on liquidity, since negative market returns decrease the funding available to market makers, and would drive down the asset liquidity. Comerton-Forde *et al.* (2010) argue that stock market liquidity is related to market-maker inventories and revenues, since too much inventory and lower revenues impose a constraint on the funding availability for the market maker and decrease her incentive and ability to provide liquidity in the market.

Liquidity may also come from business conditions and monetary policy shocks. Goyenko and Ukhov (2009) associate both stock and bond market liquidity with macroeconomic variables and find that monetary policy variables first affect short term bond liquidity, then the shocks to monetary policy transfer to stock liquidity. Brennan *et al.* (2009) uses Ted spread as measure of funding availability and found that Ted spread is positively related with both buy-side and sell-side illiquidity. Næs *et al.* (2010) connect business cycle variables and stock market liquidity from an opposite way: stock market liquidity is a leading indicator for business cycle.

Since there are potentially many different sources of liquidity, it can be categorized by width, immediacy, depth, resiliency, and tightness (Hasbrouck and Schwartz, 1988; Pastor and Stambaugh, 2003). We concentrate on the effect of liquidity on the predictability of returns when there is order imbalance in the market makers' book and information on past returns. We use the liquidity ratio

$$L = \frac{|r_t|}{Vol_t}$$

proposed by Amihud(2002) to make use of the information regarding individual stock price changes(r_t) and trading volume(Vol_t). When L increases, liquidity decreases. Using the liquidity ratio, we generate a dummy variable to identify highly liquid and low liquid period. When the liquidity ratio is greater than its mean plus its standard error, the dummy variable for illiquidity equals one.

Table 3.7 is the estimation using stock returns and liquidity data at 10, 15 and 30 minute intervals. At the 10 minute interval, when the market is illiquid, the predictability of lagged return increases, which means that illiquidity makes the market more inefficient. The autocorrelation of the stock return comes partially from the illiquidity in the stock market. At the 15 minute interval, illiquidity still causes an inefficient market. Finally, at 30 minutes, since the stock price has already absorbed the new information, the stock market becomes efficient and liquidity factor cannot play a further role in the model.

Then we test whether liquidity affects the process of incorporating order imbalance information. From the previous sections, the Chinese stock market takes longer to converge to efficiency than the U.S. stock market even though information on order imbalance in China is more accessible and accurate. Because of this, it would seem more difficult for Chinese investors to arbitrage than American investors. According to the inventory effect model, when the risk averse market maker deviates from her optimal inventory, she has an incentive to change the price which leads to opposite orders from her inventory. In this way, she can adjust her inventory gradually. The changing price behavior will not stabilize until she fully adjusts inventory. Liquidity seems to be related with the process somehow. Liquidity is attractive in the sense that securities are more marketable in a continuous pricing setting. Consequently, when liquidity in the market is high, it should takes less time for the market maker to adjust her inventory. Hence, more liquidity should indicate less predictability which is equivalent to more efficiency.

In order to test this, we add an interaction term of order imbalance and illiquidity to the mean equation for GARCH-GJR, GARCH-GJR with firm dummies and fixed-effects models (within regression estimator). The predictive relationship between order imbalance and return should be stronger when the market is more illiquid (when the dummy variable equals to 1). As we can see from Table 3.8, for each model at the same time interval, the coefficient on the interaction term is the same as the coefficient on the order imbalance term, i.e. when the dummy variable for illiquidity equals one, the predictability is higher. Our result confirms that when the market is illiquid, the predictability is more pronounced. Therefore it is harder to achieve efficiency because it is more difficult for the market maker to adjust her order imbalance.

The results provide policy implications for the Chinese stock market. Firstly, the China Securities Regulatory Commission could increase liquidity in the market to increase efficiency in the market. This could be done through the transaction costs. Currently the transaction costs for Chinese stock market include a stamp tax of 0.1%, commissions of 0.3%, an order processing fee of 0.1% and other minor fees. This is higher than most the mature markets and much higher than emerging markets. To be similar to the more mature markets, the Chinese government could stop imposing the stamp tax. The U.S. government abolished its stamp tax by 1966. The Japanese government has not had one since 1999, or the Singapore government since 2001. The China Securities Regulatory Commission could also designate specialists or market makers in the market as an effective way to increase liquidity. Secondly, although we did not provide empirical evidence, asymmetric information is another factor in the process of convergence to efficiency, at least regarding information on order imbalance. The lack of regulation is considered to be one of the most significant weaknesses in the Chinese stock market. The two most shocking scandals in the history of the market in China include the Dark Curtain of Mutual Fund of 2000 and the "Yin Guang Xia" of 2001, both of which involve insider trading and regulation violations of mutual fund managers. In order to prevent future scandals from happening, greater regulation and supervision is recommended for the Chinese market.

6 Conclusion

In this paper, we use order imbalance and stock return information to evaluate the process of convergence to efficiency in Chinese stock market. Differing properties in the market structure between the Chinese and U.S. stock market (such as designated market makers, trading direction information, and asymmetric information) provokes questions of which market performs better, at least in the sense of the ease to achieve informational efficiency.

Using GARCH-GJR, GARCH-GJR with stock dummies, and fixed-effects models (within regression estimator), we provide evidence for the predictability of stock returns using past returns and order imbalance. This result is important to policy makers, practitioners and scholars because of the following three reasons. Firstly, we extend the model by Chordia and Subrahmanyam (2004) by testing the effect of not designating a market maker. The result indicates that even if no designated market maker exists, the propensity of investors in Chinese stock market to act as a market maker is high. In this case, the predictive relationship between order imbalance and stock return still holds. Secondly, it takes on average between 15 and 30 minutes for order imbalance and past stock return information to be incorporated into Chinese stock returns. This is longer than in the U.S., even though information on the direction of trade is publically available in China. Thirdly, the slowness and inefficiency in the market can be partially explained by the lack of liquidity. This drawback in the Chinese stock gives sophisticated investors enough time to arbitrage and generate profits. Policy makers and designers of the stock market in China could consider ways to decrease the information inefficiency by the changing market structure and increasing efficiency as a whole. Decreasing transaction costs, adding a market maker, and increasing regulations against insider trading are options that policy makers could first consider.

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Table 3.1 Descriptive statistics of daily stock returns

	Mean	Variance	Skewness	Kurtosis	Max	Min	J.B
SSCI	0.0439	2.339	-0.0248	8.427	9.401	-11.304	2674.3
SSECI	0.0649	2.959	-0.0219	9.173	11.634	-12.105	3312.5

Note: Daily stock returns from the Shanghai Securities Composite Index(SSCI) and Shenzhen Stock Exchange Component Index(SSECI), Jan. 4th, 2000 to May 14th, 2008. Stock return is in percentages. J.B. is Jarque-Bera statistics.

Table 3.2 Predictability of daily past returns and day of the week

	Past returns	Day of the week
Akaike Information Criteria	5901.7	5898
Bayesian Information Criteria	5945.7	5964
First lag of return	0.0196	0.0184
	(0.845)	(0.780)
Second lag of return	-0.0151	-0.0100
	(0.663)	(-0.439)
Third lag of return	0.0260	0.0295
	(1.045)	(1.178)
Fourth lag of return	0.0179	0.0161
	(0.816)	(0.717)
Tue	_	-0.0732
		(-0.803)
Wed	_	-0.277
		(-2.991)
Thu	_	-0.169
		(-1.760)
Fri	_	-0.151
		(-1.724)
Constant	0.0305	0.164
	(1.134)	(2.338)

Note: t-statistics are in parentheses. The dependent variable is daily returns of the Shanghai Securities Composite Index. Stock return is in percentages. The Akaike information criteria(AIC) and Bayesian information criteria(BIC) for each model are listed. The statistical model use is GJR-GARCH(1,1)-t. The day of the week model is compared to Monday's returns.

Table 3.3 Testing weak form efficiency of the stock market index at various time intervals

	Coefficient	10 minutes	15 minutes	30 minutes
Full sample	Constant	0.0211 (8.0442)	0.0247 (6.0971)	0.0427 (5.0236)
	First lag of return	-0.0824 (-6.215)	-0.0359 (-2.071)	-0.00417 (-0.171)
Half sample	Constant	0.0233 (6.396)	0.0287 (5.081)	0.0514 (4.386)
	First lag of return	-0.101 (-5.703)	-0.0589 (-2.634)	-0.00960 (-0.300)
Half sample	Constant	0.0243 (6.840)	0.0282 (5.145)	0.0467 (3.992)
	First lag of return	-0.0749 (-4.475)	-0.0232 (-1.0362)	-0.0218 (-0.757)

Note: The dependent variable is returns from the Shanghai (securities) Composite Index at different time intervals: 10, 15 and 30 minutes. T-statistics are in parentheses. Stock return is in percentages. The data covers 2006 and then is split into two subsamples with the same number of observations in each sample as a robustness check. The statistical model is GJR-GARCH (1,1)-t.

Table 3.4 Descriptive statistics of return and order imbalance (for 20 random stocks)

		Mean	Standard Deviation	Max	Min
10 minutes	return	0.00491	0.813	9.671	-73.063
	order imbalance	-0.00156	3.307	128.309	-175.917
15 minutes	return	0.00738	0.970	10.702	-72.800
	order imbalance	-0.00195	4.321	139.686	-215.047
30 minutes	return	0.0150	1.330	10.968	-72.866
	order imbalance	-0.00437	6.940	166.617	-386.153
60 minutes	return	0.0294	1.857	11.466	-72.668
	order imbalance	-0.0129	11.187	232.772	-673.292

Note: The table represents descriptive statistics for returns and order imbalance for a random sample of 20 stocks at each time interval: 10 minutes, 15 minutes, 30 minutes, 60 minutes. Stock return is in percentage. Order imbalance is defined as the difference between the volume of buyer initiated trade and seller initiated trade.

Table 3.5 Predictability of order imbalance on stock return at different time intervals

Model	Coefficient	10 minutes	15 minutes	30 minutes	60 minutes
GARCH-GJR	Constant	-0.000370	0.00728	0.0288	0.0386
		(-0.15)	(2.41)	(6.28)	(3.95)
	oib_{t-1}	-0.00448	-0.00242	-0.000227	-0.001127
		(-12.78)	(-2.93)	(-0.29)	(-1.52)
GARCH-GJR with firm dummies	Constant	0.0322	0.000954	-0.0759	-0.0546
		(5.35)	(0.08)	(-14.02)	(-3.85)
	oib_{t-1}	-0.00406	-0.00240	-0.000549	0.000464
		(-9.40)	(-2.67)	(-0.64)	(0.43)
Fixed effect model	Constant	0.00484	0.00725	0.0149	0.0293
		(1.95)	(2.00)	(2.11)	(2.10)
		[1.95]	[2.00]	[2.11]	[2.11]
	oib_{it-1}	-0.00470	-0.00289	-0.001363	-0.000252
		(-6.25)	(-3.44)	(-1.34)	(-0.20)
		[-5.35]	[-2.79]	[-1.26]	[-0.18]

Note: The dependent variable is current returns. In the first model, we use a GARCH-GJR(1,1) model with an estimation method of M.L.E.. Average parameter estimates of 20 randomly selected stocks are presented. T-statistics are in parentheses. In the second model, we use a GARCH-GJR model with firm dummies. Parameter estimates for the fixed-effects models (within regression estimator) are reported. Standard t-statistics are in first parentheses. T-statistics with robust standard errors are in brackets. Stock return is in percentages.

Table 3.6 Predictability of order imbalance with AR(1) model of stock return

Model	Coefficient	10 minutes	15 minutes	30 minutes	60 minutes
GARCH-GJR	Constant	-0.000458	0.00653	0.0277	0.0384
		(-0.18)	(1.99)	(5.86)	(3.92)
	First lag of return	-0.135	-0.0871	-0.0379	-0.0267
		(-62.82)	(-17.77)	(-11.30)	(-5.07)
	oib_{t-1}	0.00146	0.00112	0.00105	-0.000329
		(3.80)	(1.27)	(1.39)	(-0.43)
GARCH-GJR with firm dummies	Constant	0.0283	-0.0001642	-0.0730	-0.0370
		(4.43)	(-0.01)	(-13.22)	(-1.80)
	First lag of return	-0.178	-0.0880	-0.0418	-0.0263
		(-68.16)	(-16.18)	(-10.45)	(-2.69)
	oib_{t-1}	0.00227	0.00115	0.00107	0.00223
		(4.64)	(1.19)	(1.30)	(2.03)
Fixed effect model	Constant	0.00530	0.00776	0.0154	0.0302
		(2.14)	(2.14)	(2.19)	(2.17)
		[2.14]	[2.14]	[2.19]	[2.17]
	First lag of return	-0.0937	-0.0682	-0.0353	-0.0307
		(-30.12)	(-17.88)	(-6.53)	(-4.02)
		[-8.92]	[-7.70]	[-4.91]	[-3.23]
	oib_{it-1}	0.000107	0.000257	0.0000106	0.000775
		(0.14)	(0.30)	(0.01)	(0.61)
		[0.11]	[0.23]	[0.01]	[0.58]

Note: The dependent variable is current returns. In the first model, we use a GARCH-GJR(1,1) model with an estimation method of M.L.E.. Average parameter estimates of 20 randomly selected stocks are presented. T-statistics are in parentheses. In the second model, we use a GARCH-GJR model with firm dummies. Parameter estimates for the fixed-effects models (within regression estimator) are reported. Standard t-statistics are in first parentheses. T-statistics with robust standard errors are in brackets. Stock return is in percentages.

Table 3.7 The effect of liquidity on the predictability of past returns

	10 minutes	15 minutes	30 minutes
Constant	0.0226 (8.861)	0.0278 (7.060)	0.0494 (5.961)
First lag of return	-0.0148 (-0.930)	-0.000582 (-0.0282)	-0.0119 (-0.433)
Intercept	0.000621 (4.564)	0.00187 (4.483)	0.00483 (3.028)
h_{t-1}	0.952 (172.105)	0.916 (87.261)	0.897 (48.541)
ε_{t-1}^2	0.0424 (5.535)	0.0599 (4.664)	0.0798 (3.676)
D.F.	4.212 (18.700)	5.030 (15.540)	6.343 (9.456)
Leverage	-0.00378 (-0.475)	0.01204 (0.859)	0.000320 (0.0140)
$r_{t-1} \times \text{dum\_illq}_{t-1}$	-0.155 (-6.171)	-0.0843 (-2.556)	-0.00217 (-0.0465)

Note: The dependent variable is current stock returns. The model used is GJR-GARCH (1,1)-t. The mean equation is $r_t = C + \varphi_1 r_{t-1} + \mu r_{t-1} \times \text{dum\_illq}_{t-1} + \varepsilon_t$ with $\varepsilon_t | I_{t-1} \sim t(w)$ and $h_t = K + G_1 h_{t-1} + A_1 \varepsilon_{t-1}^2 + L_1 \varepsilon_{t-1}^2 (I[\varepsilon_{t-1} < 0])$where the interaction term is defined as the product of lagged returns and a liquidity dummy variable. Stock return is in percentages. T-statistics are in parentheses.

Table 3.8 The effect of liquidity on the predictability of order imbalance at various time intervals

Model	Coefficient	10 minutes	15 minutes	30 minutes	60 minutes
GARCH-GJR	Constant	-0.000558	0.00709	0.0275	0.0368
		(-0.23)	(2.34)	(5.68)	(3.67)
	oib_{t-1}	-0.00437	-0.00232	0.0000828	-0.000688
		(-12.44)	(-2.80)	(0.10)	(-0.88)
	oib_{t-1}	-0.0757	-0.0440	-0.0379	-0.0254
	$\times\ \mathrm{dum\_illq}_{t-1}$	(-2.03)	(-1.29)	(-6.81)	(-2.64)
GARCH-GJR with firm dummies	Constant	0.0318	0.000221	-0.0742	-0.0239
		(5.27)	(0.02)	(-12.71)	(-1.78)
	oib_{t-1}	-0.00394	-0.00230	-0.000250	-0.000819
		(-9.08)	(-2.55)	(-0.29)	(-0.83)
	oib_{t-1}	-0.0706	-0.0443	-0.0283	-0.0208
	$\times\ \mathrm{dum\_illq}_{t-1}$	(-2.25)	(-1.29)	(-3.40)	(-2.20)
Fixed effect model	Constant	0.00458	0.00700	0.0145	0.0285
		(1.84)	(1.93)	(2.05)	(2.04)
		[1.84]	[1.93]	[2.05]	[2.04]
	oib_{t-1}	-0.00453	-0.00275	-0.00123	-0.000103
		(-6.03)	(-3.27)	(-1.21)	(-0.08)
		[-5.18]	[-2.65]	[-1.13]	[-0.07]
	oib_{t-1}	-0.121	-0.0681	-0.0256	-0.0159
	$\times\ \mathrm{dum\_illq}_{t-1}$	(-5.93)	(-3.69)	(-1.82)	(-1.23)
		[-4.90]	[-4.50]	[-2.40]	[-2.09]

Note: The dependent variable is current returns. In the first model, we use a GARCH-GJR(1,1) model with an estimation method of M.L.E.. Average parameter estimates of 20 randomly selected stocks are presented. T-statistics are in parentheses. In the second model, we use a GARCH-GJR model with firm dummies. Parameter estimates for the fixed-effects models (within regression estimator) are reported. Standard t-statistics are in first parentheses. T-statistics with robust standard errors are in brackets. Stock return is in percentages.