Monetary Rules, Monetary Shocks and Stock Prices

by

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(Under the direction of William D. Lastrapes)

Abstract

The present work consists of two empirical studies on monetary and financial economics. First study employs a generalized ordered probit method to model the Federal Reserve's monetary policy reaction function. The findings indicate that the Fed takes into account not only inflation and output gap measures but also several other variables during its decision process, but the degree of its attention on each variable is choice-dependent. The threshold estimates also indicate that the Federal Reserve acts asymmetrically that it waits for relatively significant changes in the macroeconomic factors before it decides for a change in its target rates. However, once these thresholds are passed, relatively less significant changes in the economy are needed for the Federal Reserve to take action.

Second study investigates the relationship between inflation and stock returns using industry-level stock returns data. I propose using VARs with block exogeneity, and diagonality restrictions to use many variables in the model and infinite-horizon restrictions to identify aggregate shocks, i.e. money supply and productivity. The results show that the relation between inflation and stock returns depends on both the type of macro shock and industry. The relation is negative given a productivity shock, yet positive given a money supply shock. The findings also suggest that size and book-to-market ratio affect dispersion of industry portfolio returns given a macroeconomic shock.

INDEX WORDS: Ordered Probit, VAR, Taylor's Rule, Monetary Policy, Inflation

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Dedication

This dissertation is dedicated to my wonderful wife Esra, my daughter Selin and my parents for always helping me motivate throughout of my graduate studies.

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Chapter 1

Introduction

After Taylor (1993)'s seminal work, for almost two decades researchers have attempted to find whether central banks, including the Federal Reserve, are following monetary policy rules. It is especially important for empirical economists to know if central banks follow monetary policy functions because finding a well-specified monetary policy rule which characterizes the reaction function of the monetary authority could help economic agents predict the Federal Reserve's policy changes. It would decrease uncertainty about the economy and investors who have this information could earn abnormal returns for their investments.

Although most of empirical findings indicate that Federal Reserve follows a monetary policy, they do not agree on the specification of the rule. In theoretical models monetary policy rules are frequently included in a way that the monetary authority reacts only to changes in the output gap, and the difference between expected inflation and an inflation target. They basically rule out any possible information might come from other macroeconomic variables.

Another important issue that should be addressed is nonlinearity. There are several reasons to believe that monetary policy rules ought to be nonlinear.

For example, if the monetary authority has asymmetric preferences it might lead to nonlinearity in the monetary rule even if the economic structure is linear. As Blinder (1998) and Cukierman (2000) point out, central banks are biased towards recessions rather than expansions for certain reasons and this makes the monetary policy rule nonlinear. Second, in case of an inflation target with a band, interest rate changes more or less randomly if the inflation rate is within the target band. On the other hand, if the inflation rate is outside the target band, the central bank can be more aggressive in changing interest rates because of both inflationary and deflationary fears. The aggressiveness might even change depending on whether the inflation rate is below or above the target rate. Third, because recessions and booms have different characteristics, central banks should change interest rates at different phases in recessions and booms, which makes monetary policy rule specifications nonlinear. Finally, an asymmetric interest rate smoothing might cause nonlinearity in the reaction function. As Florio (2006) points out, if the central bank is more biased to recessions than to expansions a tight monetary policy would be more gradualist than a loose monetary policy.

Given the inherent nonlinearity in monetary rules, I devote the first chapter to estimating nonlinear monetary rules by employing a generalized ordered probit model using monthly data. The generalized ordered probit method eliminates the parallel regression assumption (which is assumed in ordered probit models) and reveals an important new asymmetry in the Federal Reserve's actions. The findings indicate that a more general monetary reaction function outperforms Taylor rule specifications. The Fed takes into account not only inflation and output gap measures but also other variables during its decision process, but the degree of its attention on each variable is choice-dependent. The Fed might assign different weights for each macroeconomic factors when it is trying to make a choice, for example, between a big and small decrease or a small decrease and no change in the federal funds target rate. The threshold estimates also indicate that the Federal Reserve acts asymmetrically that it waits for relatively significant changes in the macroeconomic factors before it decides for a change in its target rates. However, once these thresholds are passed, relatively less significant changes in the economy are needed for the Federal Reserve to take action. This paper also benefits from new findings in the econometrics literature on time series properties of ordered probit models and argues that using certain information criteria, i.e. AIC calculated by likelihood, constitutes the proper way to choose the right empirical model in case the latent dependent variable is non-stationary.

In the second essay, I investigate the relationship between inflation and stock returns within a supply and demand framework using VARs. Stocks are claims to real assets and they are expected to be a good hedge against both unexpected and expected inflation. Nevertheless, much empirical work finds a negative correlation between inflation (expected and unexpected) and stock returns, which is contrary to the theory and common sense. Lintner (1975), Bodie (1976), Jaffe and Mandelker (1976), Nelson (1976) and Fama and Schwert (1977) are just a few of early contributions supporting this result for the US and Gultekin (1983) and Solnik (1983) for international data.

In this respect, given the contradictory results to common sense and economics and finance theories, I elaborate the relation by addressing several problems of the previous literature. First, many researchers examine the relationship with single equation models. However, it is a well-known fact that both inflation and stock returns are not only endogenous, but also jointly dependent on common exogenous shocks like productivity and money supply shocks. Therefore, models examining inflation and stock returns in a single equation are subject to simultaneity and thus estimated coefficients will be biased.

Second, many of the papers' results are subject to multicollinearity. In particular, if money supply and inflation were used as explanatory variables for stock returns in a single equation, estimated coefficients would suffer from multicollinearity since there is a casual relationship between inflation and money supply. In this case, the estimated coefficients remain consistent and the reliability of the model would not be effected, yet testing statistical significance of estimated coefficients would not be possible. In the essay, I address multicollinearity and simultaneity problems by using VARs. I identify productivity and money supply shocks using infinite horizon restrictions by assuming long-run monetary neutrality and only productivity shocks have long-run effects on measured productivity.

Third, exogenous shocks are expected to affect each individual industry differently and thus, stock returns for each industry would be affected differently in magnitudes and dynamics. For example, banking industry is expected to be affected differently from agriculture industry in case of a money supply shock. Similarly, productivity shocks are expected to affect industries heterogenously. However, very few papers consider the importance of working with micro level data for examining the relation between inflation and stock returns. And these papers neither incorporate supply and demand shocks in their analysis nor use simultaneous models.

In the essay, I impose diagonality and block exogeneity restrictions proposed by Lastrapes (2005). While VAR eliminates possible simultaneity bias and multicollinearity problems, diagonality and block exogeneity restrictions allow us to include as many variables as in the model. I also impose infinite-horizon restrictions, proposed by Blanchard and Quah (1989), to identify the structural coefficients to distinguish the effects of money supply and productivity shocks in each individual industry portfolio. This paper attempts to fill the gap in the literature which has not yet examined the relation with simultaneous equations using both micro and macro-level data.

The findings indicate that the direction of relation between inflation and stock returns depends on the type of exogenous shock. There is a negative relation between inflation and stock returns given a productivity shock, whereas a positive relation exists given a money supply shock. On the other hand, the magnitude and sign of the relation differ across industries. The findings also suggest that industry specific features do affect the dispersion of stock returns. For instance, in the case of monetary shocks, the size effect is negative and statistically significant, indicating that industries with bigger-sized firms are affected less than industries with smaller-sized firms.

The reminder of the dissertation proceeds as follows. Chapter II examines the nonlinearity and asymmetry in the U.S. monetary policy reaction function using a generalized ordered probit model. Chapter III investigates the relationship between inflation and stock returns by using a VAR model with infinite-horizon restrictions on money supply and productivity shocks. Chapter IV offers some concluding remarks.

Chapter 2

Nonlinearity and Asymmetry in the Monetary Policy Reaction Function: A Generalized Ordered Probit Approach

2.1 Introduction

In the last two decades many economists have been interested in estimating monetary policy reaction functions because finding a well-specified monetary policy rule could help economic agents predict the Federal Reserve's policy changes and decrease the uncertainty about the economy. It would also be easier for the Federal Open Market Committee (FOMC) members to decide what they should do.

After Taylor (1993)'s seminal work, researchers have been trying to find whether the Federal Reserve follows a simple monetary rule called the Taylor rule. In his seminal work, Taylor characterizes the Federal Reserve's monetary policy in a very simple linear model. He argues that the Fed changes its target rate in two cases: when the current inflation rate deviates from its target and when the output gap changes. Since the model became popular, new versions of the rule have appeared both in empirical and theoretical papers.

Although vast majority of the estimated monetary rules are linear, researchers have started to use nonlinear monetary rules in recent years. There are indeed several reasons to believe that the Federal Reserve might be following a non-linear monetary rule as pointed out in the recent literature.

First, central banks' preferences might be asymmetric regarding the weights on deviations of inflation and/or output from their targets. Even if the economic structure is linear, asymmetric preferences (i.e. non-quadratic loss function) lead to nonlinear monetary rules.[1] Therefore, for example, if a central bank is hawkish about inflation, it is more likely to increase the interest rate more aggressively when the inflation rate is higher than its target compared to when inflation is lower than its target. Moreover, as Blinder (1998) points out, central banks are confronted with more political pressures when they use preemptive strict monetary policy to avoid high inflation than when they use preemptive loose monetary policy to avoid higher unemployment. It will create similar nonlinearity in the monetary reaction function. Cukierman (2000) also argues that this nonlinearity arises because some central banks are accountable to politicians by law, which makes them biased towards recessions rather than expansions.

By using a specific non-quadratic loss function Orphanides and Wilcox (2002) and Aksoy et al. (2006) argue that when inflation is above but close to its target, it may not be optimal to take anti-inflation actions. Instead, the central bank should wait for favorable exogenous shocks (focusing on output stabilization) because of a worsening trade-off between inflation and output. On the other hand, if inflation is too high from its target, the central bank should take anti-inflation policies. This will also create similar nonlinearity.

Second, central banks following inflation targeting with a band rather than a point target would confront non-linearity in the monetary rule. In this case, if the inflation rate is within the target band, the interest rate changes more or less randomly because the central bank pursues non-active policies by only responding to exogenous shocks to the economy. On the other hand, if the inflation rate is outside the target band, the central bank can be more aggressive in changing interest rates because of both inflationary and deflationary fears. Taylor and Davradakis (2006) based their arguments on these issues and found a significant nonlinearity in the Taylor rule for the UK. Orphanides and Wieland (2000) consider this nonlinearity and find a theoretical rationale for targeting a band in inflation targeting policy.

[1]There are several reasons to believe for non-quadratic loss functions. For more detail see Dolado et al.(2005)

Although the Fed does not pursue an inflation targeting regime, having an explicit or implicit inflation band target would cause same the nonlinearity in the Fed's policies.

Third, because recessions and booms have different characteristics, there might be some nonlinearities and asymmetries in the adjustments during business cycles. For example, Keynes (1936) states that an economy experiences sharp but short downturns in recessions and smooth but long upwards in recoveries. Therefore, the central bank should change interest rates at different phases in recessions and booms, which makes Taylor rule specifications nonlinear. Therefore, as Neftci (1984, p. 308) argues, "If the time series exhibit an asymmetric behavior over the business cycle, then a model that generates sharp drops during contractions followed by gradual movements during expansions will have 'better' predictive power. Otherwise, one would expect the 'fit' to deteriorate around turning points."

Finally, an asymmetric interest rate smoothing might cause nonlinearity in the reaction function. The literature on smoothing generally focuses on linear smoothing behavior of the central banks. However, uncertainty about the current and future state of the economy makes central banks more cautious in implementing monetary policies. As Florio (2006) investigates, central banks might adjust interest rates at different paces during strict and loose monetary policy. If the central bank is more biased to recessions than to expansions (as Cukierman (2004) argues) a tight monetary policy would be more gradualist than a loose monetary policy. In her paper, Florio (2006) finds support for an asymmetric interest rate smoothing.

Given the inherent nonlinearity in monetary rules, a nonlinear model should be introduced. In this paper I estimate nonlinear monetary rules by employing a generalized ordered probit model using monthly data. In this way, it is possible not only to make a short-run analysis about monetary policy but also to allow non-linearity in the monetary rule.

Using discrete choice models is not a new idea. However, this paper challenges or improves the literature in several aspects. First, previous literature (that used discrete choice models) has used ordered probit models which assume parallel regressions (lines) that is all parameters, β, are identical across each choice. In this paper, I generalize the previous literature, which has used the ordered probit model, by eliminating parallel lines assumptions which do not generally hold. Employing a generalized ordered probit model reveals important information for people following the Federal Reserve's actions, i.e. whether the Fed considers different variables when it is trying to make a decision for a big or small decrease rather than for a small decrease or no change. This feature of the generalized ordered probit model calculates a kind of new asymmetry in addition to nonlinearity in the monetary rule. Second, previous literature, until recently, did not pay attention to time series properties of the estimated parameters. Recent literature has showed that if the dependent variable in an ordered probit model is non-stationary, the standard errors become biased. If a researcher chooses a purely empirical model based on any information criteria, which use estimated standard errors of the coefficients, he will probably end up with a wrong model. This paper benefits from new findings in the econometrics literature and suggests information criteria which do not depend on standard errors of the explanatory variables (i.e. Akaike Information Criteria (AIC)) to select the right empirical model. Third, this paper estimates several models used in the literature to find the right empirical model and compares them explicitly.

My particular goal is to estimate a nonlinear monetary reaction function to understand whether the Fed is following a nonlinear reaction function. For this reason, I estimate several reaction function specifications for the Fed. First, I start with ordered probit models and estimate backward-looking, forward-looking, and contemporaneous Taylor rule and general monetary rule models. Backward-looking Taylor rule models fail to statistically identify the thresholds and have poor AIC statistics. Although the forward-looking Taylor rule model could identify the thresholds, its AIC is the highest among all models. The contemporaneous model fits the data better than the forward-looking Taylor rule model, but it is still not better than the backward-looking models, according to AIC statistics. I also try to specify a more general monetary rule model. For this purpose in addition to inflation and output gap measures I include additional explanatory variables used in the literature. I find that

AIC statistic is significantly lower than in the other models. Results indicate that FOMC members do use other information, such as inflation expectations, T-bill spread and recession expectations, in forming their decisions. It is important that if people's expectation of a recession for the next quarter increases, it is much more likely the Federal Reserve will decrease its key interest rate target to get rid of a possible downturn in the economy.

Threshold estimates indicate that the FOMC waits for relatively higher changes in the explanatory variables before it decides for a change in the key rates. However, once these thresholds are passed, relatively smaller changes in the explanatory variables are needed for FOMC to make a decision. This is more obvious in forward-looking and contemporaneous models.

Then, I test the parallel line assumption which is assumed in ordered probit models. The LR test results show the parallel line assumption does not hold. Therefore, I estimate a generalized ordered probit model. The general model still fits the data better. I find that the Federal Reserve considers different variables whether the decision is a big (small) increase or a big (small) decrease. For example, although the Fed does not pay attention to changes in inflation when it has to make a decision between a big and small interest rate increase, it considers inflation when it has to make a decision between small and big interest rate cut.

Although generalized ordered probit models are very flexible they might be inefficient. Therefore, I estimate all models with partially generalized ordered probit models after testing whether the parallel regression assumption holds only for some of the variables. I impose parallel line restrictions on some of the variables and select the model with the lowest AIC. The AIC statistics are improved when the models are estimated by a partially generalized ordered probit model and I find similar results with generalized ordered probit models.

To check the reliability of the results, I also use the 'variable inflation target' estimated by Ireland (2007) and two different cut points for the dependent variable. The results are found to be robust.

2.2 Taylor rules

Various different versions of monetary rules have been introduced in both empirical and theoretical papers. The most famous one is the Taylor rule. The original model introduced by Taylor (1993) is

$$i_t = r^* + \pi_t + \beta_\pi(\pi_t - \pi^*) + \beta_y y_t \tag{2.1}$$

where i_t is the federal funds target rate, r^* is the real interest rate, π_t is the rate of inflation over the previous four quarters, π^* is the inflation target, and y_t is the output gap. In his paper, Taylor sets the coefficients of output gap and deviations of inflation rate from its target equal to 0.5, both the inflation target and the real interest rate to 2. So, he ends up with the following model:

$$i_t = 1 + 1.5\pi_t + 0.5y_t \tag{2.2}$$

His model indicates that the monetary policy of the Federal Reserve between 1984 and 1992 can be described by a simple linear model. According to his model, the Federal Reserve has to increase its federal funds target rate more than an increase in the inflation rate and less than an increase in the output gap. In general, without setting the coefficients, the monetary rule (2.1) can be estimated by

$$i_t = \alpha + \theta\pi_t + \beta y_t \tag{2.3}$$

where $\alpha = r^* - \beta_\pi \pi^*$ and $\theta = 1 + \beta_\pi$. As it is easily noticeable, r^* and π_t are assumed constant.

Although Taylor found that this model can explain the monetary policy in 1980s in the US, and suggested this model to provide for future policy standings, there is a crucial downside of the model: data availability. Some of the economic data become available with a certain lag. For example, data for GDP are announced every 3 months with at least one month lag and subject to serious adjustments. The final version is announced after four months. Therefore, some economists have suggested using a backward-looking Taylor model like (2.4).

$$i_t = \alpha + \theta_\pi \pi_{t-1} + \beta_y y_{t-1} + \epsilon_t \tag{2.4}$$

However, some economists argue that central banks have been following forward-looking reaction functions. Therefore, Orphanides (2001), among others, for example, suggests a forward-looking model for the Federal Reserve:

$$i_t = \alpha + \theta_\pi [E_t(\pi_{t+k}) - \pi^*] + \beta_y E_t(y_{t+m}) + \epsilon_t \tag{2.5}$$

Whether central banks follow backward-looking or forward-looking models, many researchers such as Levin et al. (1999), and Clarida et al. (1998, and 2000) argue that central banks smooth interest rate decisions. So, the Taylor rule becomes like the following model for a forward-looking Taylor rule.

$$i_t = (1-\rho)\{\alpha + \theta_\pi [E_t(\pi_{t+k}) - \pi^*] + \beta_y E_t(y_{t+m})\} + \rho i_{t-1} + \epsilon_t \tag{2.6}$$

However, there are still several researchers who disagree with this idea. Rudebusch (2002) and Soderlind et al. (2005), for example, argue that imposing interest rate smoothing in the model generates much more interest rate predictability than we see in real life. Whether or not their argument is true, interest rate smoothing is being used in almost all of the policy reaction function estimations.

In recent years, beside these linear models, several papers have used non-linear models to estimate the Taylor rule. For example, Qin and Enders (2008) employ exponential and logarithmic nonlinear, and usual time series models using quarterly data. Their logistic specification for the forward-looking version is given in (2.7).

$$i_t = \alpha_0 + \alpha_1 E_t \pi_{t+1} + \alpha_2 E_t y_t + \alpha_3 i_{t-1} + \alpha_4 i_{t-2} + \theta(\beta_0 + \beta_1 E_t \pi_{t+1} + \beta_2 E_t y_t + \beta_3 i_{t-1} + \beta_4 i_{t-2}) + \epsilon_t \tag{2.7}$$

where $\theta = 1 + exp[-\gamma(i_{t-1} - c)]^{-1}$, $\gamma \geq 0$.

They find that the type of Taylor rule differs across periods, i.e. pre- and post-Greenspan periods. Their results provide evidence of nonlinearity in the Fed's behavior especially during the 1975:Q3-1995:Q4. Also, almost all versions of the rule used in their paper suggest that the Fed followed the Taylor principle during both the Volcker and Greenspan periods.

Petersen (2007) also finds similar results by employing the Smooth Transition Regression technique using a contemporaneous Taylor rule. He uses conditional maximum likelihood and non-linear least squares methods to estimate the model. He finds that the Federal Reserve followed a non-linear Taylor rule during 1985-2005, and a linear Taylor rule during 1960-1979.

Taylor and Davradakis (2006) use four main models for the United Kingdom to look for the evidence of Taylor rule behavior of the Bank of England an under inflation targeting regime between 1992 and 2003. They find evidence of nonlinear Taylor rule in the UK, and although the Bank of England announces that it pursues a symmetric inflation target, in practice it does not.

There are also other types of nonlinear monetary rules which let researchers use monthly data in the Taylor rule specifications. Dueker (1999), for example, estimates a backward-looking five-choice ordered probit model with core inflation, output gap and a smoothing variable, and finds relatively symmetric thresholds for upper and lower cutpoints. However, his results point out that the Fed waits for bigger changes in the economy to decide for a change in the federal funds rate. Vanderhart (2000) estimates several backward-looking ordered probit models with 5 choices for the sample August 1987-July 1999. He finds that changes in industrial production and precursors of final good inflation affect the Fed's interest rate decisions whereas other variables such as CPI and unemployment do not. His results indicate that significant increases in explanatory variables are necessary for small increases in the federal funds rate. Once these thresholds are passed, small changes in explanatory variables are enough for bigger increases or decreases in the target rate.

Dolado et al. (2005), however, find just the opposite result for the US. They use an ordered probit model with 5 choices to estimate reaction functions for Germany, France, Spain, US, and Euro area for the period January 1984-September 2001 (for the US). They compare, different from other papers, constant and non-constant inflation targets (from the Council of Economic Advisors reports) in their monetary rule specification. Their results for the US are contradictory to Vanderhart (2000) and Dueker (1999) in which they find that relatively smaller increases in explanatory variables are sufficient for the Fed to decide for a change in the target rates. Moreover, their results indicate that it is easier for the Fed to make a big decrease decision than a big increase decision which supports Blinder (1998) and Cukierman (2000).

Similarly, Hamilton and Jorda (2002) estimate a 5-choice ordered probit with a different explanatory variable set. They find that only the lags of change in the Fed funds rate and the spread between the six-month Treasury bill rate and the Fed funds rate influence the FOMC's decision on the Fed funds. Their results indicate that if the Fed increases the funds rate in the previous period, then it is more likely that the Fed will increase the rates in the current month. Moreover, if the 6-month T-bill rate is above the Fed funds rate, then it is again more likely to see an increase in the Fed funds rate. Their thresholds estimates support Dolado et al. (2005)'s results that show small changes in explanatory variables are enough for small increases (decreases) in the Fed funds but once those thresholds are passed, explanatory variables must increase significantly for big increases (decreases) in the Fed funds rate. They find symmetric thresholds indicating no bias in the Fed's policy decisions.

Hu and Phillips (2004b) introduce properties of ordered probit models for time series models for the first time, although Phillips et al. (2007) correct some of Hu and Phillips (2004b)'s previous results. Their results are worth mentioning because their results, in my opinion, somehow overshadow previous literature using ordered probit models. They show that the thresholds will be sample size dependent when y^*, the latent dependent variable in the model, is nonstationary and in case any of the explanatory variables is trend stationary, MLE would have neither a maximum nor a boundary. Moreover, if the variables in the model are all non-stationary, then all the parameters including the thresholds converge at the rate of $n^{3/4}$. However, surprisingly, if the variables include stationary variables, there would be multiple convergence rates: $n^{3/4}$ (faster) for non-stationary variables and $n^{1/4}$ (slower) for stationary variables.

Hu and Phillips (2004a) is the first paper which takes these results into account. They use a 3-choice ordered probit backward-looking model and find that lagged inflation, consumer confidence, unemployment claims, industrial growth and changes in interest rates influence the Fed's decision. Their results also indicate an asymmetry for market intervention that big changes in the explanatory variables are necessary for an increase in the Fed funds rate, whereas small changes in the explanatory variables are enough for a decrease in the Fed funds rate.

Kim et al. (2007) use Hu and Phillips's (2004b) and Phillips et al.'s (2007) results in their 3-choice ordered probit models. As they point out, when y^* is non-stationary, the standard errors become biased. So, they argue that correcting the standard errors of the estimated coefficients might be crucial if the model selection criteria are completely empirical. However, what they miss is that using information criteria which do not use coefficients' standard errors would be resistant to this biasedness.

2.3 Generalized Ordered Probit Model

The major advantage of the generalized ordered probit model is its flexibility so that ordinary probit and ordered probit models are the special cases of the generalized ordered probit model. Previous literature has only used ordered probit models. However, it is a widely accepted fact that an ordered probit model depends on the parallel lines assumption which usually does not hold.

Suppose that a latent variable y_t^* is determined by

$$y_t^* = \beta_j' x_t - \epsilon_t \qquad e|x \sim N(0,1) \tag{2.8}$$

and let α_j be an unknown threshold parameters and define

$$y_t = \begin{cases} 1 & \text{if } -\infty < y_t^* \leq \alpha_1 \\ 2 & \text{if } \alpha_1 < y_t^* \leq \alpha_2 \\ \vdots & \\ j & \text{if } \alpha_{j-1} \leq y_t^* < \infty \end{cases} \tag{2.9}$$

The conditional probabilities of the generalized ordered probit model can be calculated by

$$P(Y_t = 1|x) = \phi(\alpha_1 - \beta_1' x_t)$$

$$P(Y_t = j|x) = \phi(\alpha_j - \beta_j' x_t) - \phi(\alpha_{j-1} - \beta_{j-1}' x_t) \qquad j = 2, ..., M-1$$

$$P(Y_t = M|x) = 1 - \phi(\alpha_{j-1} - \beta_{J-1}' x_t)$$

where M is the number of categories of the ordinal dependent variable and ϕ is the standard normal distribution. As can easily be noticed from above, ordered probit is a special case of the generalized ordered probit model. When $\beta_j = \beta$ the generalized ordered probit model becomes an ordered probit model where the parallel line assumptions are imposed. Also, when $M = 2$ with $\beta_j = \beta$ (parallel line assumption), the model becomes a binary probit model.

The parallel line assumption is important because it assumes a constant effect of independent variables on the probability of Y. However, the effect of an explanatory variable might have different effects (or no effect at all) in different categories j. This can be shown as

$$\frac{P(Y_t = j|x)}{\partial X} \neq \frac{P(Y_t = j'|x)}{\partial X} \qquad \forall j \neq j' \tag{2.10}$$

Therefore, if the model does not have a parallel lines assumption, then not only will cdf shift to the right but also its shape will change when any independent variable changes. By relaxing the parallel lines assumption, any possible specification bias (stemming from functional form) is avoided.

The parameters are estimated by maximum likelihood. For each t, the loglikelihood function is

$$L = \prod_{j=1}^{J} \prod_{t=1}^{T} P(y-j)^{d_{tj}}$$

where d_{tj} is dummy variable for each of the j categories and $d_{tj} = 1$ if the observation t is in category j and $d_{tj} = 0$ otherwise.

The loglikelihood function can be calculated as

$$\begin{aligned} lnL &= \sum_{y=1} ln[\phi(\alpha_1 - \beta_1' x_t)] \\ &+ \sum_{y=2} ln[\phi(\alpha_2 - \beta_2' x_t) - \phi(\alpha_1 - \beta_1' x_t)] \\ &\vdots \\ &+ \sum_{y=J} ln[1 - \phi(\alpha_{J-1} - \beta_{J-1}' x_t)] \end{aligned} \tag{2.11}$$

Although the parameters in the generalized ordered probit model can be estimated, some but not all of the variables might violate the parallel line assumption. If at least one of the variables does not violate the parallel line assumption, then it is efficient to estimate the model with the parallel line assumption for those variables and without the parallel line assumption for the variables which violate the parallel line assumption. Therefore, βs will be different in different categories if the parallel line assumption does not hold and $\beta_j = \beta$ if the parallel line assumption holds.

2.4 Data

In estimation of the generalized ordered probit model, I use monthly data with the largest sample interval available: from September 1982 to December 2007. All the data used in the paper are accessible from the Federal Reserve Bank of St.Louis, the University of Michigan and the Federal Reserve Bank of Philadelphia. Table (2.1) gives the summary statistics of the variables used in the model and Figure (2.1) displays the Federal funds target rate and changes in the Federal funds target rate. I use three sets of variables: inflation measures, output measures, and monetary variables.

Inflation measures consist of monthly and annual percentage changes of the Consumer Price Index (CPI), the Core Consumer Price Index (CPI excluding food and energy), and Personal consumption expenditures. Data also include the 12-month-ahead inflation expectation and consumer sentiment which are obtained from the University of Michigan Survey of Consumers. The 12-month-ahead inflation expectation is basically the percentage change of the median expected price in the next 12 months. Consumer sentiment is an index equal to 100 in 1966. It gives an indication of the future course of the economy. An increase in the index indicates consumers' positive assessments of the economy. Implicit inflation targets are obtained from Ireland (2007). He estimates the Fed's inflation target (based on GDP Deflator) for the sample 1954-2004 using quarterly data. In this paper, I assume the Fed does not change its inflation target within each quarter, and its summary statistics are displayed for the sample 1982:09-2004:05.

Output measures include total capacity utilization, industrial production, new housing unit starts, the civilian unemployment rate, recession expectations and the Purchasing Managers Index (PMI). Monthly and annual percentage changes of industrial production and new housing unit starts are used. Total capacity utilization is an index showing the percentage of total capacity of the total industry is operating. I use its deviation from 80 percent as suggested by Hamilton and Jorda (2002). The unemployment rate is used in its original form and absolute change. Recession expectation is expectations of people on the probability of a decrease in real GDP (real GNP prior to 1992) in the current and the following two quarters obtained from the Survey of Professional Forecasters (SPF). I assumed that this expectation does not change within the quarters. It should be noted that the probability of a decline refers to a quarter-over-quarter decline in the level of real GDP. PMI is a composite index published by the Institute for Supply Management. It is estimated through surveys with purchasing managers. PMI is between 0 and 100 and for example, a PMI above 50 percent indicates more respondents reporting "better conditions" than "worse conditions" and means the manufacturing sector is expanding. Therefore, I used its deviation from 50 following Hamilton and Jorda (2002).

I also include stock prices in the models following Smets(1997) and Bordo and Jeanne(2002), among others. They argue that stock prices might have pro-cyclical effects due to bubbles. Since federal reserve is also responsible for financial stability in the US, it might monitor stock prices.

Monetary variables include T-bill spread, M2 and the Federal funds target rate. The T-bill spread is the difference between monthly average of the interest rate of 6-month Treasury bills and fed funds rate. M2 represents monetary stock, and its percentage change from previous month and a year are used in the model. The Federal funds target rate is the short-term interest rate target of the FOMC. The Federal Reserve began announcing changes in its policy stance beginning in 1994, and began to explicitly state its target level for the federal funds rate beginning in 1995. Data between September 1982 and December 1993 are calculated by Thornton (2005).[2]

2.5 Model

This paper follows the literature in modeling the monetary policy rule that the Federal Reserve is believed to be following.

[2] He argues that the FOMC began targeting the funds rate before 1994 and constructed the target series using reports such as the verbatim transcripts of FOMC meetings, the FOMC Blue Book, the Report of Open Market Operations, Money Market Conditions, and etc.

$$i_t^* = \beta' x_t - \epsilon_t$$
$$y_t^* = i_t^* - i_{t-1} \tag{2.12}$$

where i_t^* is the unobserved federal funds target rate, i_t is the announced Federal funds target rate, and x_t is a vector of exogenous explanatory variables. x_t also includes lags, and expectations when it is necessary.

The model assumes the FOMC has 5 choices about adjusting interest rates. The FOMC can decide large or small reductions, no change and large or small increases. The study follows Hamilton and Jorda (2002) to define the analyzed data y_t where y_t^* is the actual value for the change in the Federal funds target rate.

$$y_t = \begin{cases} 1 & \text{if } -\infty < y_t^* \leq -0.4375 \\ 2 & \text{if } -0.4375 < y_t^* \leq -0.125 \\ 3 & \text{if } -0.125 < y_t^* < 0.125 \\ 4 & \text{if } 0.125 \leq y_t^* < 0.4375 \\ 5 & \text{if } 0.4375 \leq y_t^* < \infty \end{cases} \tag{2.13}$$

2.6 Estimation Results

In this section I estimate several monetary rules, and only six of them are displayed in Table (2.2), which are selected based on $AIC = -2 * ln(L) + 2 * p$, where ln(L) is the log-likelihood of the model and p is the number of parameters. It should be noted that this calculation of AIC does not depend on the standard errors of the estimated coefficients. It uses the likelihood of the estimated model and it is set to 1 by assumption since the probit model is employed. Therefore, calculated AIC is robust to any biasedness in estimated standard errors of the coefficients.

In all models, I use only one of the inflation and one of the output (gap) measures listed in Table (2.1). $Cap80_t$ is the total capacity utilization's deviation from 80 percent, i_{t-1} is the first lag of the Federal funds target rate, π_t^e is the 12-month-ahead inflation expectation,

ΔIP_t is the annual percentage change in Industrial Production, π_t is the inflation rate (annual percentage change in PCE), $TBillSpread_t$ is the difference between 6-month T-bill rate and fed funds rate, and $RecessNext_t$ is the expectations of people on the probability of a decrease in real GDP in the current quarter.

I estimate these models first by using the ordered probit method with maximum likelihood estimation. Keep in mind that the interpretation of the estimated coefficients in ordered probit models is slightly different from that in the linear models. We cannot interpret directly from the estimated coefficients unless we calculate the marginal effects. However, a positive coefficient still indicates that higher values on the explanatory variable make it more likely that the Fed will increase the Federal funds target rate, while a negative coefficient indicates just the opposite.

The first two columns in Table (2.2) display backward-looking Taylor rules like equation (2.4) with two and four lags of a smoothing term which are commonly used in the literature. These two backward-looking models fail to statistically identify two of the thresholds, which indicates these models cannot discriminate between a decision of a big and small decrease and between a decision of a small decrease and no change in the federal funds rate. They also have higher AIC statistics than other models. PCE inflation and total capacity utilization are estimated significant and positive as expected. Smoothing terms (only two lags) are significant; the first lag is positive and the second lag is negative, implying that the Federal Reserve is changing the Federal funds target rate slowly. If the Fed changed its key rate last month, it is more likely to see a change in the current in the same direction. On the other hand, if the Fed changes its key rate two months ago, then it is more likely to see a change in the current month in the opposite direction.

The third column shows a forward-looking Taylor rule which includes inflations expectations. However, inflation expectations' coefficient is not statistically significant. The third threshold is significantly not different from zero. Therefore, we can accept that all the thresholds are identified (one of them is zero). The thresholds are asymmetric, indicating that the

FOMC waits for relatively higher changes in the explanatory variables before it decides for a change in the key rates. However, once these thresholds are passed, smaller changes in the explanatory variables are needed for FOMC to decide for a big increase.

The fourth column shows a contemparaneous Taylor model. Like the first two models, PCE and the total capacity utilization gap can explain changes in the Federal funds target rate. Although the model fits the data better than the forward-looking model, it is still not better than the backward-looking models according to AIC statistics. The difference between second and third threshold estimates indicates that the Fed is reluctant to make changes in its target rate unless something very important happens.

I also try to specify a more general monetary rule. For this purpose, I again use only one of the inflation, one of the output gap measures and all possible explanatory variables including forward, backward and contemporaneous variables. I follow the general-to-specific approach where I start with the most general model and drop a variable which reduces the AIC most first. I continue until dropping any of the variable does not reduce AIC. I displayed the best result with two and four lags of smoothing variables in Table (2.2) in the fifth and sixth columns, respectively. Among all these monetary rule estimations the most general model (model 6 in this case) is the one which explains changes in the Federal funds target rate best. Its AIC statistic is significantly lower than in the other models. Results indicate that the FOMC does use other information, such as inflation expectations, T-bill spread, capacity utilization and recession expectations, in forming its decisions. It is important that if people's expectation for a recession for the next quarter increases, it is much more likely the Federal Reserve will decrease its key interest rate target to eliminate a possible downturn in the economy. The estimated thresholds indicate similar results with the fourth model that the FOMC waits for big changes in the explanatory variables before it decides for a change. However, if the Fed decides to increase the Federal funds rate, it waits for smaller changes for a big increase in the fed fund rates.

Then, I test the parallel line assumption which is assumed in ordered probit models. To test whether the parallel line assumption holds, I employed the Likelihood Ratio (LR) test mentioned in Long and Feese (2006) by comparing four binary probit models making an adjustment for the correlation between the binary outcomes defined by $y \leq j$:

$$P(Y_i \leq j|x) = \phi(\alpha_j - \beta_j' x_{it}) \qquad j = 1, 2, 3, 4$$

To test the parallel line assumption, I sum the separate log-likelihoods of the 4 binary models, subtract the log-likelihood of the ordered model from that value, and multiply by -2. This statistic is distributed as $\chi_{(k*J)}$. A significant test result shows (smaller than 0.05) that the parallel regression assumption can be rejected at the 0.05 level.[3] I did not employ a Wald test (i.e. the Brant test, which is used more frequently in the ordered probit estimations) because if standard errors were biased because of nonstationarity in y^* it would mislead us to a different model. However, using the LR test will eliminate this possibility, since the test uses the regression variance (which is equal to 1) compatible with probit models which assume the variance equal to 1.

The LR test results show the parallel regression assumption does not hold. Therefore, we have to proceed with relaxing the parallel regression assumption and estimate a generalized ordered probit model. It basically relaxes the restriction and allows each coefficient to be different for each category of y_t. Estimation results are given in Tables (2.3) through (2.7). In all cases the generalized ordered probit model fits the data better than ordered probit models. In addition, model six still fits the data better than the remaining models.

The interpretation of the estimated coefficients in the generalized ordered probit model can be a little bit tricky. Since the model has 5 categories, there are four panels in which you see the same variables with possibly different estimated coefficients. The first panel compares category 1 with categories 2, 3, 4 and 5, the second panel compares categories 1 and 2 with 3, 4, and 5, the third panel compares categories 1, 2 and 3 with 4, and 5, the fourth compares

[3]The test results are available upon request from the author.

categories 1, 2, 3, and 4 with 5. Therefore, a positive coefficient in the first panel means that an increase in that variable would make it more likely that the decision of the Federal Reserve will be a small decrease in the key rates rather than a big decrease.

Because model six fits the data better, I interpret its estimation results in detail. According to the results displayed in Table (2.7), an increase in T-bill spread increases the probability that the Federal funds target rate will be in the upper category, and the Federal Reserve always considers this variable whether the decision is a big (small) increase or a small (big) decrease but does not consider for a decision between small increase and no change. Inflation is not significant in the fourth panel. It means, for example, that an increase in inflation does not make it more or less likely that the decision of the Fed will be a small increase rather than a big increase. In other words, we can argue that the Fed does not pay attention to lag of inflation when it has to make a decision between a big and small interest rate hike. However, an increase in inflation expectations makes an increase in the federal funds rate more likely when the Fed tries to decide for a small decrease or no change (no change and small increase). In addition, an increase in the capacity utilization, for example, increases the probability of a higher target rate except in the second panel.

Although generalized ordered probit models are very flexible, they might be inefficient since this method eliminates all parallel regression assumptions, even though the assumption may only be violated by one or a few of them. Therefore, it estimates too many coefficients at the same time and decreases the degrees of freedom drastically, especially if there are many explanatory variables. The partially generalized ordered probit method improves this inefficiency by only relaxing the parallel regression assumption for those variables where it is not justified. Hence, I tested whether the parallel regression assumption holds only for some of the variables. With the help of this test, I put parallel regression restrictions on some of the variables and selected the model with lowest AIC. The AIC statistics are improved when the models are estimated by the partially generalized ordered probit model. The results are given in Tables (2.8) through (2.12).

The estimated coefficients can be interpreted like generalized ordered probit models. Model 6 still has the lowest AIC. As you may notice, some of the coefficients are identical in different panels. This points out that the parallel regression assumption holds only for those variables. Table (2.12) shows the results for model 6 and shows that T-bill spread, consumer expectations, and lag of recession expectations in the next quarter affect the FOMC members' decision in all panels. Any change in recession expectations in the next quarter decreases the probability of an increase in the Fed funds target rate, except in the fourth panel. Therefore, an increase in capacity utilization would not increase the probability of a big increase.

2.7 Robustness Check

All models estimated in the previous part assume the Fed has a constant inflation target throughout the whole sample. Ireland (2007) calculates implicit inflation targets based on the GDP Deflator for the Federal Reserve for the sample 1954-2004 using quarterly data. Since Ireland's estimations are quarterly, and monthly data are unavailable, I assume that the Fed's inflation target does not change within quarters and targets are similar for PCE. To match Ireland (2007)'s sample period I have estimated all the models using the same data set until the third quarter of 2004 (Table (2.13)) and compared the results with models estimated using Ireland's inflation target. I include the variable inflation targets by subtracting them from the inflation rate, which is consistent with monetary rule models in the literature. The results shown in Table (2.14) indicate that the results are robust against changing the assumption of constant inflation targets.[4]

It is also important to check the results whether they depend on the predetermined cut points for the dependent variable. For this reason, I have changed the cut point values in (2.13) and replaced them with values which are used by, for example, Vanderhart (2000) as displayed in equation (2.14).

[4]Since the results are very similar, I only report the ordered probit models results.

$$y_t = \begin{cases} 1 & \text{if } -\infty < y_t^* < -0.25 \\ 2 & \text{if } -0.25 \leq y_t^* < 0 \\ 3 & \text{if } y_t^* = 0 \\ 4 & \text{if } 0 < y_t^* \leq 0.25 \\ 5 & \text{if } 0.25 < y_t^* < \infty \end{cases} \tag{2.14}$$

Ordered probit estimation results for these new cut points can be seen in Table (2.15).[5] Although (2.14) fits the data worse, the results are very similar and the order of the models based on AIC statistics are still the same. I also used another cut point displayed in (2.15).

$$y_t = \begin{cases} 1 & \text{if } -\infty < y_t^* \leq -0.25 \\ 2 & \text{if } -0.25 < y_t^* \leq -0.125 \\ 3 & \text{if } -0.125 < y_t^* < 0.125 \\ 4 & \text{if } 0.125 \leq y_t^* < 0.25 \\ 5 & \text{if } 0.25 \leq y_t^* < \infty \end{cases} \tag{2.15}$$

The results for the model using (2.15) can be seen in Table (2.16). This model fits the data better (lower AIC statistic) than the model using (2.13), but the results in general and the order of the models (based on AIC) are still same. Therefore, the results seem fairly robust to changing predetermined cut points.[6]

2.8 Conclusion

Although vast majority of the literature on monetary rules is focused on linear models, there are several reasons to believe that the Federal Reserve might be following a non-linear monetary rule. Recent theoretical papers have also shown that it might be even optimal

[5] Results for partially and generalized ordered probit results are not reported to save space and are available upon request from the author.

[6] To check robustness of the results estimating the same models for two sub-samples is a usual method in recent literature. However, the sample that this paper covers almost coincides with Alan Greenspan's chairmanship. Therefore, there is no plausible reason to think there has been any structural change in the monetary policy.

for the central banks to follow a non-linear monetary reaction function. Following these theoretical papers, the present study uses a nonlinear model, a generalized ordered probit model, to formalize the nonlinearity in the monetary policy reaction function of the Federal Reserve. I find that employing a (partially)generalized ordered probit model increases in-sample performance. The findings indicate that a more general monetary reaction function outperforms Taylor rule specifications. The Fed takes into account not only inflation and output gap measures but also several other variables during its decision process, but the degree of its attention on each variable is choice-dependent. In other words, the Fed might assign different weights for each macroeconomic factors when it is trying to make a choice, for example, between a big and small decrease or a small decrease and no change in the federal funds target rate. The threshold estimates also indicate that the Federal Reserve acts asymmetrically that it waits for relatively significant changes in the macroeconomic factors before it decides for a change in its target rates. However, once these thresholds are passed, relatively less significant changes in the economy are needed for the Federal Reserve to take action. This paper also benefits from new findings in the econometrics literature on time series properties of ordered probit models and argues that using certain information criteria, i.e. AIC, is sufficient to choose the right empirical model in case the latent dependent variable is non-stationary.

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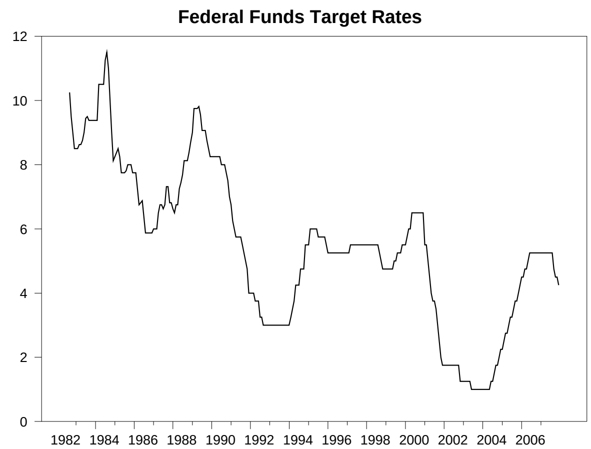
Table 2.1: Data Summary Statistics

Variable	**N**	**Mean**	**Std. Dev**	**Min**	**Max**
Inflation Measures:					
CPI - Monthly % Change	304	0.3	0.2	-0.5	1.3
CPI - Annual % Change	304	3.1	1.1	1.1	6.4
CPI, less food and energy - Monthly % Change	304	0.3	0.1	-0.2	0.7
CPI, less food and energy - Annual % Change	304	3.2	1.1	1.1	5.9
PCE - Monthly % Change	304	0.5	0.5	-2.0	3.0
PCE - Annual % Change	304	6.4	1.7	2.5	11.6
12-month-ahead inflation expectation	304	3.1	0.5	0.4	4.8
Consumer sentiment (1996=100)	304	91.4	9.3	63.9	112
Implicit Inflation Target	261	2.7	0.9	1.7	5.6
Output Measures:					
Total capacity utilization	304	80.5	3.1	70.8	85.1
Total capacity utilization deviation from 80	304	0.5	3.1	-9.2	5.1
Industrial Production - Monthly % Change	304	0.3	0.6	-1.6	2.2
Industrial Production - Annual % Change	304	3.0	3.4	-6.9	12.5
PMI - Minus 50	304	2.2	5.1	-11.2	19.9
New housing unit starts ('000)	304	1562.4	271.6	798	2292
New housing unit starts - Monthly % Change	304	0.2	7.1	-26.4	24.0
New housing unit starts - Annual % Change	304	3.1	19.5	-48.5	96.2
Recession expectation current	304	13.5	15.7	1.4	86.4
Recession expectation next quarter	304	15.3	11.2	4.0	70.0
Recession expectation two quarters later	304	16.1	7.0	6.2	54.5
Unemployment Rate	304	5.9	1.4	3.8	10.8
Change in Unemployment Rate	304	0.0	0.2	-0.7	0.5
Stock Returns - Monthly % Change	304	0.9	4.2	-21.8	13.2
Monetary Variables:					
M2 - Monthly % Change	304	0.5	0.3	-0.3	2.8
M2 - Annual % Change	304	5.7	2.7	0.3	13.0
T-bill Spread	304	-0.3	0.4	-1.6	0.8
Federal funds target rate	304	5.5	2.4	1.0	11.5



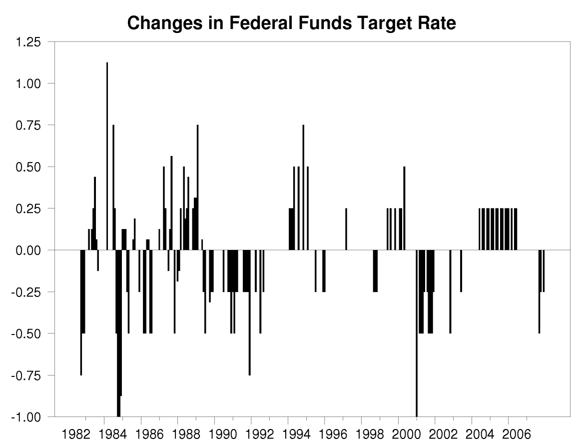


Figure 2.1: Federal Funds Target Rate and Changes in the Federal Funds Target Rate

Table 2.2: Ordered Probit Estimation Results

	(1)	(2)	(3)	(4)	(5)	(6)
π_{t-1}	0.432***	0.430***			0.355***	0.368***
	(6.80)	(6.93)			(4.82)	(4.96)
$Cap80_{t-1}$	0.0895***	0.103***				
	(3.33)	(4.13)				
i_{t-1}	1.150***	1.130***	1.373***	1.132***	0.727*	0.845**
	(3.65)	(3.77)	(4.61)	(3.76)	(2.31)	(2.59)
i_{t-2}	-1.787***	-1.400***	-1.466***	-1.368***	-0.902**	-1.637**
	(-3.54)	(-4.82)	(-5.01)	(-4.69)	(-2.93)	(-3.14)
i_{t-3}	0.848					1.196*
	(1.69)					(2.28)
i_{t-4}	-0.474					-0.579
	(-1.60)					(-1.78)
π^e_t			0.231			
			(1.59)			
ΔIP_t			0.103***			
			(4.45)			
π_t				0.362***		
				(6.25)		
$Cap80_t$				0.108***	0.107***	0.100**
				(4.26)	(3.50)	(3.17)
π^e_{t-1}					0.296	0.314
					(1.83)	(1.85)
$RecessNext_t$					-0.0555***	-0.0558***
					(-5.56)	(-5.59)
$RecessNext_{t-3}$					0.0334***	0.0354***
					(3.57)	(3.54)
$TbillSpread_t$					0.643**	0.682**
					(2.79)	(2.93)
τ_1	-0.400	-0.425	-1.135**	-0.678*	-0.264	-0.142
	(-1.37)	(-1.48)	(-2.77)	(-2.40)	(-0.54)	(-0.29)
τ_2	0.296	0.262	-0.485	0.0232	0.558	0.695
	(1.04)	(0.94)	(-1.21)	(0.09)	(1.18)	(1.43)
τ_3	2.494***	2.449***	1.537***	2.177***	3.013***	3.172***
	(7.87)	(7.91)	(3.79)	(7.32)	(5.93)	(6.08)
τ_4	3.459***	3.399***	2.427***	3.093***	4.012***	4.193***
	(10.02)	(10.04)	(5.71)	(9.59)	(7.55)	(7.69)
Observations	301	303	303	302	302	301
AIC	613.6	615.7	648.0	619.3	571.3	568.1

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.3: Generalized Ordered Probit Estimation Results - Model 1 & 2

	(1)		(2)	
1				
π_{t-1}	0.390***	(3.81)	0.373***	(3.77)
$Cap80_{t-1}$	0.155**	(2.89)	0.172***	(3.44)
i_{t-1}	1.709**	(2.60)	1.382*	(2.42)
i_{t-2}	-2.690**	(-2.61)	-1.755**	(-3.20)
i_{t-3}	0.917	(0.99)		
i_{t-4}	-0.286	(-0.51)		
α	1.254**	(2.58)	1.470***	(3.37)
2				
π_{t-1}	0.373***	(4.44)	0.385***	(4.73)
$Cap80_{t-1}$	0.0855*	(2.25)	0.0994**	(2.84)
i_{t-1}	1.428**	(3.01)	1.428**	(3.17)
i_{t-2}	-1.904**	(-2.60)	-1.774***	(-4.08)
i_{t-3}	0.587	(0.81)		
i_{t-4}	-0.449	(-1.04)		
α	0.562	(1.50)	0.500	(1.43)
3				
π_{t-1}	0.613***	(5.79)	0.594***	(5.88)
$Cap80_{t-1}$	0.107**	(2.61)	0.111**	(2.87)
i_{t-1}	0.593	(1.39)	0.554	(1.37)
i_{t-2}	-1.221	(-1.76)	-0.824*	(-2.09)
i_{t-3}	0.781	(1.12)		
i_{t-4}	-0.431	(-1.08)		
α	-3.643***	(-6.99)	-3.556***	(-7.05)
4				
π_{t-1}	0.173	(0.74)	0.390*	(2.07)
$Cap80_{t-1}$	0.0766	(1.19)	0.183**	(2.91)
i_{t-1}	-0.614	(-0.74)	0.316	(0.64)
i_{t-2}	1.732	(1.14)	-0.391	(-0.82)
i_{t-3}	1.251	(1.09)		
i_{t-4}	-2.227**	(-2.59)		
α	-4.073***	(-3.72)	-4.276***	(-4.19)
Observations	301		303	
AIC	605.4		605.5	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.4: Generalized Ordered Probit Estimation Results - Model 3

	(3)	
1		
π_t^e	0.557*	(2.17)
ΔIP_t	0.108**	(2.74)
i_{t-1}	1.654**	(2.88)
i_{t-2}	-1.894***	(-3.35)
α	1.087	(1.76)
2		
π_t^e	0.265	(1.21)
ΔIP_t	0.123***	(4.00)
i_{t-1}	1.531***	(3.44)
i_{t-2}	-1.716***	(-3.92)
α	0.908	(1.64)
3		
π_t^e	0.270	(1.32)
ΔIP_t	0.0451	(1.42)
i_{t-1}	1.156**	(2.96)
i_{t-2}	-1.179**	(-3.06)
α	-1.798**	(-3.08)
4		
π_t^e	0.567	(1.84)
ΔIP_t	0.263***	(3.59)
i_{t-1}	0.413	(0.81)
i_{t-2}	-0.375	(-0.73)
α	-4.999***	(-4.43)
Observations	303	
AIC	636.9	

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.5: Generalized Ordered Probit Estimation Results - Model 4

	(4)	
1		
π_t	0.303**	(3.16)
$Cap80_t$	0.194***	(3.83)
i_{t-1}	1.303*	(2.21)
i_{t-2}	-1.647**	(-2.92)
α	1.777***	(3.95)
2		
π_t	0.365***	(4.53)
$Cap80_t$	0.114**	(3.22)
i_{t-1}	1.263**	(2.72)
i_{t-2}	-1.601***	(-3.59)
α	0.581	(1.62)
3		
π_t	0.485***	(5.35)
$Cap80_t$	0.0990**	(2.59)
i_{t-1}	0.657	(1.64)
i_{t-2}	-0.871*	(-2.22)
α	-3.092***	(-6.72)
4		
π_t	0.163	(1.40)
$Cap80_t$	0.177**	(3.03)
i_{t-1}	0.361	(0.76)
i_{t-2}	-0.315	(-0.66)
α	-3.378***	(-5.43)
Observations	302	
AIC	603.5	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.6: Generalized Ordered Probit Estimation Results - Model 5

1		
π^e_{t-1}	-0.0201	(-0.03)
π_{t-1}	0.999***	(3.88)
$Cap80_t$	0.665***	(3.49)
i_{t-1}	2.655*	(2.09)
i_{t-2}	-3.473**	(-2.80)
$RecessNext_t$	-0.0883**	(-2.90)
$RecessNext_{t-3}$	0.136**	(2.89)
$TbillSpread_t$	2.128**	(2.68)
α	2.397	(1.46)
2		
π^e_{t-1}	0.976	(1.89)
π_{t-1}	0.411*	(2.16)
$Cap80_t$	0.120	(1.35)
i_{t-1}	0.543	(0.60)
i_{t-2}	-0.944	(-1.06)
$RecessNext_t$	-0.125***	(-4.17)
$RecessNext_{t-3}$	0.0191	(0.82)
$TbillSpread_t$	1.743**	(2.59)
α	0.973	(0.71)
3		
π^e_{t-1}	0.791	(1.76)
π_{t-1}	0.754***	(3.56)
$Cap80_t$	0.161*	(1.97)
i_{t-1}	0.525	(0.66)
i_{t-2}	-0.796	(-1.01)
$RecessNext_t$	-0.134*	(-2.40)
$RecessNext_{t-3}$	0.0530	(1.73)
$TbillSpread_t$	0.677	(1.10)
α	-6.759***	(-4.39)
4		
π^e_{t-1}	0.524	(0.56)
π_{t-1}	0.199	(0.46)
$Cap80_t$	0.343*	(2.24)
i_{t-1}	-0.137	(-0.12)
i_{t-2}	0.846	(0.71)
$RecessNext_t$	-0.0775	(-0.71)
$RecessNext_{t-3}$	-0.0743	(-0.94)
$TbillSpread_t$	3.391*	(2.30)
α	-8.478**	(-2.69)
Observations	302	
AIC	559.6	

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.7: Generalized Ordered Probit Estimation Results - Model 6

1 π^e_{t-1}	-0.0970	(-0.15)
π_{t-1}	1.044***	(3.81)
$Cap80_t$	0.699***	(3.40)
i_{t-1}	3.765*	(2.43)
i_{t-2}	-6.568**	(-2.62)
i_{t-3}	2.355	(1.13)
i_{t-4}	-0.323	(-0.24)
$RecessNext_t$	-0.0953**	(-3.06)
$RecessNext_{t-3}$	0.145**	(2.86)
$TbillSpread_t$	2.287**	(2.60)
α	2.215	(1.31)
2 π^e_{t-1}	1.050*	(1.99)
π_{t-1}	0.423*	(2.20)
$Cap80_t$	0.134	(1.45)
i_{t-1}	0.883	(0.91)
i_{t-2}	-2.314	(-1.48)
i_{t-3}	0.846	(0.56)
i_{t-4}	0.188	(0.21)
$RecessNext_t$	-0.129***	(-4.14)
$RecessNext_{t-3}$	0.0128	(0.51)
$TbillSpread_t$	1.821**	(2.62)
α	0.817	(0.59)
3 π^e_{t-1}	0.800	(1.66)
π_{t-1}	0.789***	(3.63)
$Cap80_t$	0.150	(1.82)
i_{t-1}	0.666	(0.80)
i_{t-2}	-1.849	(-1.43)
i_{t-3}	1.741	(1.32)
i_{t-4}	-0.854	(-1.03)
$RecessNext_t$	-0.133*	(-2.38)
$RecessNext_{t-3}$	0.0608	(1.80)
$TbillSpread_t$	0.775	(1.17)
α	-7.021***	(-4.37)
4 π^e_{t-1}	-0.861	(-0.63)
π_{t-1}	-0.0814	(-0.13)
$Cap80_t$	0.277	(1.77)
i_{t-1}	-1.357	(-0.59)
i_{t-2}	9.811*	(2.08)
i_{t-3}	-1.137	(-0.41)
i_{t-4}	-5.776**	(-2.80)
$RecessNext_t$	-0.00431	(-0.04)
$RecessNext_{t-3}$	0.0798	(1.10)
$TbillSpread_t$	5.794**	(3.01)
α	-10.11*	(-2.38)
Observations	301	
AIC	554.1	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.8: Partial Generalized Ordered Probit Estimation Results - Models 1 & 2

	(1)		(2)	
1				
π_{t-1}	0.457***	(6.96)	0.459***	(7.17)
$Cap80_{t-1}$	0.178***	(3.71)	0.196***	(4.41)
i_{t-1}	0.981**	(3.08)	0.948**	(3.13)
i_{t-2}	-1.839***	(-3.39)	-1.387***	(-4.72)
i_{t-3}	0.773	(1.53)		
i_{t-4}	-0.326	(-0.83)		
α	1.129*	(2.47)	1.299**	(3.20)
2				
π_{t-1}	0.457***	(6.96)	0.459***	(7.17)
$Cap80_{t-1}$	0.109**	(3.11)	0.119***	(3.66)
i_{t-1}	0.981**	(3.08)	0.948**	(3.13)
i_{t-2}	-1.637**	(-3.13)	-1.348***	(-4.59)
i_{t-3}	0.773	(1.53)		
i_{t-4}	-0.517	(-1.48)		
α	0.357	(1.04)	0.315	(0.96)
3				
π_{t-1}	0.457***	(6.96)	0.459***	(7.17)
$Cap80_{t-1}$	0.0783*	(2.20)	0.0864*	(2.54)
i_{t-1}	0.981**	(3.08)	0.948**	(3.13)
i_{t-2}	-1.476**	(-2.75)	-1.153***	(-3.90)
i_{t-3}	0.773	(1.53)		
i_{t-4}	-0.479	(-1.47)		
α	-2.976***	(-8.15)	-2.968***	(-8.24)
4				
π_{t-1}	0.457***	(6.96)	0.459***	(7.17)
$Cap80_{t-1}$	0.0982	(1.73)	0.169**	(3.02)
i_{t-1}	0.981**	(3.08)	0.948**	(3.13)
i_{t-2}	0.270	(0.30)	-1.051***	(-3.49)
i_{t-3}	0.773	(1.53)		
i_{t-4}	-2.060**	(-2.72)		
α	-5.363***	(-8.57)	-4.675***	(-8.94)
Observations	301		303	
AIC	598.2		599.8	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.9: Partial Generalized Ordered Probit Estimation Results - Model 3

	(3)	
1		
π_t^e	0.347*	(2.32)
ΔIP_t	0.112**	(3.10)
i_{t-1}	1.293***	(4.28)
i_{t-2}	-1.493***	(-5.03)
α	1.407**	(2.93)
2		
π_t^e	0.347*	(2.32)
ΔIP_t	0.132***	(4.47)
i_{t-1}	1.293***	(4.28)
i_{t-2}	-1.494***	(-5.02)
α	0.706	(1.64)
3		
π_t^e	0.347*	(2.32)
ΔIP_t	0.0476	(1.53)
i_{t-1}	1.293***	(4.28)
i_{t-2}	-1.316***	(-4.40)
α	-2.052***	(-4.50)
4		
π_t^e	0.347*	(2.32)
ΔIP_t	0.218**	(3.02)
i_{t-1}	1.293***	(4.28)
i_{t-2}	-1.289***	(-4.20)
α	-3.944***	(-6.91)
Observations	303	
AIC	631.5	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.10: Partial Generalized Ordered Probit Estimation Results - Model 4

	(4)	
1		
π_t	0.329***	(3.75)
$Cap80_t$	0.206***	(4.27)
i_{t-1}	0.931**	(3.06)
i_{t-2}	-1.297***	(-4.36)
α	1.701***	(4.07)
2		
π_t	0.386***	(5.04)
$Cap80_t$	0.123***	(3.64)
i_{t-1}	0.931**	(3.06)
i_{t-2}	-1.287***	(-4.35)
α	0.517	(1.51)
3		
π_t	0.465***	(5.25)
$Cap80_t$	0.0926*	(2.46)
i_{t-1}	0.931**	(3.06)
i_{t-2}	-1.136***	(-3.78)
α	-3.026***	(-6.67)
4		
π_t	0.147	(1.27)
$Cap80_t$	0.165**	(2.83)
i_{t-1}	0.931**	(3.06)
i_{t-2}	-0.892**	(-2.91)
α	-3.256***	(-5.25)
Observations	302	
AIC	599.7	

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.11: Partial Generalized Ordered Probit Estimation Results - Model 5

1		
π^e_{t-1}	0.441*	(2.56)
π_{t-1}	0.362***	(4.82)
$Cap80_t$	0.124***	(3.89)
i_{t-1}	0.334	(1.03)
i_{t-2}	-0.680*	(-2.19)
$RecessNext_t$	-0.0423***	(-3.78)
$RecessNext_{t-3}$	0.0289**	(3.02)
$TbillSpread_t$	0.732**	(3.08)
Constant	0.570	(0.99)
2		
π^e_{t-1}	0.441*	(2.56)
π_{t-1}	0.362***	(4.82)
$Cap80_t$	0.124***	(3.89)
i_{t-1}	0.360	(1.12)
i_{t-2}	-0.680*	(-2.19)
$RecessNext_t$	-0.0706***	(-5.47)
$RecessNext_{t-3}$	0.0289**	(3.02)
$TbillSpread_t$	0.732**	(3.08)
Constant	0.160	(0.30)
3		
π^e_{t-1}	0.441*	(2.56)
π_{t-1}	0.362***	(4.82)
$Cap80_t$	0.124***	(3.89)
i_{t-1}	0.590	(1.88)
i_{t-2}	-0.680*	(-2.19)
$RecessNext_t$	-0.0647**	(-2.78)
$RecessNext_{t-3}$	0.0289**	(3.02)
$TbillSpread_t$	0.732**	(3.08)
Constant	-3.811***	(-6.07)
4		
π^e_{t-1}	0.441*	(2.56)
π_{t-1}	0.362***	(4.82)
$Cap80_t$	0.124***	(3.89)
i_{t-1}	0.693*	(2.18)
i_{t-2}	-0.680*	(-2.19)
$RecessNext_t$	-0.0590	(-1.55)
$RecessNext_{t-3}$	0.0289**	(3.02)
$TbillSpread_t$	0.732**	(3.08)
Constant	-5.533***	(-7.50)
Observations	302	
AIC	553.0	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.12: Partial Generalized Ordered Probit Estimation Results - Model 6

1	π^e_{t-1}	0.438*	(2.45)
	π_{t-1}	0.373***	(4.94)
	$Cap80_t$	0.117***	(3.56)
	i_{t-1}	0.434	(1.28)
	i_{t-2}	-1.310*	(-2.52)
	i_{t-3}	1.163*	(2.23)
	i_{t-4}	-0.627	(-1.93)
	$RecessNext_t$	-0.0427***	(-3.81)
	$RecessNext_{t-3}$	0.0321**	(3.14)
	$TbillSpread_t$	0.764**	(3.19)
	α	0.472	(0.80)
2	π^e_{t-1}	0.438*	(2.45)
	π_{t-1}	0.373***	(4.94)
	$Cap80_t$	0.117***	(3.56)
	i_{t-1}	0.456	(1.37)
	i_{t-2}	-1.310*	(-2.52)
	i_{t-3}	1.163*	(2.23)
	i_{t-4}	-0.627	(-1.93)
	$RecessNext_t$	-0.0707***	(-5.45)
	$RecessNext_{t-3}$	0.0321**	(3.14)
	$TbillSpread_t$	0.764**	(3.19)
	α	0.0717	(0.13)
3	π^e_{t-1}	0.438*	(2.45)
	π_{t-1}	0.373***	(4.94)
	$Cap80_t$	0.117***	(3.56)
	i_{t-1}	0.683*	(2.10)
	i_{t-2}	-1.310*	(-2.52)
	i_{t-3}	1.163*	(2.23)
	i_{t-4}	-0.627	(-1.93)
	$RecessNext_t$	-0.0656**	(-2.80)
	$RecessNext_{t-3}$	0.0321**	(3.14)
	$TbillSpread_t$	0.764**	(3.19)
	α	-3.888***	(-6.13)
4	π^e_{t-1}	0.438*	(2.45)
	π_{t-1}	0.373***	(4.94)
	$Cap80_t$	0.117***	(3.56)
	i_{t-1}	0.793*	(2.41)
	i_{t-2}	-1.310*	(-2.52)
	i_{t-3}	1.163*	(2.23)
	i_{t-4}	-0.627	(-1.93)
	$RecessNext_t$	-0.0586	(-1.55)
	$RecessNext_{t-3}$	0.0321**	(3.14)
	$TbillSpread_t$	0.764**	(3.19)
	α	-5.691***	(-7.60)
Observations	301		
AIC	550.5		

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.13: Ordered Probit Estimation Results - Sample: 1982:09-2004:05

	(1)	(2)	(3)	(4)	(5)	(6)
π_{t-1}	0.429***	0.417***			0.371***	0.379***
	(6.33)	(6.28)			(4.72)	(4.80)
$Cap80_{t-1}$	0.0971***	0.102***				
	(3.54)	(4.03)				
i_{t-1}	1.127***	1.064***	1.322***	1.112***	0.727*	0.860*
	(3.42)	(3.41)	(4.29)	(3.57)	(2.23)	(2.53)
i_{t-2}	-1.773***	-1.320***	-1.381***	-1.322***	-0.913**	-1.625**
	(-3.34)	(-4.36)	(-4.54)	(-4.36)	(-2.87)	(-2.97)
i_{t-3}	0.556					0.915
	(1.06)					(1.68)
i_{t-4}	-0.163					-0.335
	(-0.53)					(-0.99)
π_t^e			0.147			
			(0.91)			
ΔIP_t			0.0986***			
			(4.22)			
π_t				0.341***		
				(5.64)		
$Cap80_t$				0.105***	0.116***	0.109***
				(4.07)	(3.65)	(3.34)
π_{t-1}^e					0.204	0.251
					(1.10)	(1.29)
$RecessNext_t$					-0.0525***	-0.0529***
					(-5.19)	(-5.23)
$RecessNext_{t-3}$					0.0363***	0.0358***
					(3.75)	(3.47)
$TbillSpread_t$					0.452	0.496*
					(1.85)	(2.02)
τ_1	-0.339	-0.416	-1.186**	-0.622*	-0.295	-0.148
	(-1.10)	(-1.39)	(-2.77)	(-2.13)	(-0.58)	(-0.28)
τ_2	0.382	0.293	-0.524	0.0821	0.538	0.699
	(1.28)	(1.01)	(-1.25)	(0.29)	(1.08)	(1.36)
τ_3	2.624***	2.526***	1.547***	2.275***	3.001***	3.183***
	(7.77)	(7.71)	(3.65)	(7.26)	(5.60)	(5.75)
τ_4	3.332***	3.230***	2.208***	2.955***	3.741***	3.932***
	(9.21)	(9.16)	(5.02)	(8.80)	(6.74)	(6.88)
Observations	257	259	259	259	258	257
AIC	524.1	524.8	552.0	531.5	491.5	490.6

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.14: Ordered Probit Estimation Results (Using Ireland (2007)'s Variable Inflation Targets) - Sample: 1982:09-2004:05

	(1)	(2)	(3)	(4)	(5)	(6)
$[\pi_{t-1} - \bar{\pi}_{t-1}]$	0.367***	0.357***			0.346***	0.359***
	(5.39)	(5.38)			(4.28)	(4.42)
$Cap80_{t-1}$	0.0443	0.0509*				
	(1.74)	(2.15)				
i_{t-1}	1.332***	1.275***	1.322***	1.304***	0.864**	1.006**
	(4.12)	(4.18)	(4.29)	(4.27)	(2.69)	(3.00)
i_{t-2}	-1.785***	-1.375***	-1.381***	-1.388***	-0.918**	-1.669**
	(-3.39)	(-4.55)	(-4.54)	(-4.60)	(-2.89)	(-3.06)
i_{t-3}	0.525					0.919
	(1.01)					(1.69)
i_{t-4}	-0.164					-0.308
	(-0.53)					(-0.92)
π_t^e			0.147			
			(0.91)			
ΔIP_t			0.0986***			
			(4.22)			
$[\pi_t - \bar{\pi}_t]$				0.289***		
				(4.62)		
$Cap80_t$				0.0637**	0.0665*	0.0590*
				(2.63)	(2.35)	(2.01)
π_{t-1}^e					0.337	0.396*
					(1.84)	(2.06)
$RecessNext_t$					-0.0545***	-0.0548***
					(-5.42)	(-5.46)
$RecessNext_{t-3}$					0.0371***	0.0364***
					(3.78)	(3.49)
$TbillSpread_t$					0.597*	0.646**
					(2.49)	(2.68)
τ_1	-0.799**	-0.860**	-1.186**	-1.002***	-0.315	-0.135
	(-2.90)	(-3.20)	(-2.77)	(-3.74)	(-0.61)	(-0.26)
τ_2	-0.101	-0.172	-0.524	-0.319	0.508	0.703
	(-0.38)	(-0.67)	(-1.25)	(-1.25)	(1.00)	(1.35)
τ_3	2.073***	1.995***	1.547***	1.815***	2.949***	3.167***
	(7.08)	(7.04)	(3.65)	(6.55)	(5.46)	(5.66)
τ_4	2.756***	2.675***	2.208***	2.476***	3.676***	3.904***
	(8.74)	(8.70)	(5.02)	(8.28)	(6.59)	(6.77)
Observations	257	259	259	259	258	257
AIC	536.3	536.6	552.0	542.7	495.8	494.4

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.15: Ordered Probit Estimation Results Using Different Cut Points (Equation 14)

	(1)	(2)	(3)	(4)	(5)	(6)
π_{t-1}	0.427***	0.421***			0.336***	0.351***
	(6.81)	(6.90)			(4.67)	(4.83)
$Cap80_{t-1}$	0.0813**	0.0942***				
	(3.06)	(3.83)				
i_{t-1}	1.166***	1.118***	1.400***	1.120***	0.709*	0.860**
	(3.74)	(3.77)	(4.75)	(3.77)	(2.29)	(2.68)
i_{t-2}	-1.881***	-1.364***	-1.470***	-1.333***	-0.857**	-1.737***
	(-3.76)	(-4.76)	(-5.08)	(-4.63)	(-2.83)	(-3.37)
i_{t-3}	0.983*					1.315*
	(1.98)					(2.55)
i_{t-4}	-0.507					-0.585
	(-1.73)					(-1.84)
π_t^e			0.208			
			(1.45)			
ΔIP_t			0.0895***			
			(3.94)			
π_t				0.357***		
				(6.25)		
$Cap80_t$				0.0989***	0.0921**	0.0853**
				(3.96)	(3.06)	(2.75)
π_{t-1}^e					0.264	0.291
					(1.65)	(1.74)
$RecessNext_t$					-0.0543***	-0.0547***
					(-5.49)	(-5.53)
$RecessNext_{t-3}$					0.0303**	0.0317**
					(3.28)	(3.23)
$TbillSpread_t$					0.553*	0.610**
					(2.45)	(2.67)
τ_1	-0.266	-0.301	-1.070**	-0.541	-0.258	-0.119
	(-0.91)	(-1.06)	(-2.64)	(-1.94)	(-0.54)	(-0.24)
τ_2	0.395	0.348	-0.454	0.123	0.515	0.671
	(1.40)	(1.26)	(-1.14)	(0.45)	(1.11)	(1.40)
τ_3	2.490***	2.425***	1.462***	2.170***	2.813***	3.002***
	(7.98)	(7.97)	(3.65)	(7.42)	(5.72)	(5.92)
τ_4	3.453***	3.374***	2.338***	3.086***	3.800***	4.009***
	(10.13)	(10.12)	(5.59)	(9.69)	(7.37)	(7.56)
Observations	301	303	303	302	302	301
AIC	635.7	639.2	674.3	642.8	599.3	594.4

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.16: Ordered Probit Estimation Results Using Different Cut Points (Equation 15)

	(1)	(2)	(3)	(4)	(5)	(6)
π_{t-1}	0.480***	0.485***			0.347***	0.359***
	(7.05)	(7.27)			(4.39)	(4.51)
$Cap80_{t-1}$	0.0890**	0.103***				
	(3.21)	(3.99)				
i_{t-1}	1.132***	1.131***	1.399***	1.111***	0.650*	0.773*
	(3.46)	(3.62)	(4.51)	(3.55)	(1.98)	(2.27)
i_{t-2}	-1.744***	-1.444***	-1.507***	-1.395***	-0.842**	-1.585**
	(-3.34)	(-4.76)	(-4.94)	(-4.59)	(-2.62)	(-2.90)
i_{t-3}	0.864					1.233*
	(1.65)					(2.21)
i_{t-4}	-0.556					-0.610
	(-1.81)					(-1.79)
π^e_t			0.236			
			(1.53)			
ΔIP_t			0.107***			
			(4.45)			
π_t				0.434***		
				(6.93)		
$Cap80_t$				0.110***	0.0885**	0.0833*
				(4.16)	(2.75)	(2.53)
π^e_{t-1}					0.449*	0.451*
					(2.30)	(2.23)
$RecessNext_t$					-0.0692***	-0.0693***
					(-5.37)	(-5.37)
$RecessNext_{t-3}$					0.0278**	0.0302**
					(2.72)	(2.77)
$TbillSpread_t$					0.615*	0.674**
					(2.51)	(2.72)
Constant	0.287	0.293	-0.608	0.129	0.472	0.566
	(0.96)	(1.00)	(-1.42)	(0.45)	(0.85)	(0.99)
Constant	0.354	0.360	-0.545	0.197	0.554	0.649
	(1.18)	(1.22)	(-1.28)	(0.68)	(1.00)	(1.14)
Constant	2.590***	2.584***	1.484***	2.392***	3.097***	3.215***
	(7.74)	(7.87)	(3.45)	(7.56)	(5.22)	(5.30)
Constant	2.740***	2.731***	1.615***	2.535***	3.251***	3.373***
	(8.11)	(8.24)	(3.74)	(7.94)	(5.45)	(5.53)
Observations	301	303	303	302	302	301
AIC	541.8	542.6	580.5	544.4	497.5	495.8

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Chapter 3

The Relationship Between Inflation and Stock Returns: Industry Level Analysis with Supply and Demand Shocks

3.1 Introduction

In the US, there has been substantial empirical research focused on the relationship between inflation and stock returns, especially during the late 70s and 80s, when inflation was a real issue. Stocks are claims to real assets, and we expect them to be good hedge against both unexpected and expected inflation. Nevertheless, much empirical work finds negative correlation between inflation (expected and unexpected) and stock returns contrary to the theory and common sense. These early empirical results caused researchers to term this phenomenon the "stock return-inflation puzzle."

As outlined in Giammarino (1998), the relationship between inflation and stock returns can be illustrated by using a dividend-discount model. Under perfect market conditions, the stock price is calculated as the present value of the expected real cash flow assuming the firm distributes all free cash flow as a dividend to its shareholders

$$S_t = \frac{EC_t}{Er_t^*} \tag{3.1}$$

where S_t is the stock price, C_t is real cash flow, r_t^* is the required real return and E is the expectation operator. Note that everything is in real terms and inflation is assumed to be zero. Suppose that inflation is non-zero. Assuming that inflation causes both revenues and costs to increase, we should include nominal expected cash flow, NC_t, instead of C_t. In addition, the real discount rate becomes the nominal discount rate

$$(1 + ER_t(\pi_t)) \equiv (1 + Er_t^+)(1 + E\pi_t) \tag{3.2}$$

where R_t is the nominal discount rate, π_t is rate of inflation and r_t^+ is the required real return given inflation is positive. With the introduction of inflation, dividend-discount model becomes

$$S_t^* = \frac{ENC_t}{ER_t - g(E\pi_t)} \tag{3.3}$$

and when equity is a perfect hedge against inflation

$$\frac{EC_t}{Er_t^*} = \frac{ENC_t}{ER_t(\pi_t) - g(E\pi_t)} \tag{3.4}$$

To accept the fact that stocks are a perfect hedge against inflation, we would assume cash flows must increase one-for-one with inflation. In this case, dividend-discount model becomes

$$\frac{EC_t}{Er_t^*} = \frac{EC_t(1 + E\pi_t)}{ER_t(\pi_t) - E\pi_t} \tag{3.5}$$

This condition binds if

$$ER_t(\pi_t) = Er_t^* + E\pi_t + (E\pi_t \times Er_t^*) \tag{3.6}$$

which is basically the Fisher equation as can be written as Eq.(3.2). In his seminal book, Fisher (1930) reaches a similar conclusion where he argues that the real interest rate is independent of nominal variables (i.e. monetary measures) and nominal interest rate is equal to sum of real interest rate and expected inflation rate. The well-known Fisher equation can be written as

$$(1 + ER_t) = (1 + Er_t^*) \times (1 + E\pi_t) \tag{3.7}$$

The Fisher equation implies that any increase in expected inflation would match with an increase in the nominal interest rates. Many researchers used the Fisher equation to argue that a one-to-one positive relation exists between expected inflation and stock returns, thus indicating hedging against inflation.

However, many studies find opposite results. Lintner (1975), Bodie (1976), Jaffe and Mandelker (1976), Nelson (1976) and Fama and Schwert (1977) are among early contributions supporting a negative relationship between inflation and stock returns for the US, and Gultekin (1983) and Solnik (1983) for international data.

Given the contradictory results to common sense and economics and finance theories, many researchers attempted to find possible explanations by using both aggregate and industry-level data. Nevertheless, researchers are still finding conflicting results, which have motivated me to focus on this issue. In this respect, this paper elaborates on the literature in several ways and I believe revealing the relationship between inflation and stock returns at the industry level would help investors make their portfolio decisions efficiently under macroeconomic shocks.

There are three main problems in the approaches that researchers have used until now. First, there have been many papers published on this relation, yet most of the models used in these papers violate basic econometric assumptions including zero correlation between the error term and explanatory variables (no simultaneity). For example, it is a well-known fact that both inflation and stock returns are endogenous but jointly dependent on common exogenous shocks, specifically productivity and money supply shocks. Therefore, if inflation and stock returns were used in a single equation model, it would be subject to a simultaneity problem and estimated coefficients will be inconsistent, biased and inefficient. Second, many of the papers suffer from the multicollinearity problem. If money supply and inflation were used as explanatory variables for stock returns in a single equation, estimated coefficients would suffer from multicollinearity. In this case, although the estimated coefficients remain consistent and the reliability of the model would not be affected, statistical significance would not be reliable. For example, if we are interested in the sign of the coefficient which shows the direction of the relation between inflation and stock returns would not be possible to test due to biased standard errors. Few papers realized these problems and propose vector autoregressions starting with Lee(1992). Third, macro shocks are likely to affect each individual industry differently and, thus, stock returns in each industry would be affected differently in magnitudes and dynamics. For example, the effects of a monetary shock on the banking industry are expected to be different from effects on the agriculture industry. Similarly, a productivity shock is expected to affect labor-intensive industries more than less labor-intensive industries given that productivity is measured as output per worker or per hour. Very few papers consider the importance of working with micro level data in examining the relation between inflation and stock returns.

To respond to all these issues, I focus on the the dynamic responses of industry portfolio returns to aggregate shocks, money supply and productivity, in particular. Although these two shocks may affect the relationship between inflation and stock returns together, I assume these two shocks are orthogonal to analyze their unique effects on the relation. I use Vector autoregressions (VARs) with long-run (infinite horizon) restrictions to identify these aggregate shocks. VAR eliminates possible simultaneity bias and multicollinearity problems. A recent paper by Bjornland and Leitemo (2009) also uses a VAR model but identifies the model by using Cholesky decomposition along with a long-run restriction. Although I also use long-run restrictions, I diverge from Bjornland and Leitemo (2009) by following Lastrapes (2005) who proposes diagonality and block exogeneity restrictions and more importantly, looking at disaggregate data. This method allows us to identify the structural coefficients to distinguish the effects of money supply and productivity shocks in each individual industry portfolio. This paper attempts to fill the gap in the literature which has not examined the relation through simultaneous equations using both micro- and macro-level data.

The results indicate that the direction of relation between inflation and stock return depends on the type of the macro shock. The relation is negative given a productivity shock, but positive given a money supply shock. Additionally, the relation differs across industries. Examining 3 different industry descriptions (5, 30 and 49 industries) gives more insight about the relation. Under 30 industry portfolios, industries such as food, household, beer, clothes, chemicals, textiles and retail reacts to a productivity shock differently compared to aggregate stock return. In case of a money supply shock, the dispersion among impulse responses becomes larger. Results in 49 industry portfolios tell a similar story.

The findings also suggest that industry specific features do affect dispersion of real stock returns. Size and book-to-market ratio of industries do have an important role in explaining dispersion of mean IRFs especially in case of money shocks for both 30 and 49 industry portfolios. In case of monetary shocks, the size effect is negative and statistically significant indicating that industries with bigger-sized firms are affected less than industries with smaller firms. This effect is more obvious in the 49 industry portfolio. Although the B/M ratio is insignificant for mean IRFs, in case of median IRFs, it also becomes statistically significant. In case of a productivity shock, industry portfolios are affected positively by a B/M factor indicating that industry portfolios with high B/M ratios increases more than industry portfolios with low B/M ratios. Variances of productivity and monetary shocks are almost in all cases are estimated statistically not different from zero ruling out any possible scale effects with available information in hand. In general, size and B/M explains dispersion of real stock returns better when it is described as maximum value of IRFs.

3.2 Literature Survey

Early studies such as Lintner (1975), Bodie (1976), Jaffe and Mandelker (1976), Nelson (1976) and Fama and Schwert (1977), among others, find a negative relationship which has motivated many other researchers, including me, to focus on this relationship. Fama and Schwert (1977) find a negative relationship between inflation and stock returns, yet they could not come up with a solid answer for a source of this negative relation. Sharpe (2000) suggests that inflation lowers the expected earnings growth of a firm and causes a higher required rate of returns which both decrease the value of a stock.

Fama (1981), however, proposes a "proxy hypothesis" where he shows that a decrease in real activity decreases money demand. Assuming money supply is fixed, a decrease in money demand would increase prices, which makes the relationship between real activity and inflation negative. He finds that adding real activity variables into the model does not eliminate this negative relation. However, including the monetary base does eliminate the negative relation. Therefore, he argues that the relation between stock returns and inflation is positive and the negative relation between inflation (both expected and unexpected) and stock return is spurious. Later, Mandelker and Tandon (1985) provide support for Fama's finding using international data including that of the U.S.

Geske and Roll (1983) follow a different approach and argue that the negative correlation between stock returns and inflation does not necessarily indicate causality. Instead, a countercyclical monetary response to a negative shock might be the reason behind this negative correlation and therefore, the relation might be spurious. They argue that a negative shock in real output would be signaled by the stock market. A negative shock in real output means higher unemployment and lower tax revenues for the government, which increases borrowing requirements. In a recession, the government would increase borrowing and the Fed would increase the money supply, which would eventually lead to inflation. Rational investors would realize this sequence would happen and adjust all prices including nominal interest rates and stock prices without a delay. Therefore, we will experience a negative contemporaneous relationship between stock returns and inflation.

On the other hand, Kaul (1987) argues that a complete money demand and supply analysis must be done to understand the inflation-stock return relation. Contrary to Fama's (1981) findings, he finds that inclusion of real activity variables eliminates expected inflation effects in the model. However, it does not reduce the effects of change in expected inflation, which is consistent with Fama's (1981) findings. He discovers that the inflation stock return relation varies over time and depends on the interaction of money demand and supply. He argues that money demand, together with countercyclical monetary policies, causes the negative inflation-stock return relation that we experienced in the postwar era. However, he also finds that during the prewar era (1926-1940) the relation between anticipated real activity and inflation was either positive or insignificant due to procyclical policies. Kaul (1990) reaches similar results for Canada, UK, Germany and US under different monetary regimes. He finds a negative relation between real stock returns and changes in expected inflation in all countries and argues that countercyclical monetary policies are the main reason. He also finds that the relation between real stock returns and changes in expected inflation depends on the operating targets of the monetary policy in which the relation is stronger under interest rate regimes than under money supply regimes.

Boudoukh and Richardson (1993) employ a long-run approach to the inflation stock-return relation. By using two centuries of data (1802-1990) for the UK and US, they find a positive relation between long-horizon nominal stock returns and both ex ante and ex post long-term inflation. More recently, Kim and In (2005) investigate the relation in different time horizons with the help of wavelet analysis. They find a positive relation in the short run (1 month) and long run (128 month) but a negative relation in the intermediate time horizon.

Since the 1990s, researchers have started using vector autoregressions (VAR). Lee (1992), for example, uses VAR to explain the relationship. He finds that inflation has little explanatory power for real activity in the presence of interest rates, which is negatively related with shocks in inflation. He identifies the shocks by imposing a recursive structure and finds no causal relation between stock returns and money supply and neither with inflation. Therefore, he argues that the negative correlation between stock returns and inflation "may not be reliable (that is, causal) relation for purposes of prediction" (p. 1602). Hess and Lee (1999) follow a more comprehensive approach in which they use a VAR model to emphasize the relative importance of supply and demand shocks at the same time for Germany, UK, Japan and the US. They argue that supply shocks cause a negative relation, whereas demand shocks cause a positive relation. They show that the relation depends on the relative importance of supply and demand shocks and varies pre and post-war period.

Rapach (2001) uses structural VAR to examine the effects of macro shocks on US real stock returns. He follows Lastrapes's (1998) methodology to identify the shocks. His results support Fama (1981), showing that aggregate supply shocks are the main source of the negative relation in the postwar period. He shows that positive supply shocks increase real stock returns and decrease inflation at the same time.

Du (2006) also uses VAR considering possible structural breaks and finds 3 structural breaks during the 1926-2001 period: 1939:4, 1952:2, and 1974:3. Therefore, he estimates his model in 4 sub-samples and finds a positive relation only in the first period. He argues it was due to procyclical monetary policy. His results show that in the 1952:3-1974:3 period the negative relation is strong and was due to supply shocks.

Lastrapes (1998) uses a VAR and long-run (both infinite and finite) money neutrality to estimate the dynamic responses of bond yields and real equity price indices for eight countries including the US. He finds that a negative relation is possible due to the relative importance of real shocks (i.e. aggregate supply shock as in Fama (1981)) supporting Hess and Lee (1999), and stocks are a good hedge against inflation when money supply is the source of inflation.

More recently, Bjornland and Leitemo (2009) estimate a structural VAR with a combination of short-run and long-run restrictions. They argue that there is a strong relation between the interest rate and real stock prices. They use $X_t = [y_t, \pi_t, c_t, \triangle s_t, i_t]$ where y_t is the industrial production index, π_t is inflation, c_t is the commodity price index, $\triangle s_t$ is the return in the $SP500$ index and i_t is the federal funds rate.

$$\begin{bmatrix} y_t \\ \pi_t \\ c_t \\ \triangle s_t \\ i_t \end{bmatrix} = B(L) \begin{bmatrix} S_{11} & 0 & 0 & 0 & 0 \\ S_{21} & S_{22} & 0 & 0 & 0 \\ S_{31} & S_{32} & S_{33} & 0 & 0 \\ S_{41} & S_{42} & S_{43} & S_{44} & S_{45} \\ S_{51} & S_{52} & S_{53} & S_{54} & S_{55} \end{bmatrix} \begin{bmatrix} \varepsilon_t^y \\ \varepsilon_t^\pi \\ \varepsilon_t^c \\ \varepsilon_t^{SP} \\ \varepsilon_t^i \end{bmatrix}$$

To identify structural coefficients, instead of putting restrictions on either S_{45} or S_{55}, they assume monetary policy cannot affect real stock prices in the long run by imposing long-run restrictions. They find that inflation and real stock returns move in the same direction in the case of monetary policy shocks and real stock return shocks.

Not all papers on this issue use aggregate data. VanderHoff and VanderHoff (1986) investigate the relationship for seven industries.[1] They find a negative relation between real stock returns and inflation, but adding changes in the expected real income variable eliminates this negative relation in total industry and five of the individual industries. Therefore, their results support Fama's (1981) findings. They also find that in industries (i.e. Transportation/Utilities and Wholesale/Retail Trade) which have a negative relationship, depreciation expenses are significant, indicating inflation-induced tax increases might cause stock prices to fall in those industries. However, for Transportation/Utilities they assert that regulatory lag may influence their results.

Boudoukh *et al.* (1994) investigate the cross-sectional correlation between stock return and expected inflation with industry-level data. They argue that the correlation of stock returns of industries and expected inflation depends on cyclical movements in industry output. They argue that some industries are affected by business cycles more than the other industries. For example, Food and Beverage, Tobacco and Utilities are considered necessities and therefore they are less affected by recessions than other industries. Their results show that noncyclical industries such as Tobacco, Food and Beverage and Petroleum Products

[1] They test four hypothesis: Tax Hypothesis [Feldstein (1980; 1982)], Risk Hypothesis [Malkiel (1979)], Alternative-asset Hypothesis [Hendershott (1981)], Proxy Hypothesis [Fama (1981)]

have a positive correlation with expected inflation, while the remaining industries have a negative correlation. However, this correlation for total industry is found to be positive in the long run. They also execute the same methodology for short-run analysis and find similar results. However, they do not provide any role for monetary policy.

Wei and Wong (1992) test the relationship for nineteen industries. Their results support Fama's proxy hypothesis in all industries for stock returns and expected inflation except for returns and unexpected inflation in non-natural resource industries. They also find little evidence for the nominal contracting hypothesis. The sensitivity of the relation between expected inflation and returns is positively related to the level of real assets and negatively to the debt ratio in postwar period.

Kim and In (2006) employ a nonlinear time series method, wavelet analysis, to examine the issue with industry-level data. Their findings suggest a negative correlation between industry stock returns and inflation in the intermediate and short run. Only in Energy, Chemical and Healthcare industries, which provide necessities, is the correlation found to be positive, similar to Boudoukh *et al.*'s (1994) results. They also find that the absolute value of correlation differs among industries.

Luintel and Paudyal (2006) extend the industry-level approach to international data. They test the relation for the UK common stocks using aggregate and industry-level data and considering structural breaks. They find evidence for cointegration for all industries and their results indicate that UK common stocks hedge against inflation in the long run. However, they only regress stock prices on commodity prices. Therefore, their results might be spurious as Fama (1981) had mentioned decades ago.

3.3 Empirical Methods

As previously noted, I am interested in measuring the relationship between inflation and industry-level stock returns where both of them are affected by macroeconomic shocks using

Vector autoregressions (VARs). Having 49 industry-level stock returns and six macroeconomic variables makes estimation unfeasible unless I impose some restrictions on the model. In this study, I follow Lastrapes (2005), who imposes block exogeneity and diagonality restrictions for this purpose.

Assume that data generation process of the linear dynamic model is given as

$$A_0 Z_t = A_1 Z_{t-1} + ... + A_p Z_{t-p} + u_t \tag{3.8}$$

where u_t is a white noise process and $Z_t = \begin{pmatrix} z_{1t} \\ z_{2t} \end{pmatrix}$. z_{1t} is a $n_1 \times 1$ and z_{2t} is a $n_2 \times 1$ vector where $n = n_1 + n_2$. Consistent with the literature, I assume that fundamental innovations are mutually independent and its variance normalized to 1, $E u_t u_t' = I$. Vector of endogenous variables is defined as

$$Z_t = \begin{bmatrix} port_{it} \\ a_t \\ r_t \\ y_t \\ \frac{m_t}{P_t} \\ s_t \\ m_t \end{bmatrix}$$

where $i = 1, ...n_1$, $port_{it}$ is the portfolio price of industry i, a_t is a measure of productivity, r_t is the nominal interest rate, y_t is output, m_t/P_t is real money balances, s_t is the stock price index and m_t is nominal money stock. The structural model in (3.8) is estimated using the following reduced form

$$Z_t = A_0^{-1} A_1 Z_{t-1} + ... + A_0^{-1} A_p Z_{t-p} + A_0^{-1} u_t \tag{3.9}$$

$$= B_1 Z_{t-1} + ... + B_p Z_{t-p} + \epsilon_t, \quad E\epsilon_t \epsilon_t \equiv \Sigma \tag{3.10}$$

where $B_i = A_0^{-1}A_1$, $\epsilon_t = A_0^{-1} \times u_t$ and ϵ_t is the one-step ahead prediction error with variance-covariance matrix Σ. This autoregressive reduced form can also be demonstrated by a structural moving average after simple derivation

$$Z_t = (A_0 - A_1L - ...A_1L^p)^{-1}u_t \tag{3.11}$$

$$= (D_0 + D_1L + D_2L^2 + ...\infty)u_t \tag{3.12}$$

$$= D(L)u_t \tag{3.13}$$

where $D(L)$ is the dynamic multiplier of the structural shocks. However, $D(L)$ cannot be identified without explicit restrictions to the model. Therefore, we first estimate the reduced-form moving average version of the structural model, which can be represented by

$$Z_t = (I - B_1L - .... - B_pL^p)^{-1}\epsilon_t \tag{3.14}$$

$$= (I + C_1L + C_2L^2 + ...\infty)\epsilon_t \tag{3.15}$$

$$= C(L)\epsilon_t \tag{3.16}$$

Eq (3.16) and $\epsilon_t = A_0^{-1} \times u_t$ help us connect the structural and reduced-form equations. The relation between structural and reduced form equations implies that $D_0 = A_0^{-1}$ and $D_i = C_iD_0$.

$$\Sigma = E\epsilon_t\epsilon_t^{'} \tag{3.17}$$

$$= ED_0u_tu_t^{'}D_0^{'} \tag{3.18}$$

$$= D_0D_0^{'} \tag{3.19}$$

My main objective is to estimate the reduced form autoregressive model and calculate reduced-form moving average coefficients (i.e. ϵ_t, C(L) and ϵ_t). Then, by imposing restrictions on $D_0^{'}$, I calculate structural coefficients D(L).

Lastrapes (2005) proposes two sets of restrictions to be able to use many variables in the model: block exogeneity and diagonality. Assume that these restrictions imply that the reduced form model in (3.10) can be represented as follows

$$\begin{pmatrix} z_{1t} \\ z_{2t} \end{pmatrix} = \sum_{i=1}^{p} \begin{pmatrix} B_{11}^i & B_{12}^i \\ 0 & B_{22}^i \end{pmatrix} \begin{pmatrix} z_{1t-i} \\ z_{2t-i} \end{pmatrix} + \begin{pmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{pmatrix} \tag{3.20}$$

The block exogeneity restriction makes $B_{21}^i = 0$ and the diagonality restriction makes B_{11}^i a diagonal matrix. In other words, diagonality restriction implies that industry portfolio returns do not affect each other, conditional on the macro variables. The block exogeneity restriction, on the other hand, assumes macro variables affect industry portfolio returns, while industry portfolio returns do not affect macro variables.

Lastrapes (2005) proves that the restricted VAR with block exogeneity and diagonality restrictions can be efficiently estimated by OLS using the following equations

$$z_{1t} = d_{it} + \sum_{i=1}^{p} B_{11}^i z_{1t-i} + \sum_{i=0}^{p} G_i z_{2t-i} + v_t \tag{3.21}$$

$$z_{2t} = d_{it} + \sum_{i=1}^{p} B_{22}^i z_{2t-i} + \epsilon_{2t} \tag{3.22}$$

where

$$G_0 = \Sigma_{12}\Sigma_{22}^{-1} \tag{3.23}$$

$$G_i = B_{12}^i - G_0 B_{22}, i = 1, ..., p \tag{3.24}$$

$$E v_t v_t' \equiv H = \Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{12}' \tag{3.25}$$

By construction, coefficients in these two sub-systems ((3.21) and (3.22)) are independent from each other. This allow us to estimate both sub-systems separately. In other words, we can estimate the z_{1t} equation by standard OLS equation by equation and z_{2t} by either unrestricted VAR as a whole system or OLS equation by equation since the right-hand-side variables are the same. Therefore, by estimating (3.21) we get Ev_tv_t, and by estimating (3.22) we get Σ_{22}. Plugging Σ_{22} into (3.23) gives us Σ_{12} given the fact that G_0 we calculate from (3.21). Then, from (3.24) we calculate B^i_{12}, and finally from (3.25) we can get Σ_{11}.

After estimating the reduced-form we need to identify the system with necessary restrictions. As is seen from (3.11) and (3.16), we can find a connection. We know that

$$\epsilon = A_0^{-1}u_t = D_0u_t \tag{3.26}$$

$$E\epsilon_t\epsilon_t = \Sigma = A_0^{-1}u_tu_t^{'}A_0^{-1'} = D_0D_0^{'} \tag{3.27}$$

The correspondence between structural and reduced-form moving average forms implies that $D_0 = A_0^{-1}$ and $D_i = C_iD_0$ for $\bigvee i$, where C_i is estimated in the reduced model. Hence, once we find D_0, we reach D_i, which gives us the structural impulse responses.

Therefore, to identify these structural IRFs, we should use identity in (3.27), which can be shown in more detail as

$$\begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{12}^{'} & \Sigma_{22} \end{pmatrix} = \begin{pmatrix} D_{11}^0D_{11}^{0'} + D_{12}^0D_{12}^{0'} & D_{12}^0D_{22}^{0'} \\ D_{22}^0D_{12}^{0'} & D_{22}^0D_{22}^{0'} \end{pmatrix} \tag{3.28}$$

After estimating the reduced form, we need only the restriction on macroeconomic variables to identify the whole system without additional restrictions on micro variables. As previously mentioned, z_{2t} is assumed block exogenous, and this restriction allows us to identify D_{22}^0 using the lower-right block of the above expression.

Once we identify D_{22}^0, we can calculate other elements of the D_0 matrix by using identity in (3.28):

$$\Sigma_{12} = D_{12}^0D_{22}^{0'} \tag{3.29}$$

$$D_{12}^0 = \Sigma_{12}(D_{22}^{0'})^{-1} \tag{3.30}$$

And

$$\Sigma_{11} = D^0_{11} D^{0'}_{11} + D^0_{12} D^{0'}_{12} \tag{3.31}$$

$$D^0_{11} D^{0'}_{11} = \Sigma_{11} - D^0_{12} D^{0'}_{12} \tag{3.32}$$

D^0_{11} can be uniquely identified from the above equation, since it is a diagonal matrix which enables us to calculate its square root by taking square roots of each component of its diagonal. After calculating D^0_{11}, D^0 becomes fully identified. Therefore, we have all the information to estimate the structural impulse response functions.

Therefore, the only problem left is to identify D^0_{22}. There have been several proposals for identification: (i) Cholesky decomposition, which imposes recursive ordering, as in Sims (1986), (ii) sign restriction, which imposes restriction on the sign of IRFs, as in Faust (1998), (iii) general contemporaneous restrictions directly on A_0, as in Blanchard and Watson (1986), (iv) infinite horizon restriction by restrictions on $D(1)$, which separates transitory from permanent components as in Blanchard and Quah (1989). These are are just some of them.

In this paper, I use infinite-horizon restrictions proposed by Blanchard and Quah (1989). Contrary to other structural identification methods, they propose placing zero restrictions on the accumulated shocks rather than D_0 or A_0. They assume that only some certain shocks (i.e. supply shocks) have long-run effects. On the other hand, demand shocks have transitory effects, so that in the long run cumulative total effects should be zero.

Suppose that $D(1)$ and $C(1)$ are the long-run cumulative lag polynomials with finite elements which require stationarity. Given that Z_t is non-stationarity, suppose that taking its first difference makes it stationary; the model can be written as

$$\Delta Z_t = D_L u_t = CL\epsilon_t \tag{3.33}$$

$$Z_t = (1-L)^{-1} D_(L) u_t \tag{3.34}$$

$$Z_t = [D_0 + (D_0 + D_1)L + (D_0 + D_1 + D_2)L^2 + \infty] u_t \tag{3.35}$$

Then, the impulse response functions of the model can be shown as

$$\frac{\partial Z_{t+k}}{\partial u_t} = \sum_{i=0}^{k} D_i \tag{3.36}$$

$$\lim_{k\to\infty} \frac{\partial Z_{t+k}}{\partial u_t} = \sum_{i=0}^{\infty} D_i = D(1) \tag{3.37}$$

Given the block exogeneity and diagonality restrictions, long run multipliers of the levels can be shown as

$$\lim_{k\to\infty} \frac{\partial Z_{t+k}}{\partial u_t} = D(1) = \begin{pmatrix} \sum_{i=0}^{\infty} D_{11}^{i} & \sum_{i=0}^{\infty} D_{12}^{i} \\ 0 & \sum_{i=0}^{\infty} D_{22}^{i} \end{pmatrix} = \begin{pmatrix} \widetilde{D}_{11} & \widetilde{D}_{12} \\ 0 & \widetilde{D}_{22} \end{pmatrix} \tag{3.38}$$

where $\widetilde{D}_{11}$ is a diagonal matrix due to the diagonality restriction. As Lastrapes (2005) proves, applying Cholesky factorization to the $\widetilde{D}_{22}$" matrix which contains long-run multipliers of the macro sub-system(z_{2t}) is sufficient to identify all structural coefficients including sub-system(z_{1t}).

3.4 Data and Estimation Results

In this paper, to be consistent with finance literature I use Fama and French's (1997) value-weighted industry portfolio returns which are widely accepted in the finance literature.[2] They define each industry by using four-digit SIC codes to assign firms to 5,30 and 49 industries "with the goal of having a manageable number of distinct industries that cover all NYSE, AMEX and NASDAQ stocks" (p.156). Increase in the number of industries allows us to have more detailed information. For example, in 30-category industry portfolios, we have an aggregate information for the finance industry. However, in 49-category industry portfolios, they disaggregate finance industry into Banking, Insurance, Real Estate, and Trading industries.

[2]Data is available at Kenneth French's homepage, *http : //mba.tuck.dartmouth.edu/pages /faculty/ken.french/data_library.html*

Fama and French form each industry portfolio by assigning each NYSE, AMEX, and NASDAQ stock to an industry portfolio at the end of June of year t based on its four-digit Compustat SIC code at that time. If Compustat SIC codes are not available, they use CRSP SIC codes for June of year t. They then compute returns from July of year t to June of year t+1. Return data used in this analysis was created by $CMPT\_IND\_RETS$ using the 200812 CRSP database.

Graphs of industry-level portfolio returns are shown in Figures (3.4), (3.8), (3.9), (3.15) and (3.16).[3] For macro variables, I use weekly hours worked, the industrial production index, the nominal money supply, the $SP500$ price index, inflation and interest rate. All but the $SP500$ returns are from the Federal Reserve Bank of St. Louis Data Base (FRED - Federal Reserve Economic Data). $SP500$ returns data are from CRSP. I measure productivity as output per hour of all persons in the non-farm business sector, nominal money supply as M2, inflation as percentage change in Consumer Price Index (CPI), and interest rate as effective federal funds rate. All macro variables except the fed funds rate are in natural log and all of them are in difference form.[4] All variables are seasonally adjusted where applicable. The sample is monthly and spans from 1965:02 to 2008:12. All macro variables used are graphed in Figure (3.1).

Following Lastrapes (2005), I estimate two sets of equations. In the first equation, I estimate each individual industry portfolio returns on its own lags, and contemporaneous and lags of aggregate variables in difference form. In the second sets of equations, I estimated an unrestricted VAR which consists of aggregate variables. Because of the block exogeneity assumption, it can be estimated by either OLS equation by equation or as a system VAR.

[3]Definitions (SIC codes) of industry classifications are reported in the appendix.

[4]In this dissertation, I assume that all series are stationary after taking first differences. Lastrapes (1998) uses a very similar model and finds that all variables in his model have a unit root and there is no cointegration. Lastrapes (2006) also finds no cointegration with quarterly data in a similar model. Keep in mind that if there were cointegration and we use variables in differences, the estimators would be biased due to model misspecification.

In both scenarios, it is estimated independent of the previous equations. These two sets of equation can be shown as

$$\Delta s_{it} = d_{it} + \sum_{j=1}^{p} b_{ij} \Delta s_{it-j} + \sum_{j=0}^{p} G_{ij} \Delta x_{t-j} + v_{it} \quad i = 1, ..n_1 \tag{3.39}$$

$$\Delta x_t = d_t + \sum_{j=1}^{p} B_j \Delta x_{t-j} + \epsilon_t \tag{3.40}$$

where n_1 is equal to the number of individual industries, x_t is the aggregate variables, Δs_{it} is the individual industry portfolio stock returns, d_{it} is a deterministic component which includes constant term and oil prices, p is the common lag length (set to 13 since I am using monthly data), b_{ij} is a scalar, G_{ij} is a 1×6 matrix. Aggregate variables include labor productivity, the short-term nominal interest rate, the industrial production index, the $SP500$ stock price index, real money balances and nominal money stock. All series are in natural log form except the short-term nominal interest rate.

Using Eq. (3.40), I plot the dynamic responses of each macro variable to productivity and monetary shocks shown in Figures (3.2) and (3.3), respectively. Each figure depicts dynamic effects of these shocks in levels and includes standard errors which are calculated by a Monte Carlo integration simulation with 500 replications.

Results support Hess and Lee (1999) for the short run analysis. In case of a productivity shock, labor productivity increases 0.2% and gradually increases up to 1%, where it stays permanently afterwards. Since we have IRFs of industrial production, the difference between these two IRFs will give us IRFs of labor. It indicates that the increase in labor productivity is just the result of an increase in output rather than a decrease in hours worked. Short-term nominal interest rate is affected in the opposite way. Interest rates decrease 0.1% just after the productivity shock but increase gradually and permanently stay around 30% higher than its pre-shock level. Real money balances increase 0.5%, but the effect of the shock disappears in the long run.

I also decompose real money balances to see the effect of productivity shock on the price level. The results indicate that first impact of the shock on price level is negative but its effect disappears in the long run. On the other hand, stock returns are affected permanently and stay 2.5% higher than its pre-shock levels. This result implies that there is a negative relation between inflation and stock returns in the short run but the relation disappears in the long run.

In Figure (3.3), IRFs of monetary shocks tell another story. When the economy is hit by a monetary shock, the first impact on productivity is negative, but its effect becomes statistically not different from zero just after two months. I found similar results for short-term interest rates and industrial production. Monetary shock decreases real money balances by 0.2% lower than its pre-shock levels even in the long run. Stock returns increased 1.5% just after the shock, but total effect decreased to 0.5% in the long run. On the other hand, the price level increased 0.4% and continued to rise up to 1% in the long run. These results support a positive relation between inflation and stock returns given a monetary shock. Results also indicate that there is no price-puzzle.

The last row in Figures (3.2) and (3.3) show IRFs of real stock prices to macroeconomic shocks. In case of a productivity shock, the total effect of the shock on real stock prices is positive even in the long-run. However, in case of a money supply shock, the total effect on real stock prices is positive in the short term but zero even in the long-run indicating imperfect hedge against inflation.

Therefore, we can conclude that the relationship between inflation and stock returns depends on the type of the macroeconomic shock. However, it is also important to investigate this relation within different individual industries. Intuitively, it is expected that each monetary shock would affect banking industry different than other industries like agriculture industry. The magnitude and the pace of the effect would also be industry dependent. For example, the effects of a money supply shock are expected to take place faster in financial industries than in other industries which are affected indirectly. In this respect, in the next sub-sections I estimate cumulative impulse responses of individual portfolio (industry level stock) returns for 5, 30 and 49 industries given money supply and productivity shocks.

3.4.1 Five Industry Portfolio Returns

I plot dynamic responses of five industry portfolio returns in Figures (3.5) and (3.6) to productivity and monetary shocks, respectively. The dotted curves are the standard errors of aggregate stock returns, and the dashed curve is the IRFs of the aggregate stock returns. IRFs of individual portfolio returns are plotted as solid curves. Figure (3.5) indicates that all but consumer goods portfolio returns respond to a productivity shock similarly. *Consumer* portfolio returns are affected less from productivity shocks compared to aggregate stock returns.

Figure (3.6) shows that the responses of each five individual industry portfolio returns to monetary shocks are similar in shape and magnitude. However, *hitech* industry portfolio returns are on the higher error band, whereas *health* industry portfolio returns are on the lower error band. This result indicates examining responses of industry-level portfolio returns might shed light on the relationship between inflation and stock returns.

In addition, I have also included a vertical line where the impulse responses are equal to the half level of the responses. Results indicate that *manufacturing* industry portfolio return is the slowest portfolio return to adjust. It takes 34 months to reach its half-life response level. On the other hand, both *other* and *hitech* industry portfolio returns are the fastest to adjust. They both reach their half-life level within the first month. On the other hand, the responses of all individual portfolio returns except *consumer* are slower to adjust to monetary shocks compared to productivity shocks.

To summarize the results, I have calculated the cross-sectional sample mean, standard deviation, median (along with 25 and 75 quartiles), and measures of kurtosis, and skewness for each forecast horizon and shock. These statistics help us understand the distribution of industry-level portfolio returns.

Figure (3.7) plots the cross-sectional distribution of five industry-level portfolio returns over the 40 quarter forecast horizon in case of productivity and money supply shocks. Given a productivity shock, the standard deviation of the initial response of industry-level portfolio returns around the mean is around 0.3%. However, it continues to rise with forecast horizon and reaches 1.0% after 40 months. Increase in standard deviation is also apparent in the standard deviation band. The standard deviation band increases as forecast horizon increases. The interquartile range is around 0.5% just after a productivity shock and increases with forecast horizon to 2% in the long run. These two statistics support Figure (3.10) that each industry-level stock returns react different to a productivity shock and the dispersion increases with forecast horizon.

Forth and fifth panels give information about the third (skewness) and forth (kurtosis) moments of the distribution of relative industry-level portfolio returns. The skewness for a normal distribution is zero, and negative values for the skewness indicate that data is left-skewed and positive values for the skewness indicate that data is right-skewed. In response to a productivity shock, the distribution of industry-level portfolio returns is initially right-skewed. However, it becomes left-skewed in the long run.

The kurtosis for a standard normal distribution is three. In this analysis, I use the excess kurtosis definition in which the standard normal distribution has a kurtosis of zero. Positive excess kurtosis indicates a fat tail and is called leptokurtic. Negative excess kurtosis indicates a flat distribution and is called platykurtic. The response distribution is initially platykurtic, but becomes leptokurtic in the long run.

The second column of the panel plots the cross-sectional distribution of industry-level portfolio returns in case of a money supply shock. Given a money supply shock, the standard deviation of the initial response of industry-level portfolio returns is relatively stable than given a productivity shock. The standard deviation of the initial response of industry-level portfolio returns around the mean is around 0.3%. It peaks at 0.5% but converges to 0.3% in the long run. The standard deviation band supports the same results. The standard deviation band around mean is almost constant throughout the forecast horizon. The interquartile range is also small and stable. These two statistics support Figure 3.6 that industry-level stock returns react very similarly to a money supply shock in case of five-industry portfolios.

The skewness statistic indicates that the distribution of industry-level portfolio returns is initially right-skewed, yet it becomes left-skewed after 24 months. The excess kurtosis statistic is inconclusive in the sense that the response distribution is initially platykurtic, but it hovers between platykurtic and leptokurtic.

3.4.2 Thirty Industry Portfolio Returns

Figures (3.10) and (3.10) plot IRFs for each of 30 individual industry portfolio returns to productivity shocks and Figures (3.12) and (3.13) to monetary shocks. The dotted curves are the standard errors of aggregate stock returns, and the dashed curve is the IRFs of the aggregate stock returns. IRFs of individual portfolio returns are plotted as solid curves.

The productivity shocks affect individual industry portfolio returns more or less similarly. IRFs of seven out of 30 of the portfolio returns are out of the standard error bands of aggregate stock returns in the long run. It means that these individual industry portfolio returns are statistically different from $SP500$ returns. These portfolios are *food*, *household*, *beer*, *clothes*, *chemicals*, *textiles*, *retail* industries. Among these portfolios, *textiles* and *clothes* have even negative long-run responses to a productivity shock. However, they are statistically not different from zero.

Given monetary shocks, more industries (compared to productivity shocks) have been affected differently. Half of the industries' IRFs are statistically different from the IRFs of aggregate stock returns. *food*, *household*, *construction*, *beer*, *fabpr*, *steel*, *books*, *autos*, *mines*, *services*, *coal*, *oil*, *financial*, *transportation*, *telecom* and *other* have statistically different IRFs from aggregate stock returns. In addition, industries such as *smoke*, *books*, *games*, *clothes*, *business equipment*, and *utilities* IRFs are out of error bands even though they return inside the error band in the long run.

Figures also indicate that the adjustment in responses is similar to five industry portfolio results in the sense that the adjustment process of industry portfolio returns is slower given a monetary shock compared to a productivity shock.

Figure (3.14) plots the cross-sectional distribution of thirty industry-level portfolio returns over the 40 quarter forecast horizon in case of productivity and money supply shocks. Given a productivity shock, the standard deviation of the initial response of industry-level portfolio returns around the mean is around 0.5% which is slightly higher than the standard deviation of five industry-level portfolio returns. It also continues to rise with forecast horizon and reaches 1.3% after 40 months. Increase in standard deviation is also apparent in the standard deviation band and the interquartile range. These two statistics also support my results that individual industry-level stock returns are affected differently due to a productivity shock and the dispersion increases with forecast horizon.

In response to a productivity shock, the distribution of industry-level portfolio returns is initially left-skewed. However, it fluctuates with the forecast horizon, yet becomes left-skewed in the long run. The kurtosis statistic also fluctuates with the forecast horizon and becomes platykurtic in the long run.

The second column of the panel plots the cross-sectional distribution of industry-level portfolio returns in case of a money supply shock. Given a money supply shock, the standard deviation of the initial response of industry-level portfolio returns is relatively stable than given a productivity shock. The standard deviation of the initial response of industry-level portfolio returns around the mean is around 0.4%. It peaks at 0.6% and becomes relative stable at that level. The standard deviation band and the interquartile range support the same results.

The skewness statistic indicates that the distribution of industry-level portfolio returns is not skewed in the long run. On the other hand, the excess kurtosis statistic indicates that the distribution of industry-level portfolio returns is platykurtic in the long run.

3.4.3 Forty-Nine Industry Portfolio Returns

Figures (3.17) and (3.18) plot IRFs of each of 49 individual industry portfolio returns after a productivity shock, and Figures (3.19) and (3.20) to a monetary shock. As in the previous part, the dotted curves are the standard errors of aggregate stock returns and the dashed curve is the IRFs of the aggregate stock returns. IRFs of individual portfolio returns are plotted as solid curves.

In response to a productivity shock, industry portfolio returns of *toys*, *health*, *Textile*, *food*, *beer*, *household*, *chemicals*, *clothes*, *fabPr*, *guns*, *gold*, *persv*, *boxes*, *construction*, *mines*, *hardware*, *retail*, *financial*, and *other* have reacted statistically differently compared to aggregate stock returns. Among these portfolio returns, *construction*, *mines*, *hardware*, *retail*, *financial*, and *Other* have stronger positive responses to the shock. On the other hand, *toys*, *health*, *textile*, *food*, *beer*, *household*, *chemicals*, *clothes*, *fabPr*, *guns*, *gold*, *persv*, and *boxes* portfolio returns have smaller responses to the productivity, and in the long run they are statistically not different from zero. In other words, for these portfolio returns there is no relation between inflation and stock portfolio returns. Furthermore, some of the industry portfolio returns such as *fun*, *lab eq*, *chips*, *real estate* and *coal* are statistically different from aggregate stock returns in the short run.

In response to a monetary shock, industry portfolios *soda*, *beer*, *fun*, *books*, *household*, *medical equipment*, *Building equipment*, *autos*, *software*, and *banks* respond significantly lower than the aggregate stock returns. However, these returns are statistically not different from zero except *beer*. On the other hand, portfolio returns of *agriculture*, *construction*, *steel*, *fabPr*, *mach*, *aero*, *ships*, *guns*, *gold*, *mines*, *coal*, *oil*, *telecom*, *busser*, *chips*, *lab eq*, *trans*, and *other* industries have significantly stronger positive responses than the aggregate stock returns. In addition, *smoke*, *cloths*, *health*, *utilities*, *boxes* and *insurance*, among others, diverge from aggregate stock return temporarily.

Figure (3.21) plots the cross-sectional distribution of forty-nine industry-level portfolio returns over the 40 quarter forecast horizon in case of productivity and money supply shocks.

The results are very similar to the case of forty-nine industry-level portfolio returns. Given a productivity shock, the standard deviation of the initial response of industry-level portfolio returns around the mean is around 0.5%. However, it continues to rise with forecast horizon and reaches 1.6% after 40 months. Increase in standard deviation is also apparent in the standard deviation band. The standard deviation band increases as forecast horizon increases similar to the interquartile range. The interquartile range is around 0.6% just after a productivity shock and increases with forecast horizon to 2.6% in the long run.

In addition, in response to a productivity shock, the distribution of industry-level portfolio returns is not skewed in the long run. The excess kurtosis statistic indicates platykurtic distribution in the long run.

The second column of the panel plots the cross-sectional distribution of industry-level portfolio returns in case of a money supply shock. Given a money supply shock, the standard deviation of the initial response of industry-level portfolio returns is relatively stable than given a productivity shock. The standard deviation of the initial response of industry-level portfolio returns around the mean is around 0.4%, peaks around 0.7% and stays at that level in the long run. The standard deviation band around mean is almost constant throughout the forecast horizon after the first couple of months. Similarly, the interquartile range is also small and stable.

The skewness statistic indicates that the distribution of industry-level portfolio returns is volatile throughout the forecast horizon, yet becomes right-skewed in the long run. The excess kurtosis statistic indicates a platykurtic distribution.

Results on 5, 30, 49 industry portfolio returns indicate that each industry is affected differently given a macroeconomic shock. However, the relation does not seem to depend on whether the industry: (i) is affected by business cycle more than the other industries as in Boudoukh *et al.* (1994), or (ii) is a non-natural resource industry as in Wei and Wong (1992), or (iii) is subject to high depreciation expenses as in VanderHoff and VanderHoff (1986).[5]

[5]In order to examine the IRFs of industry portfolio real returns, I also plot Figures (3.22)-(3.31).

In this respect, in the next section, I investigate which factors might affect the actual differences in responses of industry portfolio returns.

3.4.4 The Role of Firm-Specific Factors on Portfolio Return Dispersion

The results indicate that response of stock returns in the case of a macroeconomic shock differs across industries in magnitude and even in direction. It is essential to examine the causes of divergence among industries. In this respect, I estimate the following model

$$y_i = \beta_0 + \beta_1 Size_i + \beta_2 B/M_i + \zeta\sigma_{Shock} + \epsilon_i \quad i = 1, ..n \tag{3.41}$$

where y_i is the impulse response functions (in real terms) to a macroeconomic shock. $Size_i$ is the size of the firms in industry i in natural logarithm, B/M_i is the book-to-market ratio in industry i, and σ_{Shock} is the standard deviation of a macroeconomic shock estimated from the VAR model in the previous section. σ_{Shock} is included following Lastrapes and McMillin (2004) and Cecchetti (1999) to account for potential nonlinearities in scale effects. I estimate the model for both money and productivity shocks for 30 and 49 industries. I could not estimate the model for 5 industries because there would be only 5 observations.

Size and book-to-market factors are frequently used in the finance literature (i.e. Fama-French 3 Factor Model) to control for the associated risks. It is argued that investors demand an additional risk premium for taking on additional risk of holding small firms relative to large firms in their portfolio. In addition, investors demand an additional risk premium for taking on additional risk of holding high book-to-market stocks because book-to-market can be interpreted as a proxy for financial distress risk. For example, firms with high book value compared to their market value of equity have high book-to-market value and are considered as potentially being under financial distress.

Therefore, I estimate Eq.(3.41) using size and B/M ratios to examine whether these factors explain the dispersion of impulse responses given a monetary or a productivity shock. Keep in mind that size and B/M variables are different than the Fama-French 3 factors because I use actual values of size and B/M of firms in each industry. In the Fama-French 3 factor capital asset pricing models, however, the return difference between a portfolio of small stocks and a portfolio of large stocks ("Small minus Big", SMB) is used for a size factor and the return difference between a portfolio of high book-to-market stocks and a portfolio of low book-to-market stocks ("High minus Low", HML) is used as a B/M factor.

The results for Eq.(3.41) are given in Tables (3.1) and (3.2) for 30 and 49 industries with four different specifications and three different dependent variables. The first columns of the tables show the dependent variable y_i which is calculated in three different ways: median, maximum and mean of the impulse responses of each industry to money supply and productivity shocks. The results indicate that size and B/M variables play an important role in explaining the dispersion of mean IRFs, especially in the case of money shocks for both 30 and 49 industry portfolios. In the case of monetary shocks, the size effect is negative and statistically significant, indicating that industries with bigger firms in size are affected less than industries with smaller firms. This effect is more obvious in the 49 industry portfolio. In the case of median IRFs, B/M also becomes statistically significant. In the case of productivity shocks, industry portfolios are affected positively, indicating that industry portfolios with high B/M ratios increases more than industry portfolios with low B/M ratios. Variances of productivity and monetary shocks are almost in all cases estimated statistically not differently from zero, ruling out any possible scale effects with available information in hand.

3.5 Conclusion

The relationship between inflation and stock returns was a cynosure in 1980s when inflation was a serious problem in the U.S. Because stocks are claims to real assets, it is expected to be a good hedge against both unexpected and expected inflation. Nevertheless, numerous empirical studies find a negative correlation between inflation (expected and unexpected) and stock returns, which is contrary to theory and common sense. This chapter considers several issues in elaborating the relationship between inflation and stock returns.

This chapter focuses on the the dynamic responses of industry portfolio returns to money supply and productivity shocks using VAR with diagonality, block exogeneity and infinite horizon restrictions proposed by Lastrapes (2005). This method eliminates possible simultaneity bias and multicollinearity problems and allows us to examine heterogenous impacts of money and productivity shocks to individual industry portfolio returns.

The results indicate that the sign of the relation between inflation and stock return depends on the type of the macro shock. The relation is negative given a productivity shock, but positive given a money supply shock. Moreover, both the magnitude and sign of the relation differ across industries. The findings also indicate that size and book-to-market ratio of industries explain the dispersion of industry portfolio returns in case of a macroeconomic shock.

3.6 References

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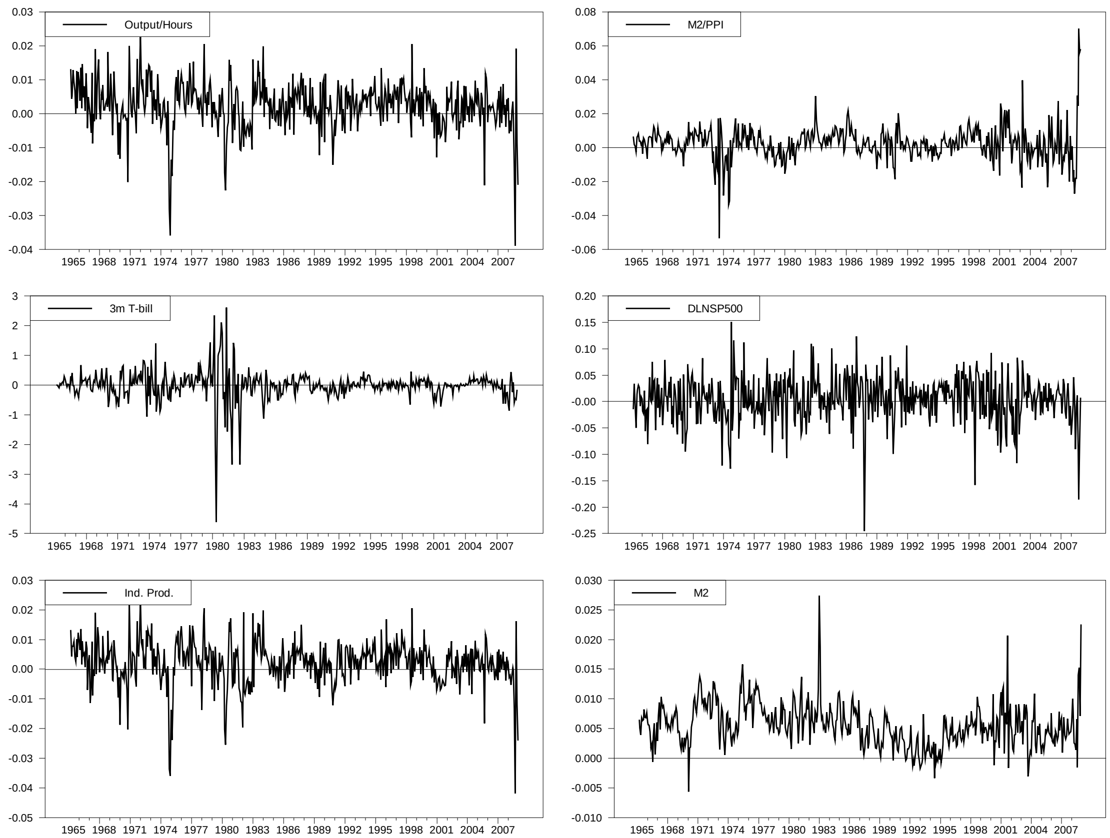

Figure 3.1: Macroeconomic Variables

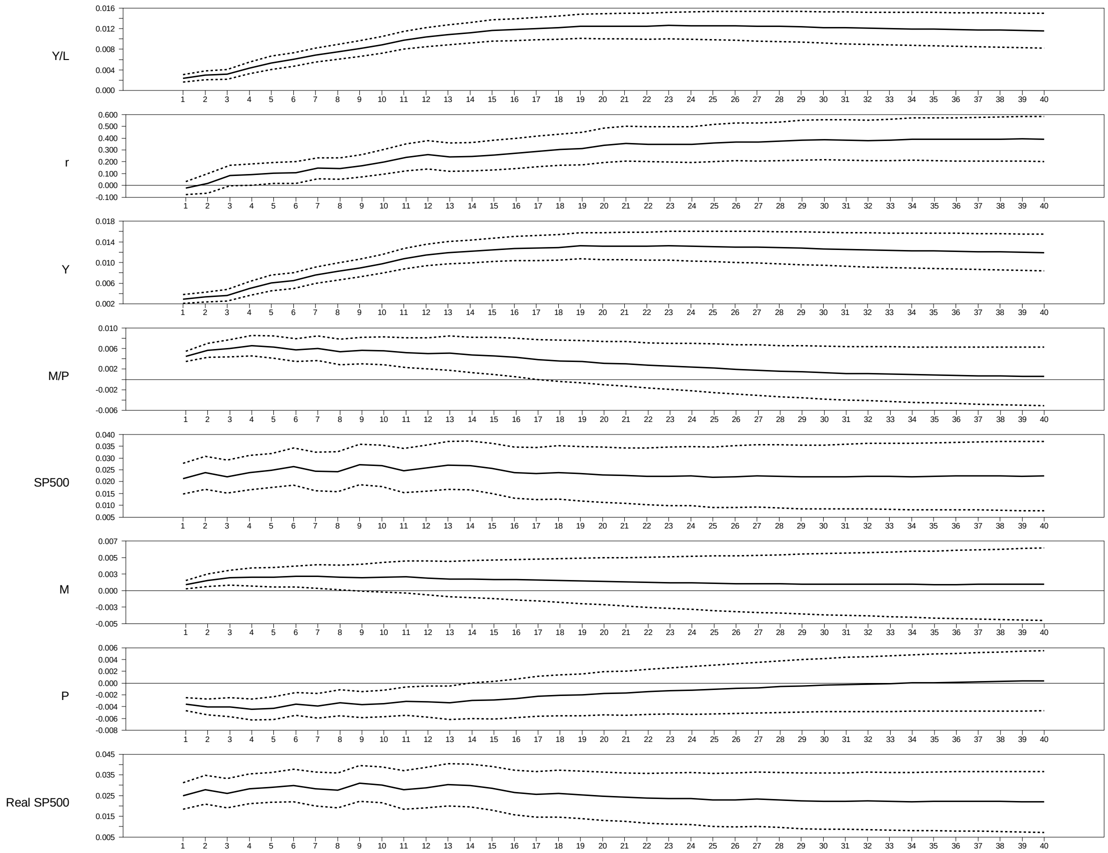

Figure 3.2: Responses of Aggregate Variables to Productivity Shock

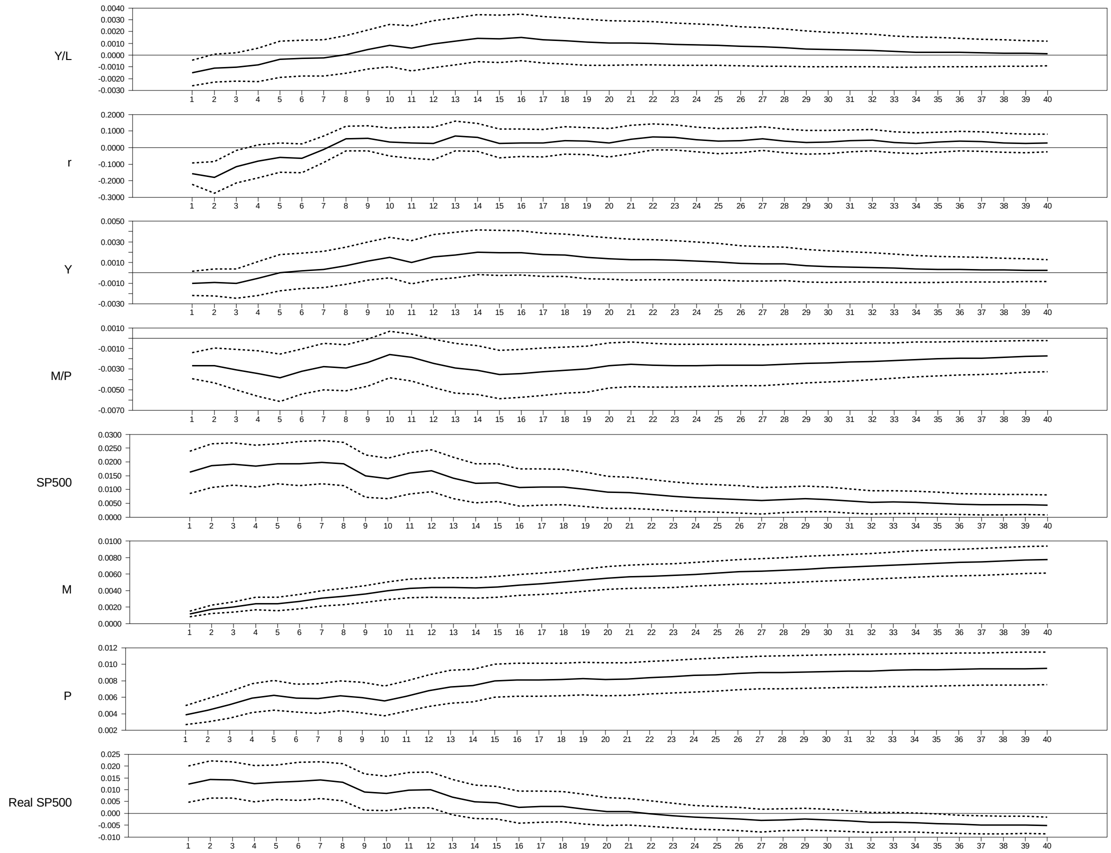

Figure 3.3: Responses of Aggregate Variables to Monetary Shock

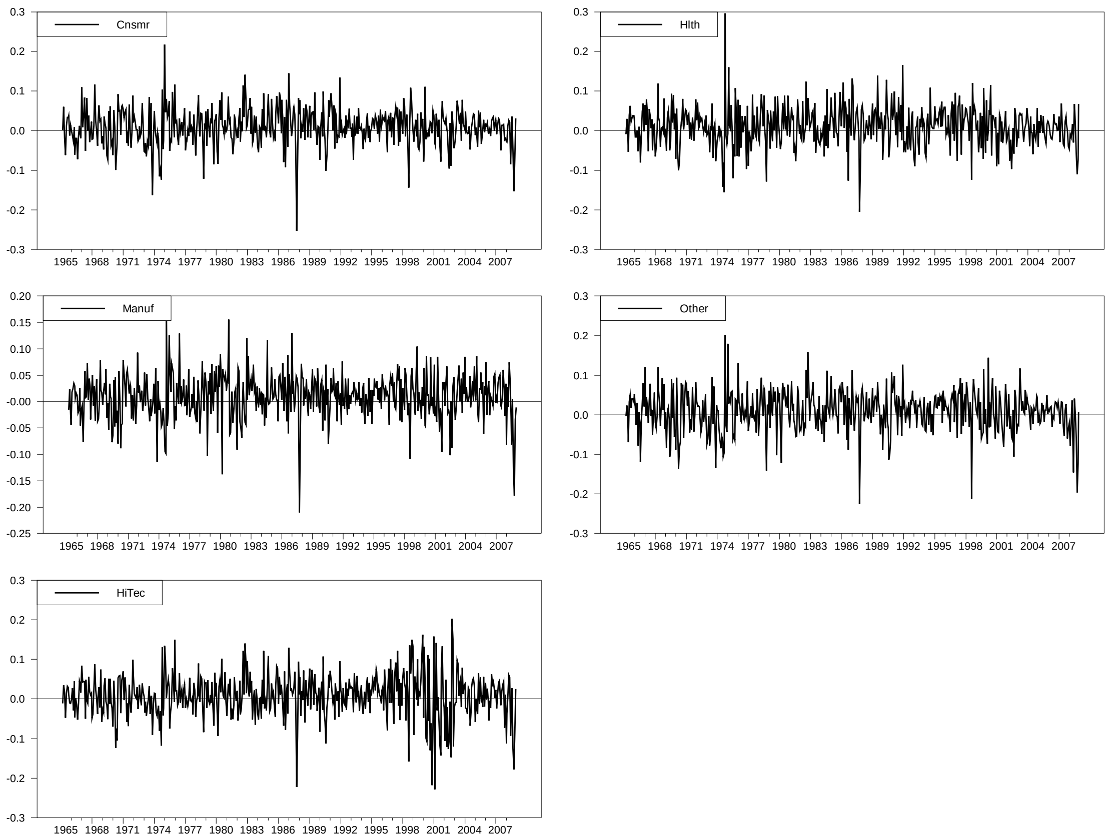

Figure 3.4: Stock Returns: 5 Industry Portfolios

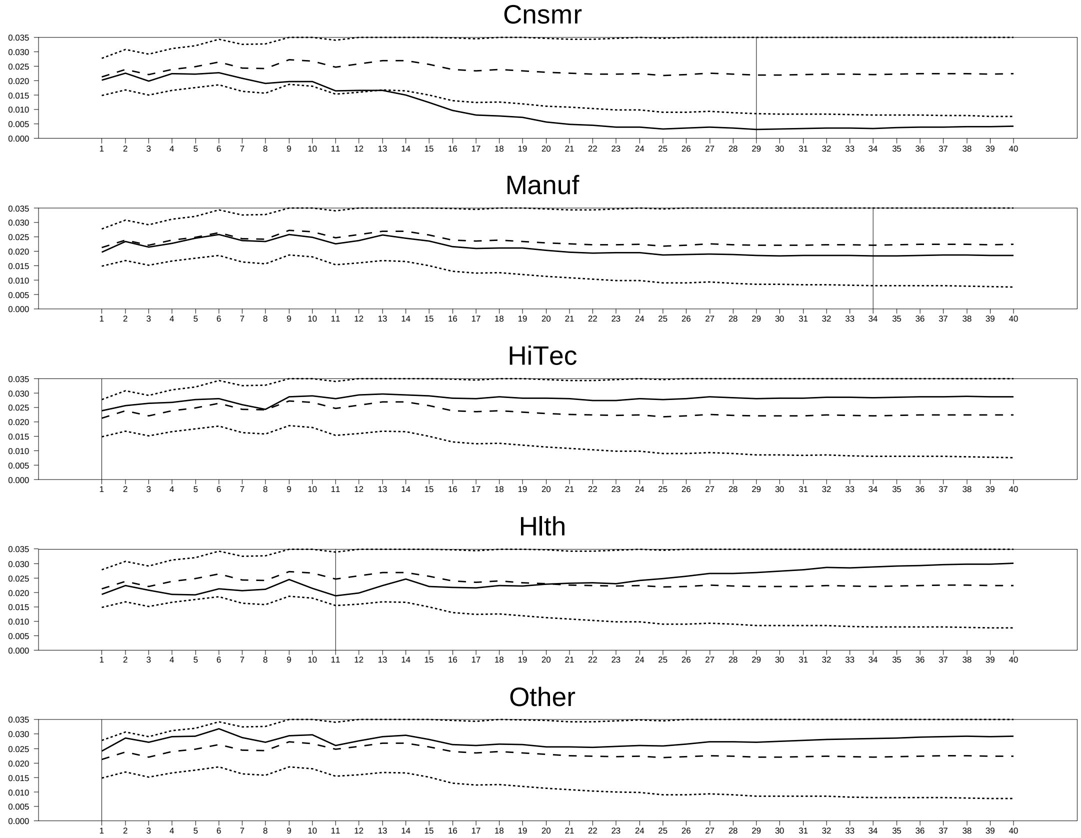

Figure 3.5: Response of Individual Industry Portfolios to Productivity Shock: Five Industry Portfolios

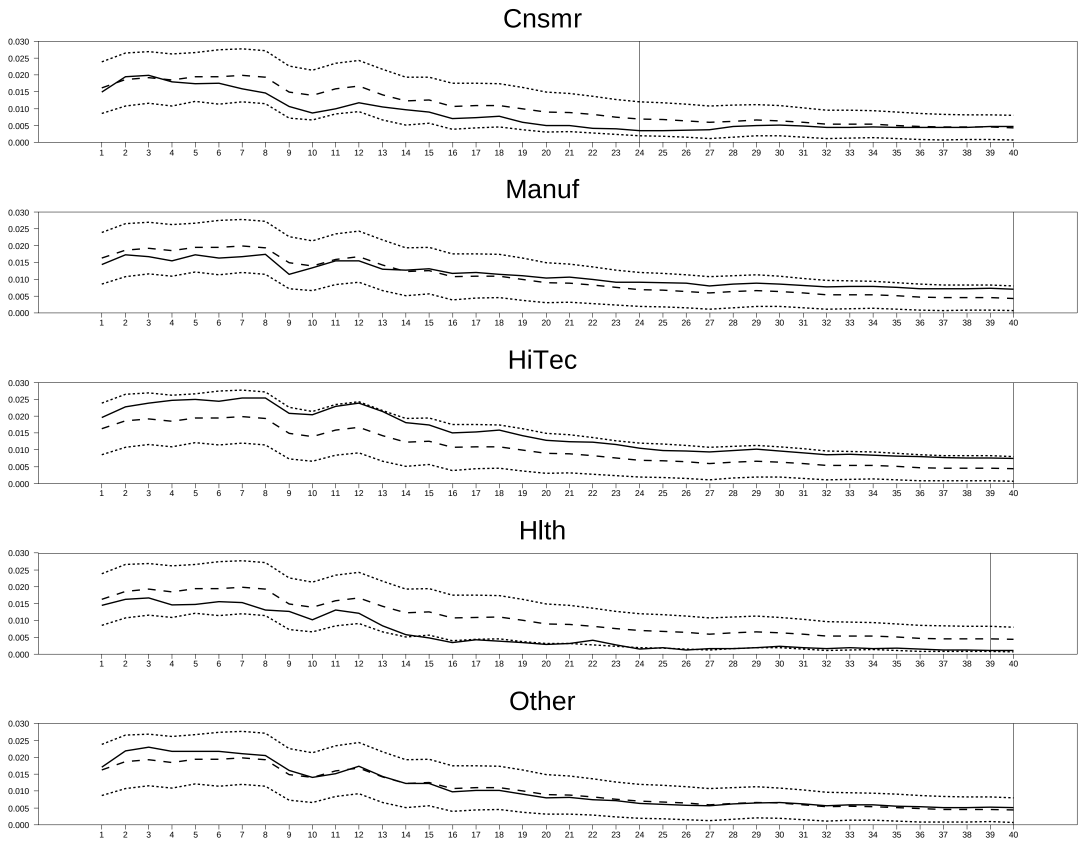

Figure 3.6: Response of Individual Industry Portfolios to Monetary Shock: Five Industry Portfolios

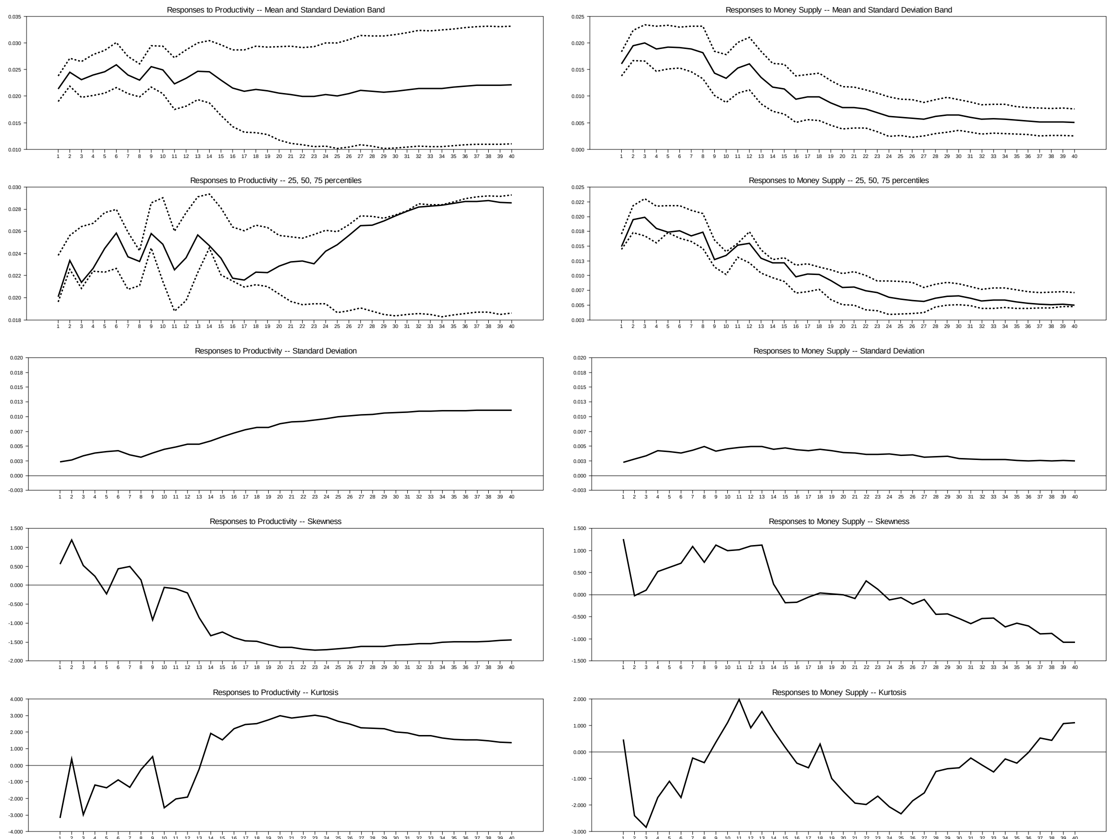

Figure 3.7: Cross-sectional Distribution of Industry-level Portfolio Returns: 5 Industry Portfolios

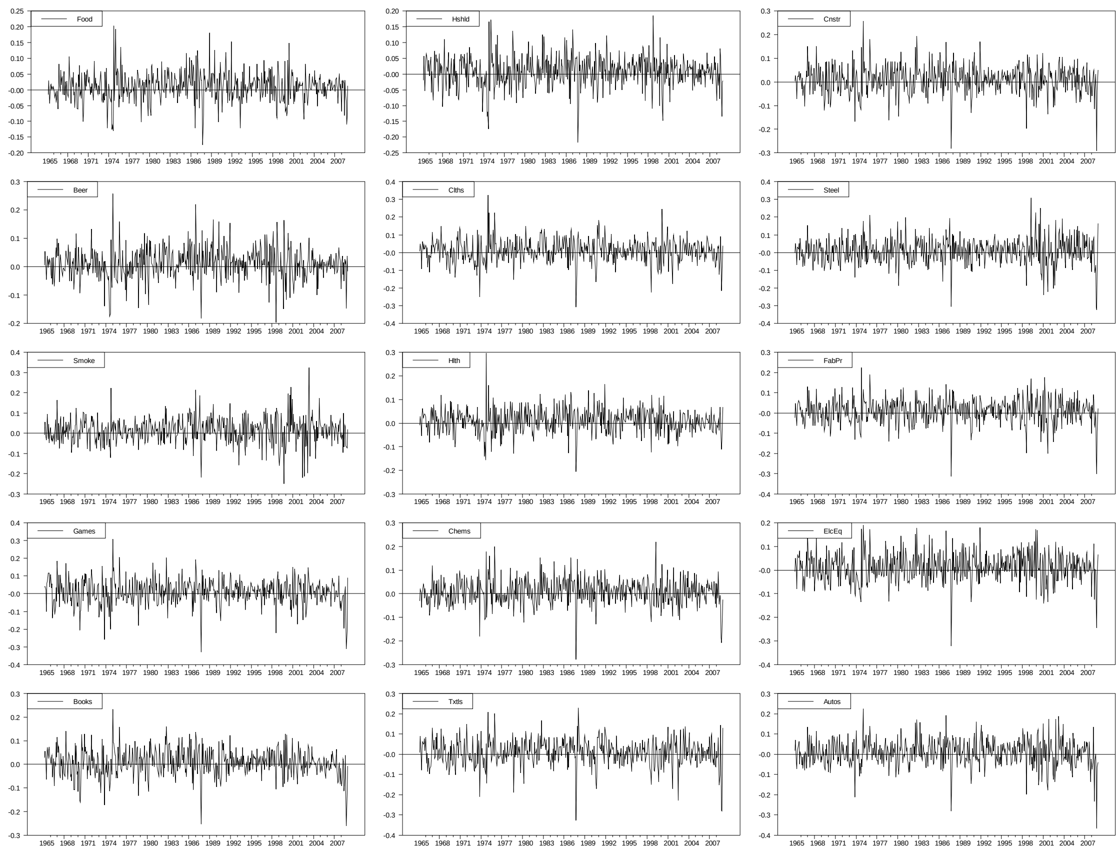

Figure 3.8: Stock Returns: 30 Industry Portfolios

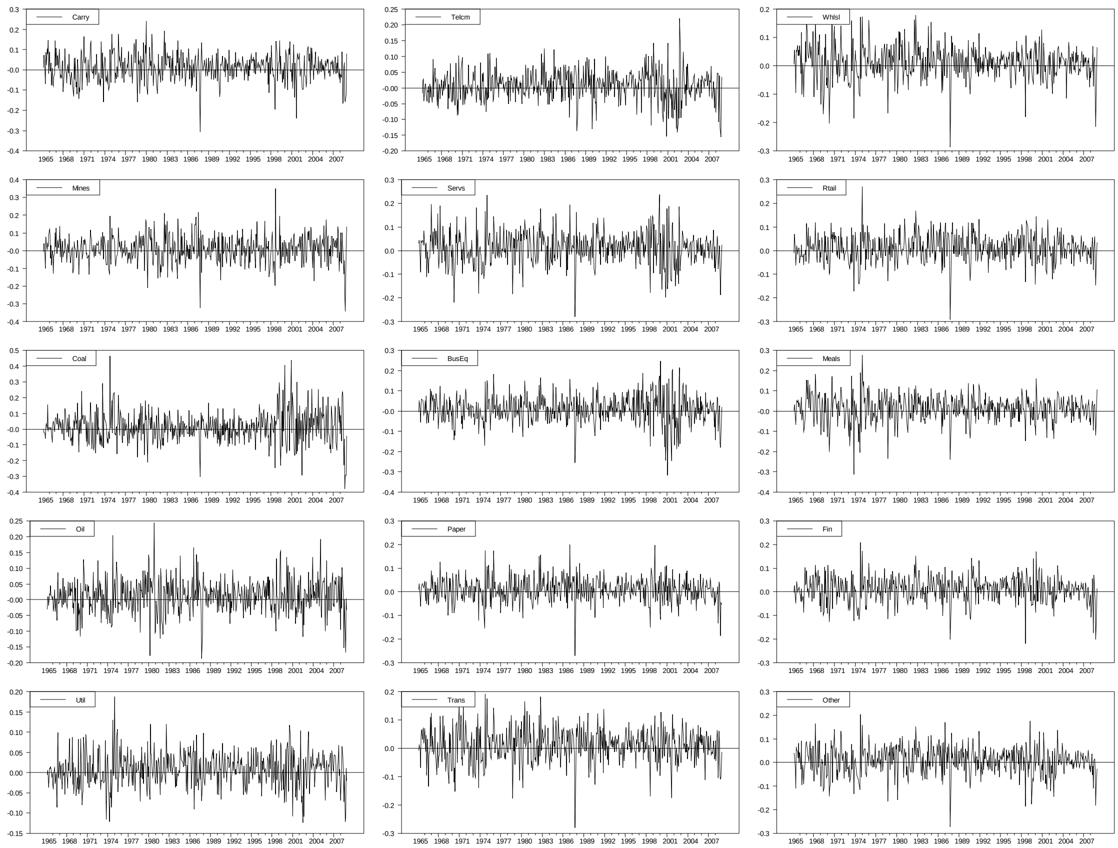

Figure 3.9: Stock Returns: 30 Industry Portfolios (Continued)

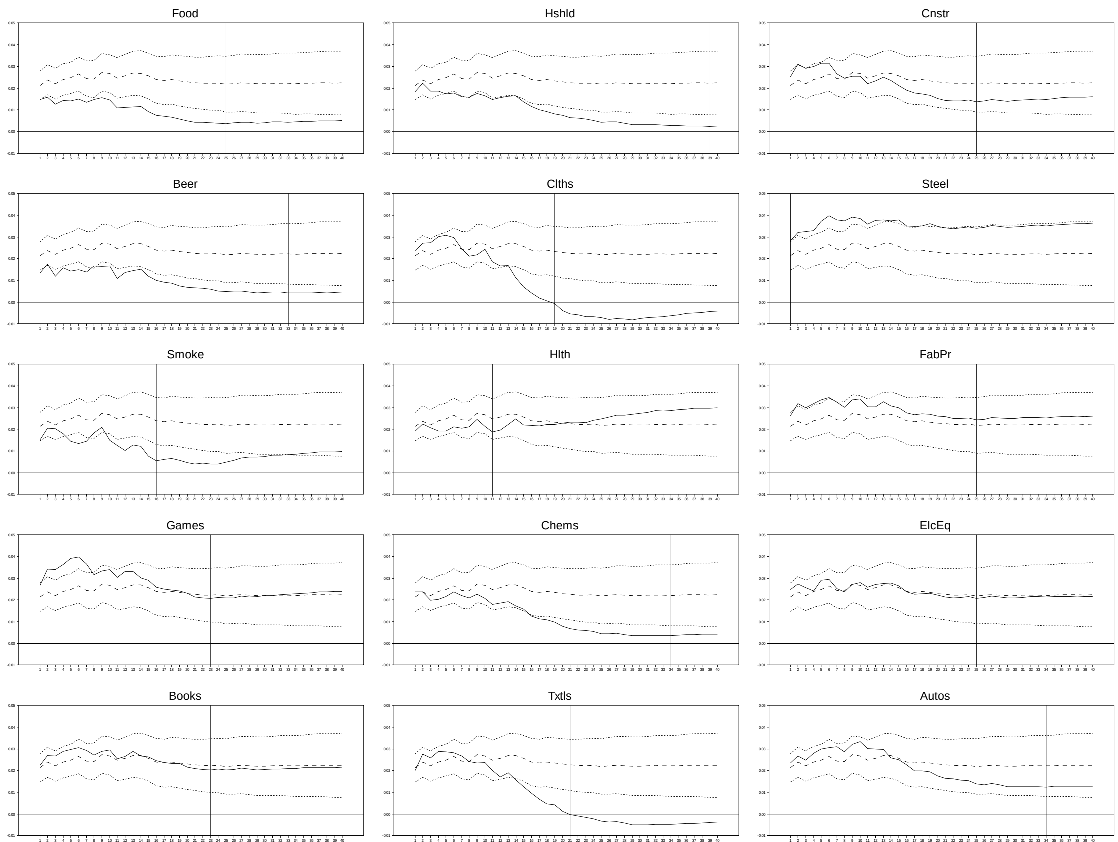

Figure 3.10: Response of Individual Industry Portfolios to Productivity Shock: 30 Industry Portfolios

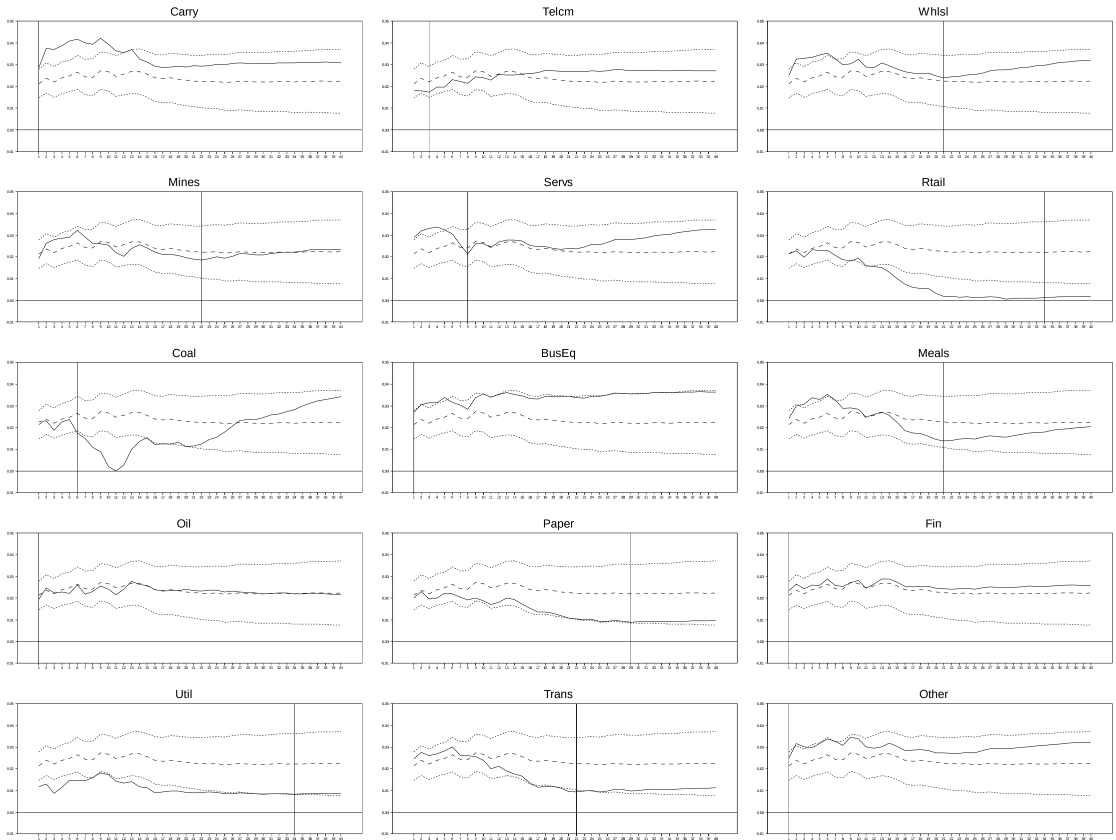

Figure 3.11: Response of Individual Industry Portfolios to Productivity Shock: 30 Industry Portfolios (Continued)

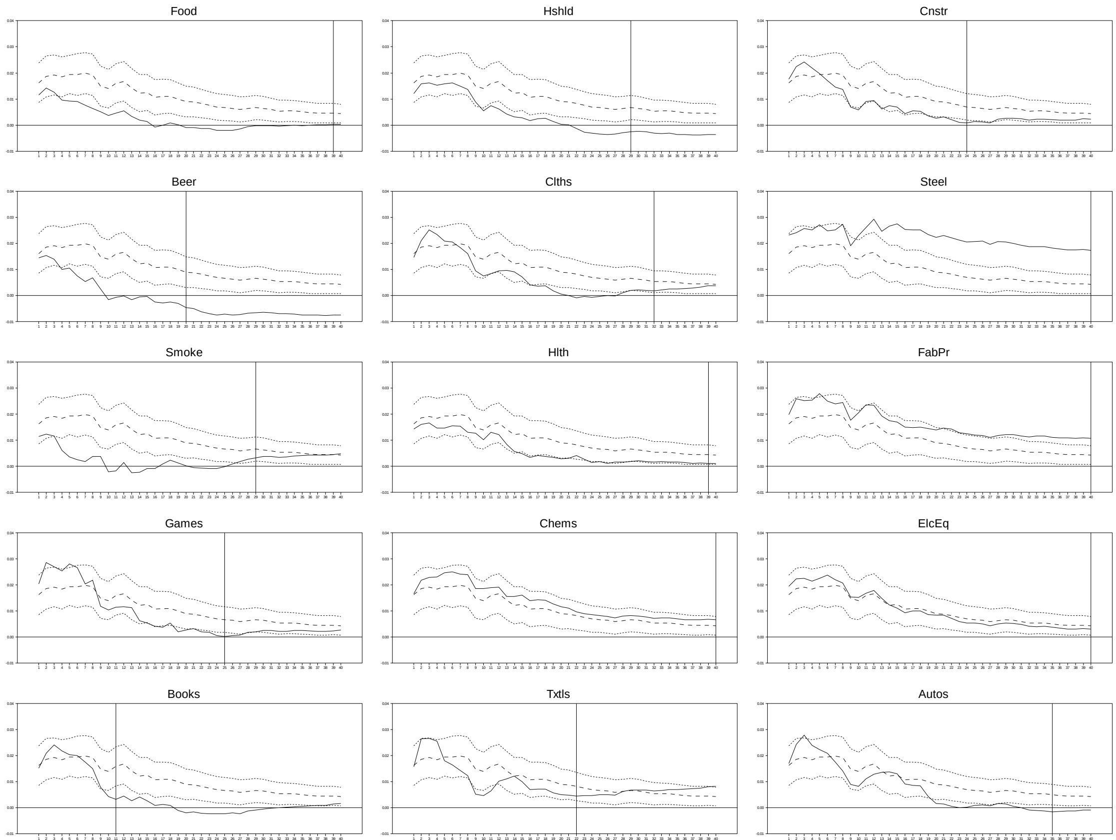

Figure 3.12: Response of Individual Industry Portfolios to Monetary Shock: 30 Industry Portfolios

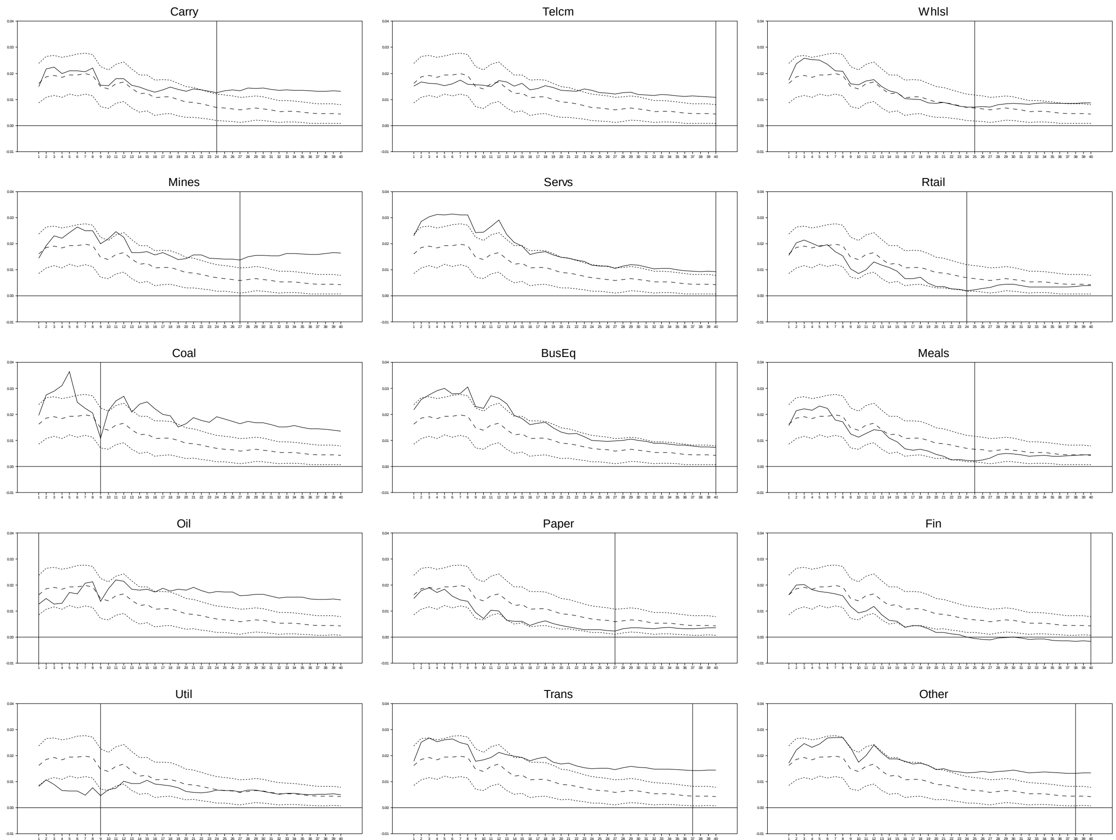

Figure 3.13: Response of Individual Industry Portfolios to Monetary Shock: 30 Industry Portfolios (Continued)

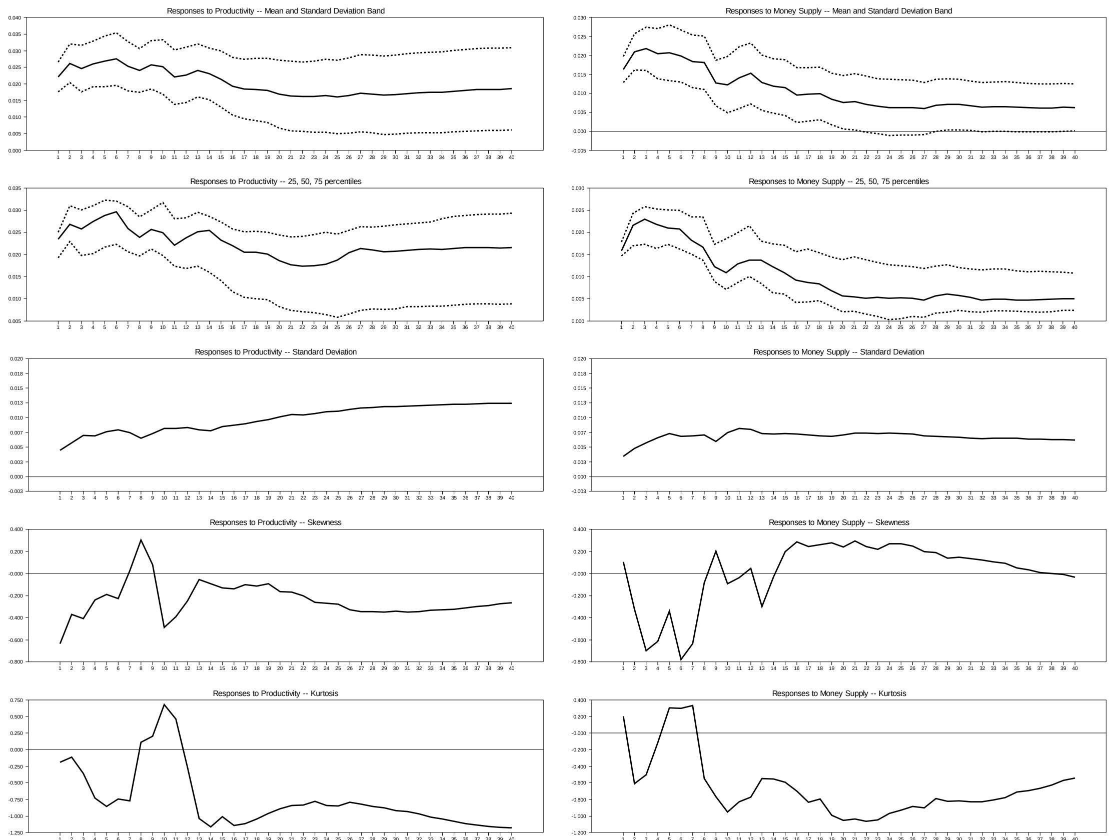

Figure 3.14: Cross-sectional Distribution of Industry-level Portfolio Returns: 30 Industry Portfolios

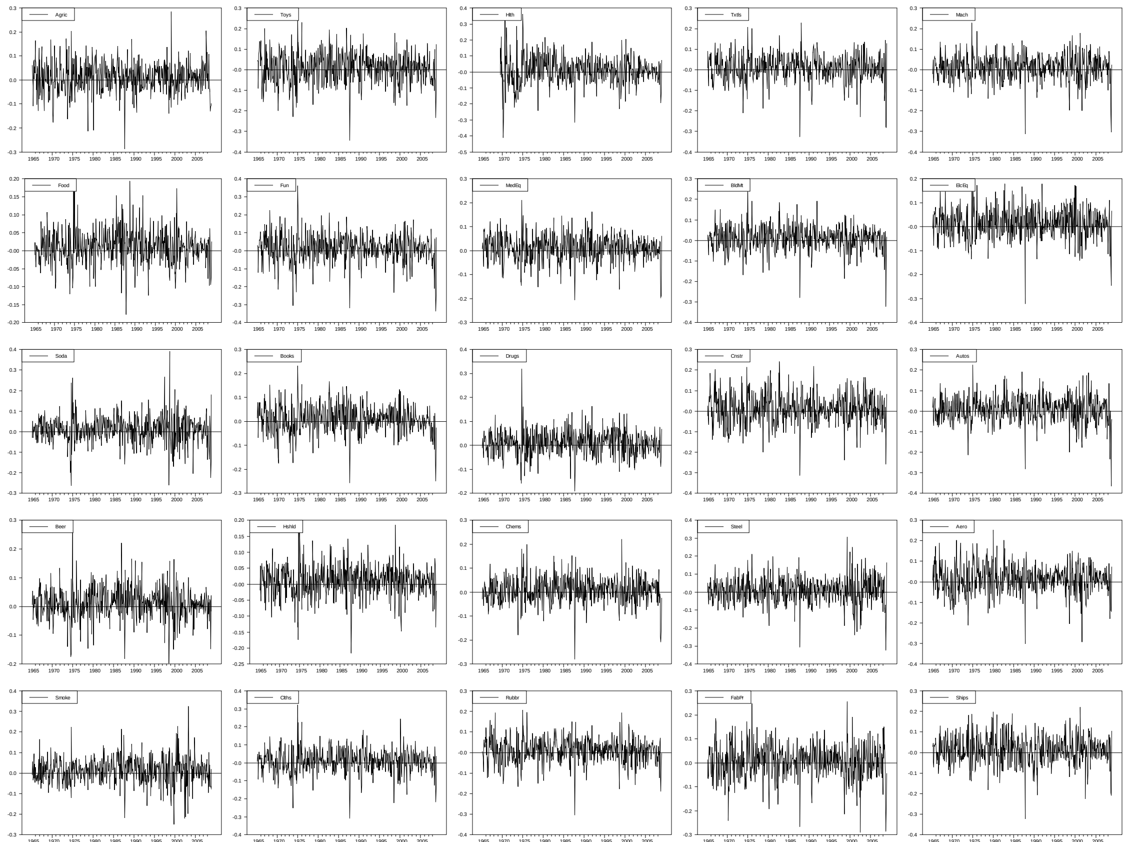

Figure 3.15: Stock Returns: 49 Industry Portfolios

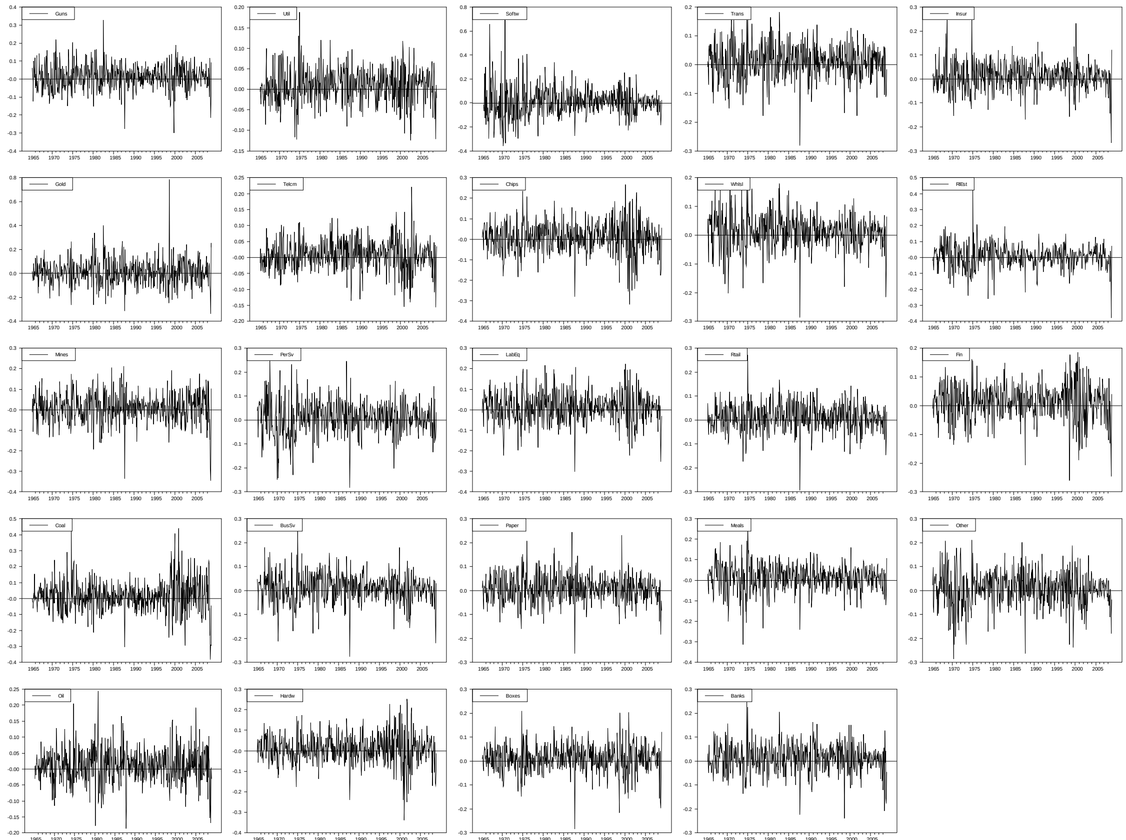

Figure 3.16: Stock Returns: 49 Industry Portfolios (Continued)

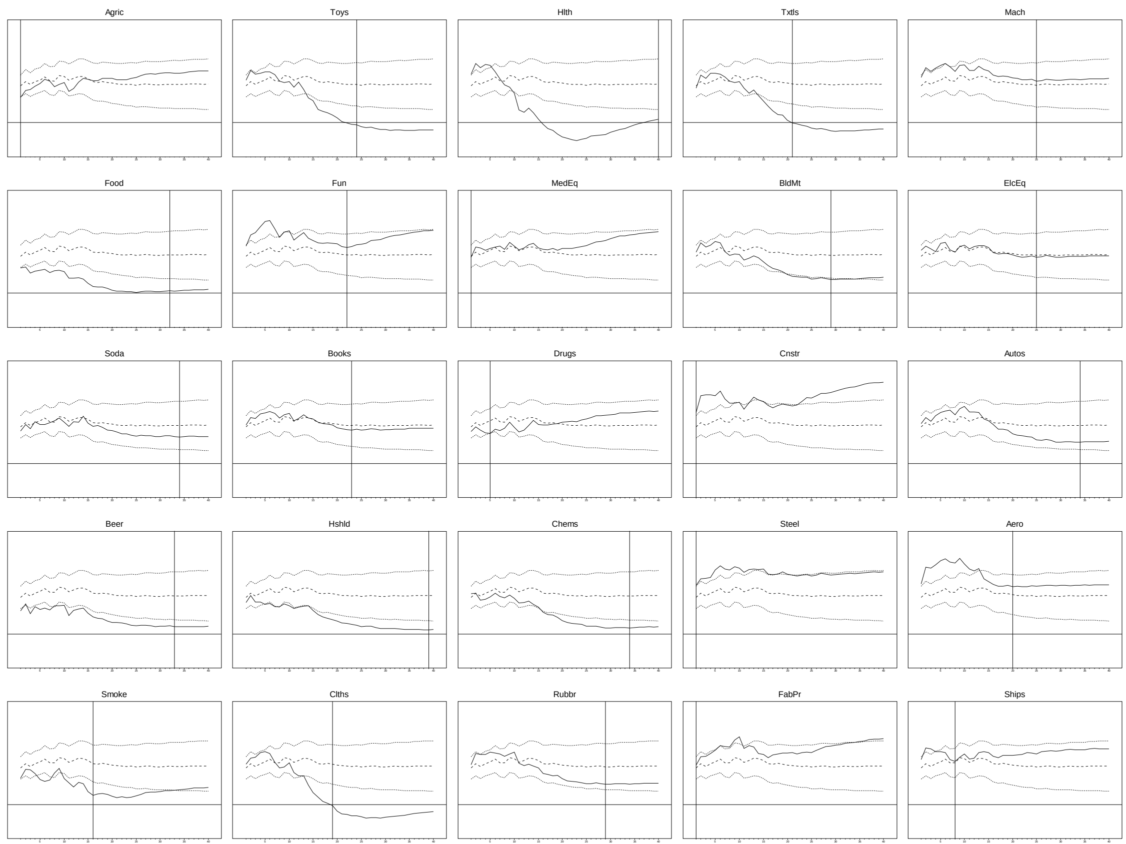

Figure 3.17: Response of Individual Industry Portfolios to Productivity Shock: 49 Industry Portfolios

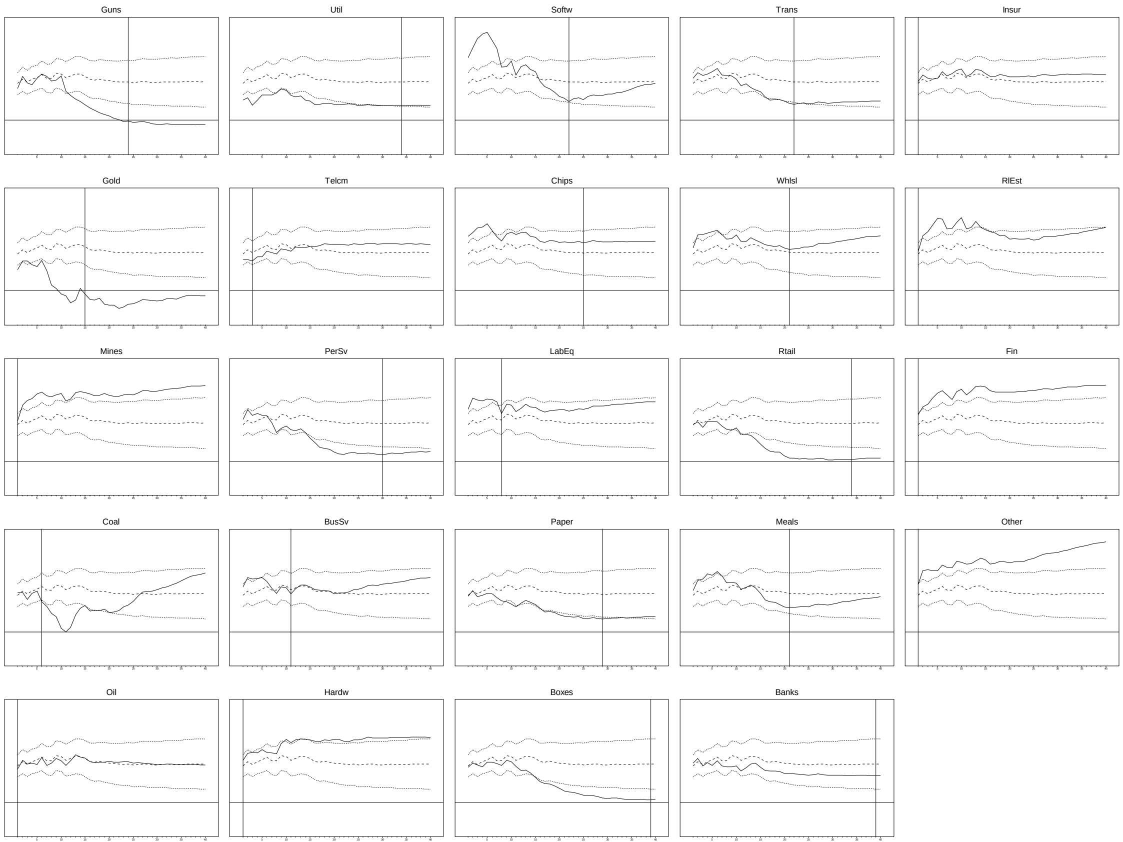

Figure 3.18: Response of Individual Industry Portfolios to Productivity Shock: 49 Industry Portfolios (Continued)

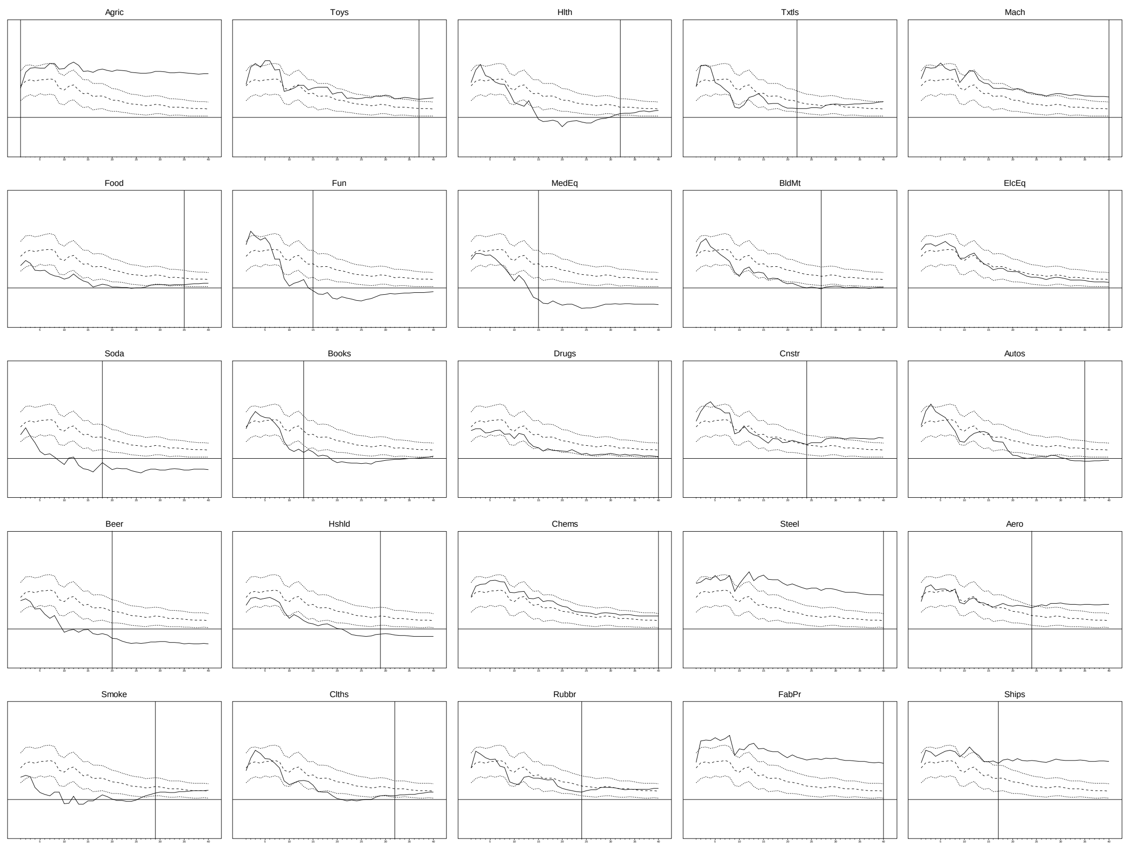

Figure 3.19: Response of Individual Industry Portfolios to Monetary Shock: 49 Industry Portfolios

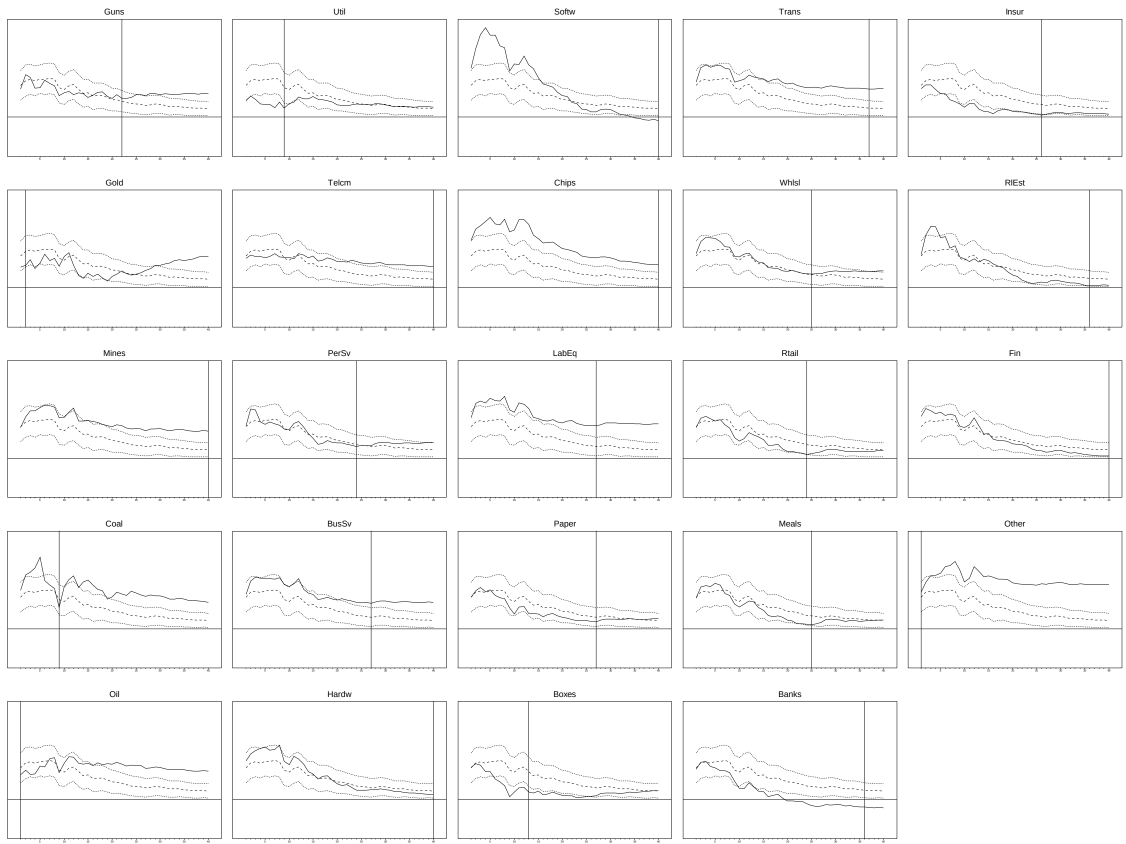

Figure 3.20: Response of Individual Industry Portfolios to Monetary Shock: 49 Industry Portfolios (Continued)

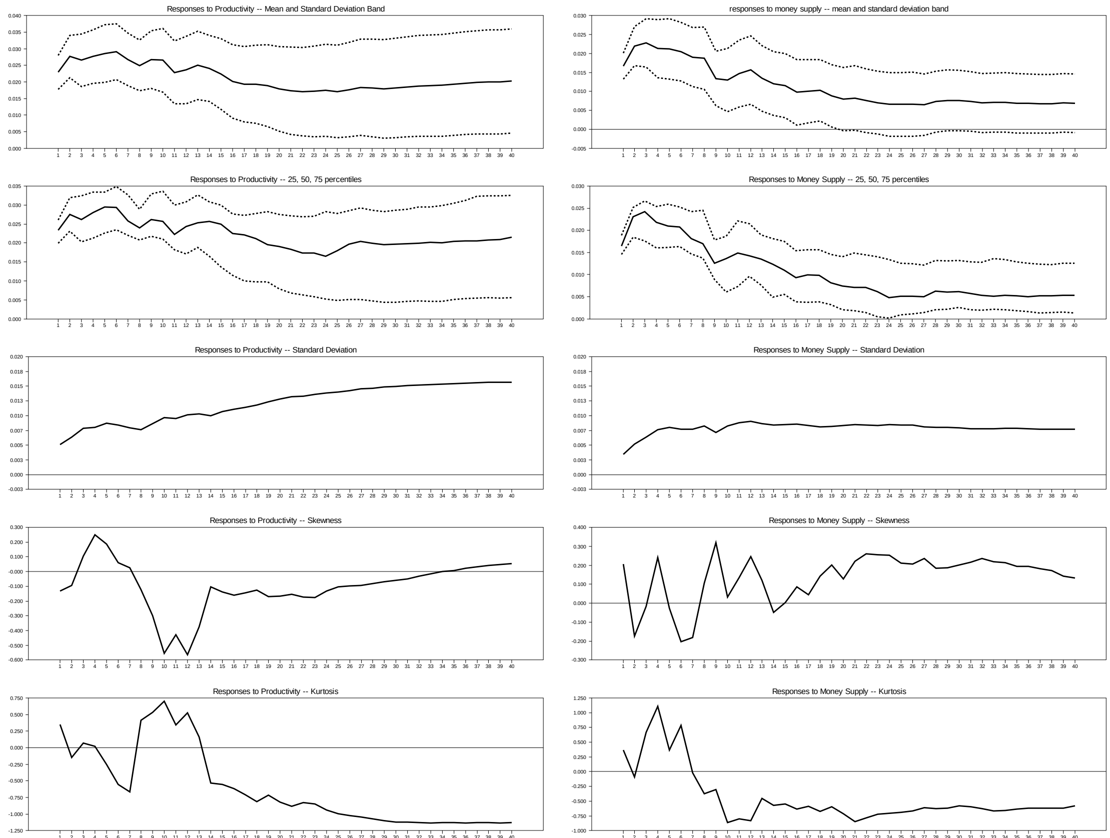

Figure 3.21: Cross-sectional Distribution of Industry-level Portfolio Returns: 49 Industry Portfolios

Table 3.1: IRF Regressions: 30 Industry Portfolios

Y	**β_0 (t-stat)**		**B_1 (t-stat)**		**β_2 (t-stat)**		**ζ (t-stat)**		**R^2**
				Productivity Shock					
IRF_{max}	0.016408	(0.203)	-0.00366	(-2.302)			1732.092	(0.604)	0.174
IRF_{max}	-0.004515	(-0.054)			0.00354	(1.588)	1173.981	(0.388)	0.096
IRF_{maz}	0.021661	(0.269)	-0.00324	(-2.008)	0.00261	(1.203)	1279.846	(0.446)	0.218
IRF_{max}	0.056915	(3.894)	-0.00322	(-2.031)	0.00273	(1.292)			0.212
IRF_{mean}	0.059669	(0.511)	-0.00236	(-1.062)			-774.208	(-0.185)	0.042
IRF_{mean}	0.048247	(0.405)			-0.00085	(-0.112)	-929.679	(-0.218)	0.002
IRF_{mean}	0.063261	(0.529)	-0.00245	(-1.070)	-0.00198	(-0.261)	-835.652	(-0.196)	0.044
IRF_{mean}	0.040060	(2.360)	-0.00245	(-1.094)	-0.00190	(-0.255)			0.043
IRF_{md}	0.104174	(0.743)	-0.00233	(-0.966)			-2554.212	(-0.515)	0.039
IRF_{md}	0.079088	(0.561)			-0.00174	(-0.190)	-2118.061	(-0.420)	0.007
IRF_{md}	0.107086	(0.741)	-0.00231	(-0.939)	-0.00128	(-0.139)	-2635.518	(-0.518)	0.040
IRF_{md}	0.032727	(2.144)	-0.00217	(-0.901)	-0.00073	(-0.081)			0.030
				Monetary Shock					
IRF_{max}	0.02184	(0.338)	-0.00285	(-2.080)			3777.725	(0.330)	0.145
IRF_{max}	-0.00632	(-0.10)			0.00377	(2.060)	3461.422	(0.301)	0.143
IRF_{maz}	0.02149	(0.344)	-0.00237	(0.001)	0.00311	(1.725)	2259.527	(0.204)	0.233
IRF_{max}	0.03393	(2.776)	-0.00238	(-1.795)	0.00314	(1.779)			0.231
IRF_{mean}	0.04978	(0.679)	-0.00258	(-1.719)			-5349.467	(-0.411)	0.099
IRF_{mean}	0.00605	(0.086)			0.00887	(1.816)	-1670.346	(-0.130)	0.110
IRF_{mean}	0.03786	(0.529)	-0.00223	(-1.516)	0.00781	(1.618)	-4547.291	(-0.359)	0.182
IRF_{mean}	0.01243	(1.148)	-0.00215	(-1.503)	0.00788	(1.661)			0.178
IRF_{md}	0.06660	(0.780)	-0.00211	(-1.327)			-9915.114	(-0.654)	0.066
IRF_{md}	0.01284	(0.164)			0.01095	(1.953)	-3602.266	(-0.252)	0.128
IRF_{md}	0.05244	(0.648)	-0.00228	(-1.516)	0.01140	(2.079)	-8388.535	(-0.586)	0.199
IRF_{md}	0.00537	(0.585)	-0.00209	(-1.440)	0.01157	(2.138)			0.188

Table 3.2: IRF Regressions: 49 Industry Portfolios

Y	β_0 (t-stat)		β_1 (t-stat)		β_2 (t-stat)		ζ (t-stat)		R^2
					Productivity Shock				
IRF_{max}	-0.00849	(-0.103)	-0.00205	(-1.434)			2188.601	(0.752)	0.056
IRF_{max}	-0.01788	(-0.241)			0.00517	(3.355)	1625.066	(0.608)	0.208
IRF_{maz}	-0.00209	(-0.028)	-0.00145	(-1.103)	0.00493	(3.172)	1508.914	(0.565)	0.229
IRF_{max}	0.04003	(3.457)	-0.00148	(-1.135)	0.00500	(3.252)			0.223
IRF_{mean}	-0.00777	(-0.067)	-0.00139	(-0.702)			1445.017	(0.351)	0.014
IRF_{mean}	-0.02584	(-0.225)			0.00429	(0.538)	1658.890	(0.403)	0.010
IRF_{mean}	-0.01247	(-0.106)	-0.00130	(-0.643)	0.00374	(0.464)	1502.800	(0.362)	0.019
IRF_{mean}	0.02969	(1.994)	-0.00134	(-0.671)	0.00366	(0.458)			0.016
IRF_{md}	0.02237	(0.165)	-0.00313	(-1.442)			588.775	(0.123)	0.045
IRF_{md}	-0.02838	(-0.210)			0.00517	(0.541)	1652.207	(0.341)	0.008
IRF_{md}	0.01485	(0.108)	-0.00318	(-1.455)	0.00572	(0.606)	749.846	(0.155)	0.053
IRF_{md}	0.03601	(2.673)	-0.00322	(-1.503)	0.00564	(0.604)			0.052
					Monetary Shock				
IRF_{max}	0.009760	(0.172)	-0.0023	(-2.061)			5196.299	(0.515)	0.092
IRF_{max}	0.037874	(0.738)			0.0049	(4.061)	-4775.886	(-0.505)	0.270
IRF_{maz}	0.055084	(1.081)	-0.0018	(-1.817)	0.0046	(3.882)	-5136.024	(-0.556)	0.320
IRF_{max}	0.027136	(3.178)	-0.0018	(-1.819)	0.0044	(3.916)			0.315
IRF_{mean}	0.106520	(1.700)	-0.0026	(-2.169)			-15664.109	(-1.402)	0.117
IRF_{mean}	0.064740	(1.045)			0.0088	(1.815)	-12254.797	(-1.087)	0.091
IRF_{mean}	0.095520	(1.544)	-0.0024	(-2.018)	0.0078	(1.645)	-14832.034	(-1.350)	0.167
IRF_{mean}	0.012813	(1.445)	-0.0022	(-1.857)	0.0081	(1.694)			0.133
IRF_{md}	0.147220	(2.091)	-0.0031	(-2.427)			-23583.134	(-1.883)	0.148
IRF_{md}	0.077500	(1.099)			0.0093	(1.658)	-15085.654	(-1.180)	0.093
IRF_{md}	0.127490	(1.832)	-0.0031	(-2.529)	0.0096	(1.812)	-20951.030	(-1.702)	0.206
IRF_{md}	0.009784	(1.263)	-0.0027	(-2.204)	0.0107	(1.987)			0.155

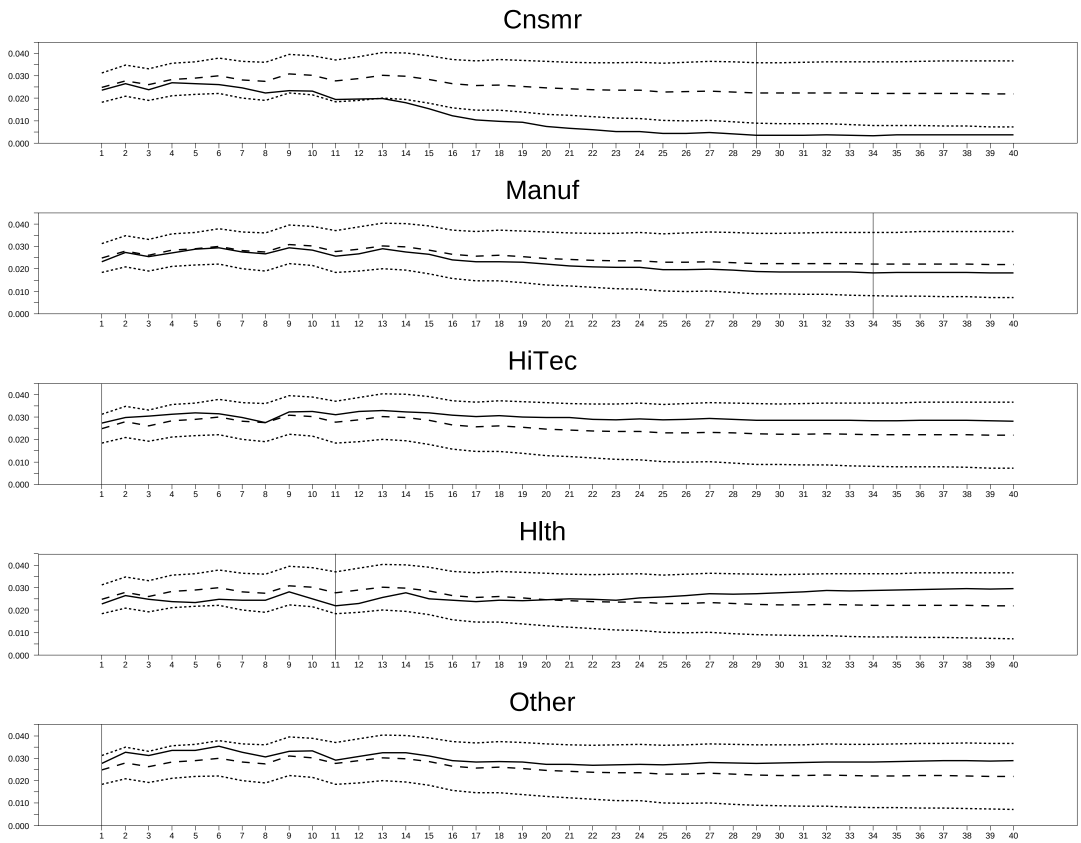

Figure 3.22: Response of Individual Industry Portfolios (in Real Terms) to Productivity Shock: Five Industry Portfolios

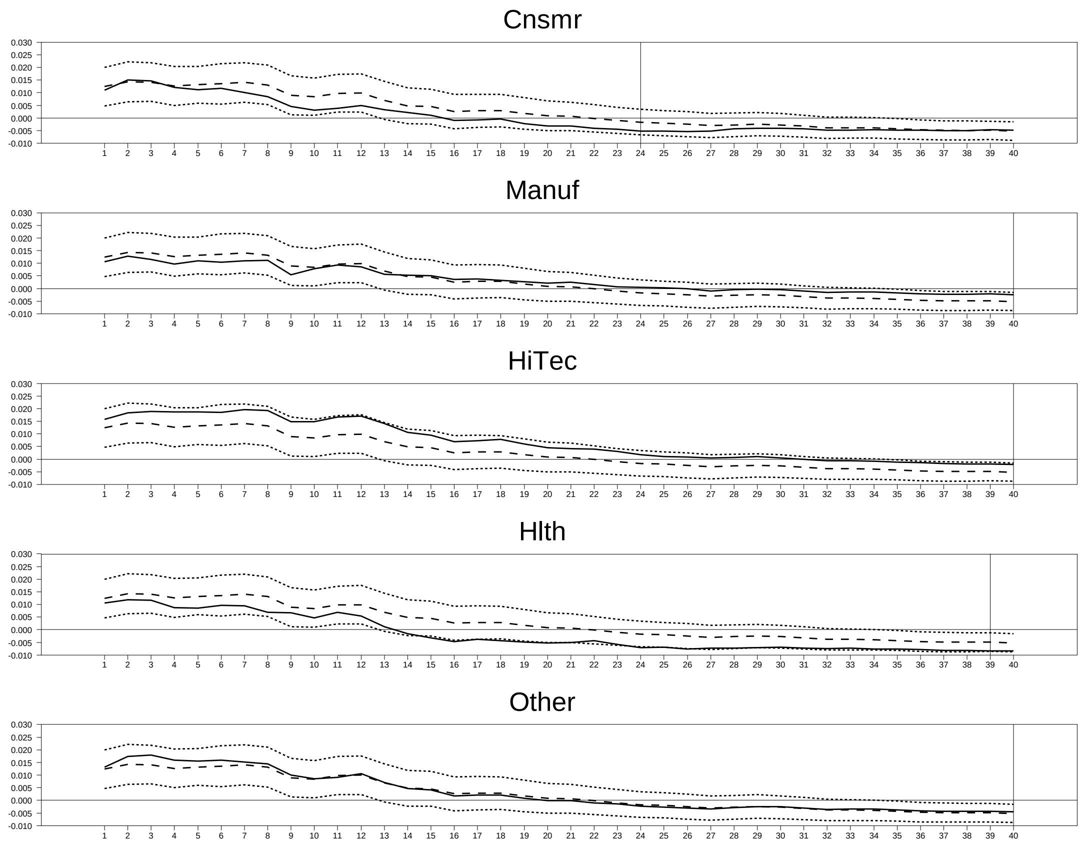

Figure 3.23: Response of Individual Industry Portfolios (in Real Terms) to Monetary Shock: Five Industry Portfolios

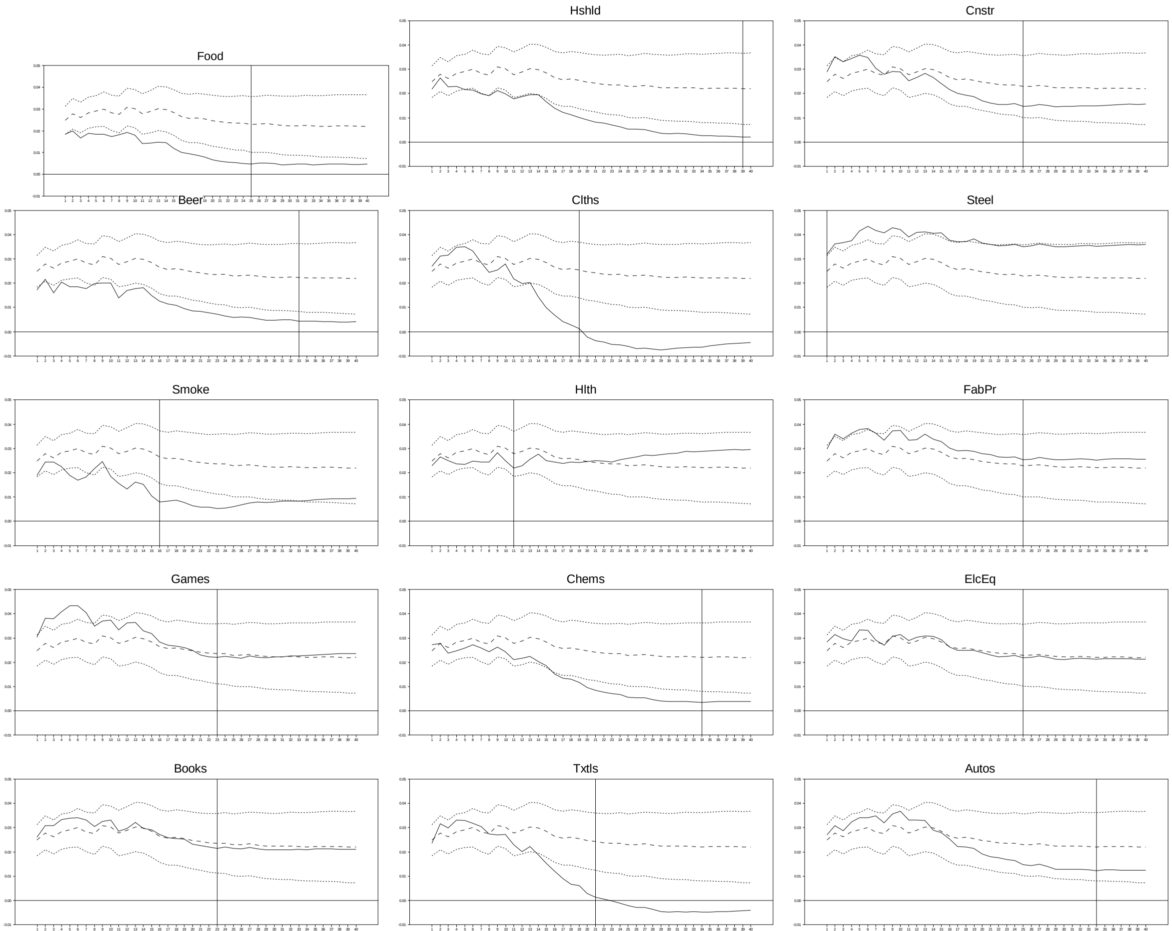

Figure 3.24: Response of Individual Industry Portfolios (in Real Terms) to Productivity Shock: 30 Industry Portfolios

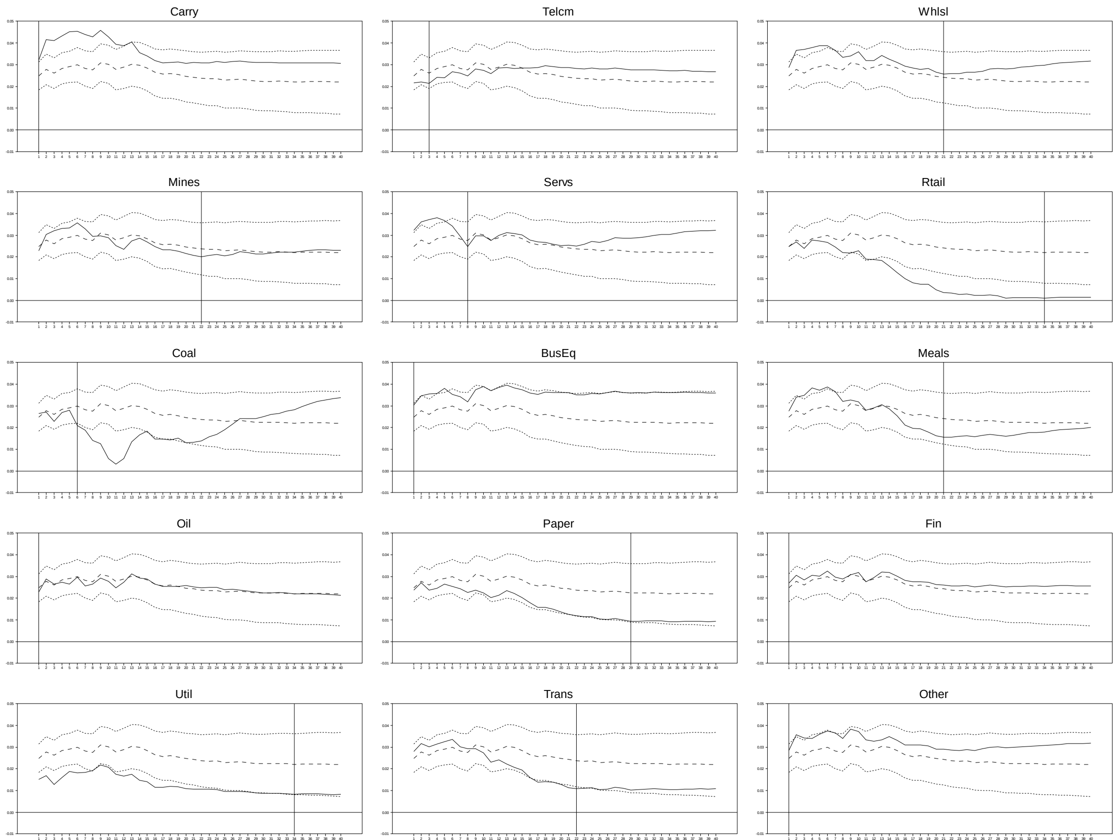

Figure 3.25: Response of Individual Industry Portfolios (in Real Terms) to Productivity Shock: 30 Industry Portfolios (Continued)

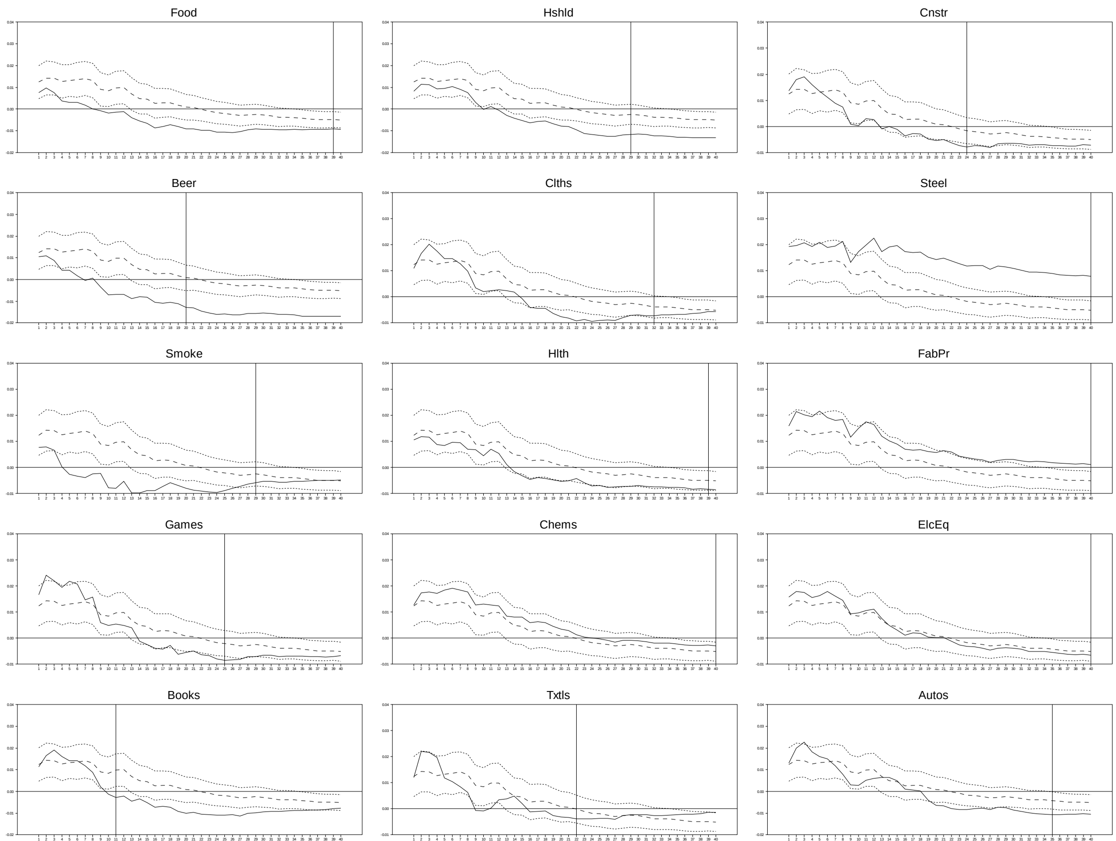

Figure 3.26: Response of Individual Industry Portfolios (in Real Terms) to Monetary Shock: 30 Industry Portfolios

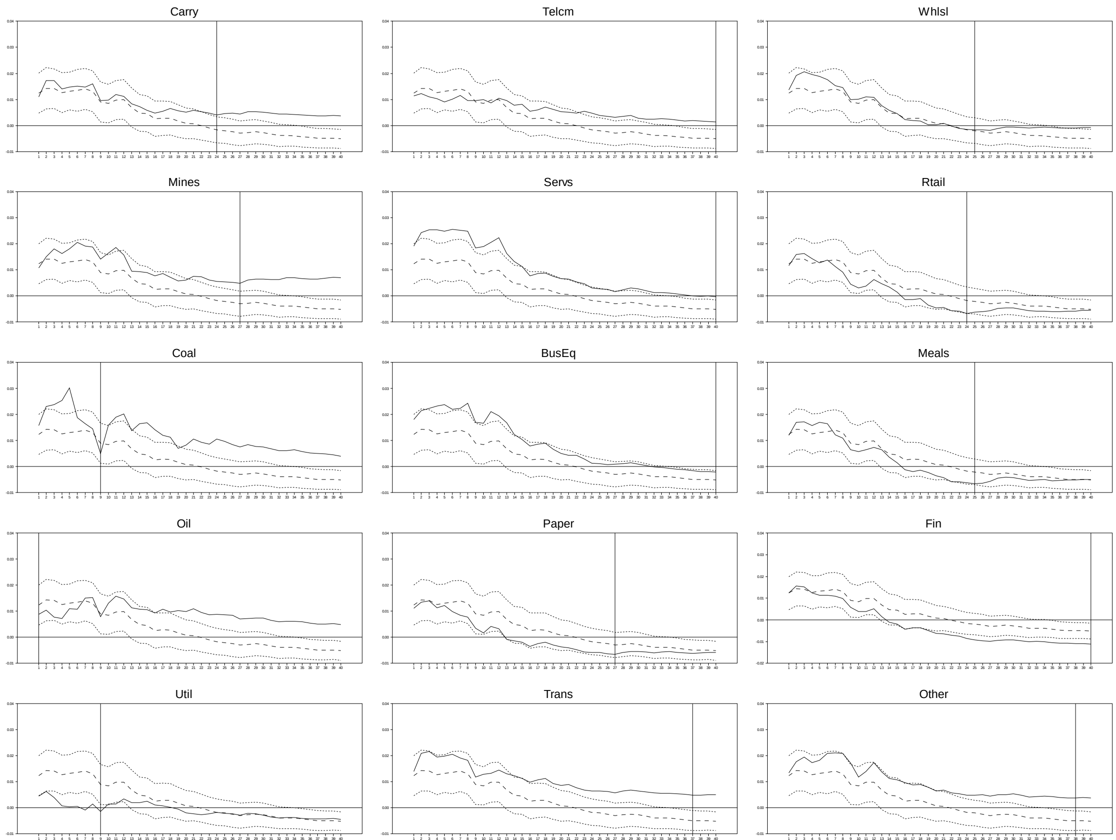

Figure 3.27: Response of Individual Industry Portfolios (in Real Terms) to Monetary Shock: 30 Industry Portfolios (Continued)

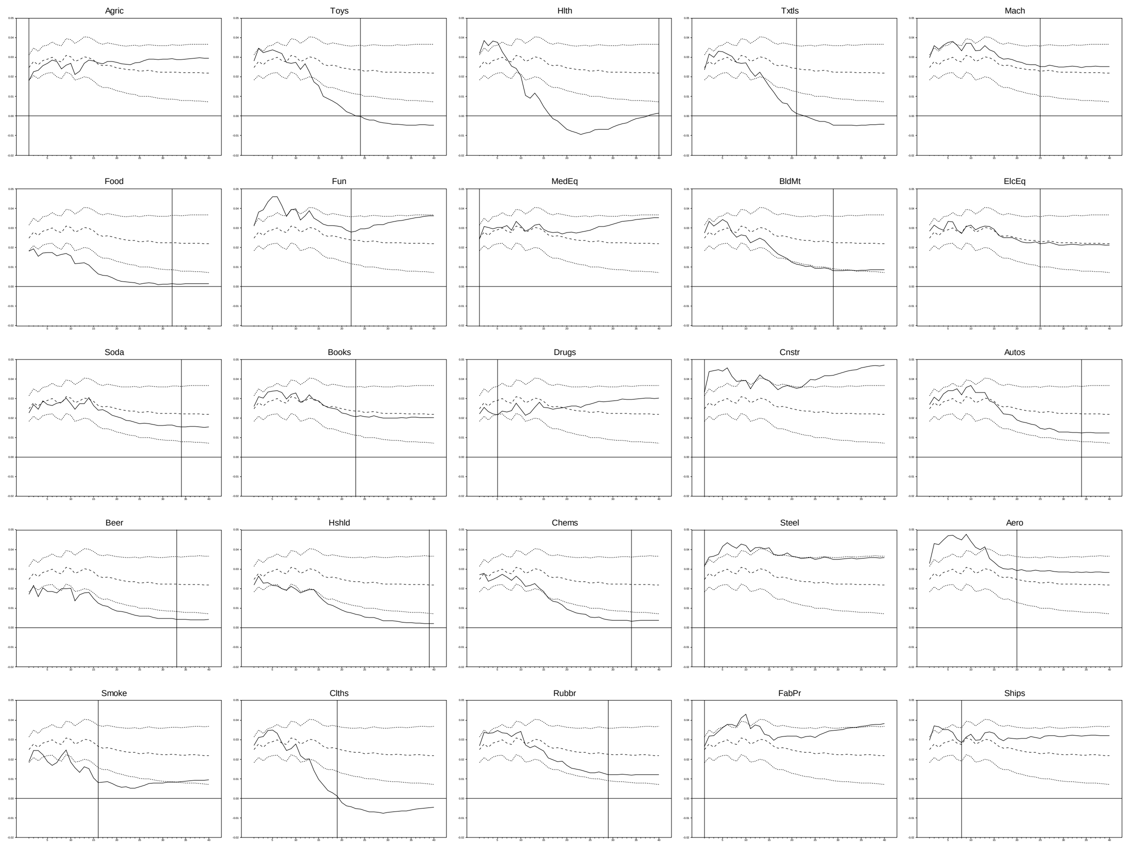

Figure 3.28: Response of Individual Industry Portfolios (in Real Terms) to Productivity Shock: 49 Industry Portfolios

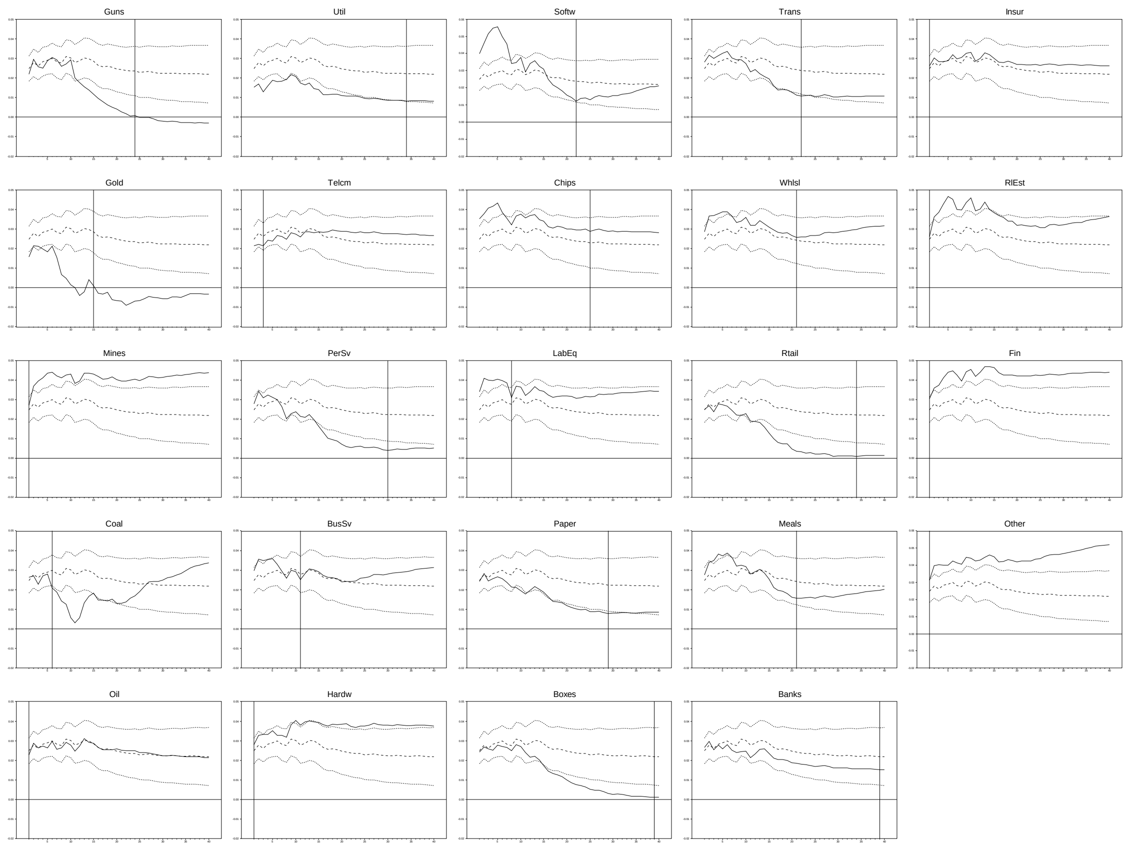

Figure 3.29: Response of Individual Industry Portfolios (in Real Terms) to Productivity Shock: 49 Industry Portfolios (Continued)

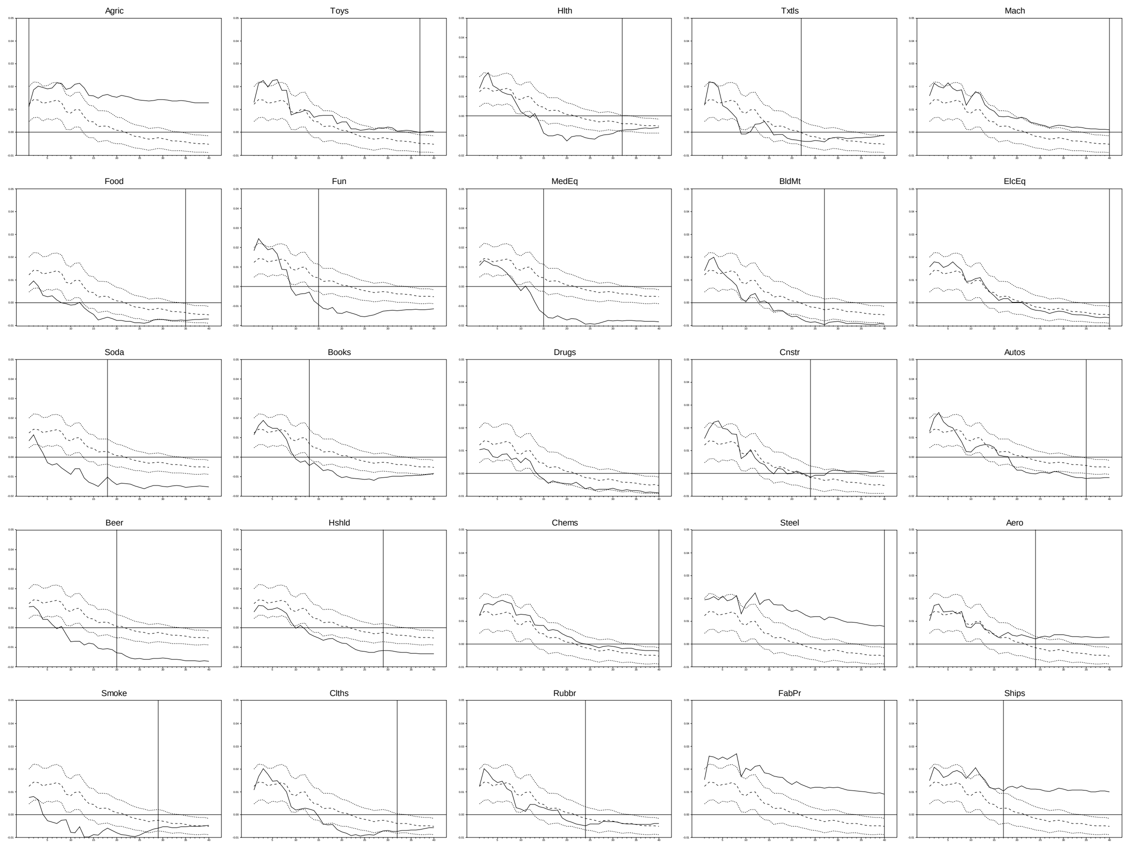

Figure 3.30: Response of Individual Industry Portfolios (in Real Terms) to Monetary Shock: 49 Industry Portfolios

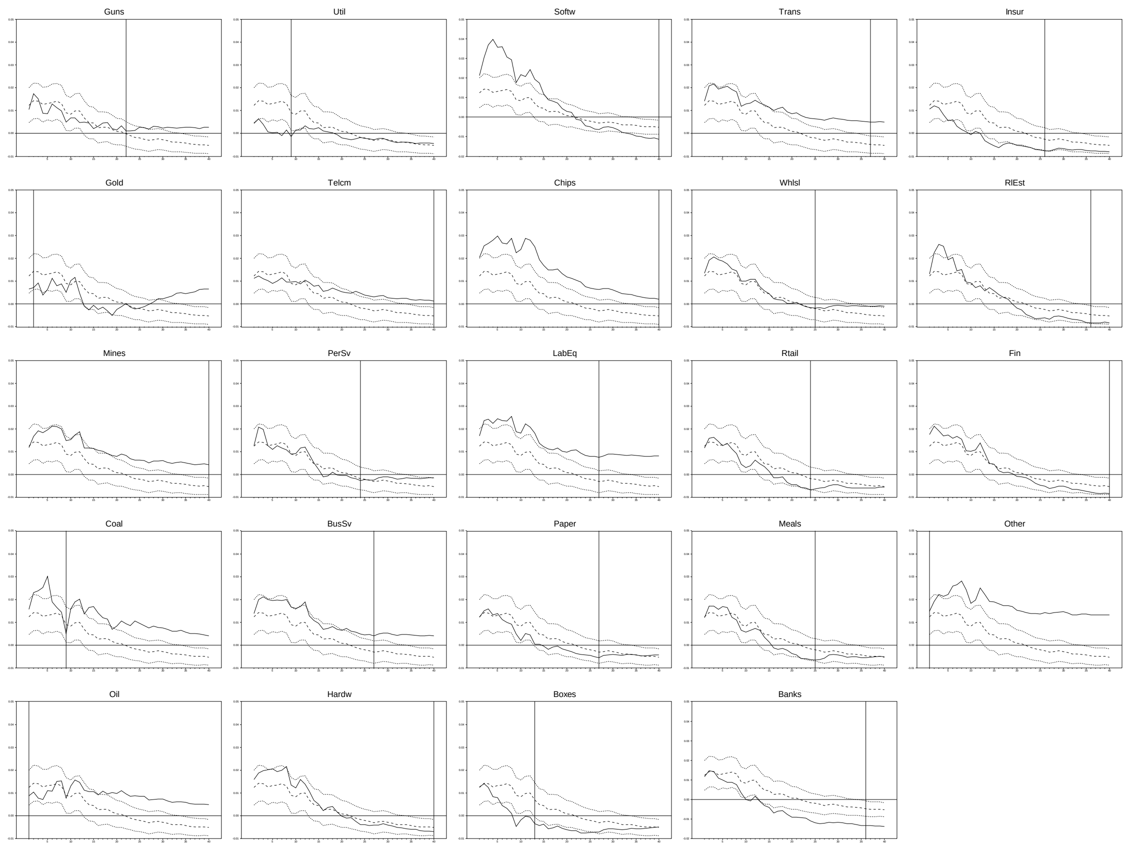

Figure 3.31: Response of Individual Industry Portfolios (in Real Terms) to Monetary Shock: 49 Industry Portfolios (Continued)

Chapter 4

Conclusion

This dissertation revisits two important issues in financial and monetary economics. Since Taylor's (1993) well-known work, many researchers have tried to find whether monetary authorities follow a specific monetary policy rule. In the first essay, I investigate a monetary policy rule for the Federal Reserve. As discussed in detail in the dissertation, there are several reasons to believe that monetary policy rules ought to be nonlinear. Therefore, I devote first chapter to this issue by estimating several monetary policy rules with a limited dependent method called generalized ordered probit which allows for nonlinearities in the monetary policy. I find that a more general monetary reaction function outperforms backward-looking, forward-looking and contemporaneous Taylor rule specifications. The results show that the Fed takes into account not only inflation and output gap measures but also several other variables during its decision process. However, its attention on each variable is choice-dependent. For example, the Fed follows different variables when it has to make a decision between small decrease and big decrease compared to small increase and big increase. In addition, the threshold estimates indicate a different nonlinearity. I find that the Federal Reserve acts asymmetrically in its monetary policies that it waits for relatively significant changes in the macroeconomic factors before it decides for a change in its target rates. However, once these thresholds are passed, relatively less significant changes in the economy are needed for the Federal Reserve to take action. The results also support monetary policy inertia in the Federal Reserve's policy function. In the chapter, I have also benefited from new findings in the econometrics literature on time series properties of ordered probit models and argue that using certain information criteria, i.e. AIC calculated by Likelihood, is the proper way to choose the right empirical model in case the latent dependent variable is non-stationary.

In the second essay, I revisit the relationship between inflation and stock returns within a supply and demand framework. Although the topic has been analyzed extensively by many scholars, there have been many flaws in their analysis. I elaborate the relation using a VAR model with block exogeneity, and diagonality, and infinite-horizon restrictions which were proposed by Lastrapes (2005). I address several problems of previous literature. The main contribution of my work is the analysis of industry portfolio returns in case of a money supply or productivity shock, though. I argue that exogenous shocks are expected to affect each individual industry differently and thus, stock returns for each industry would be affected differently in magnitudes and dynamics. For example, effects monetary shocks on banking industry are expected to be different from agriculture industry. Similarly, productivity shocks are expected to affect industries heterogeneously.

The results show that the relation between inflation and stock return depends on both the type of a macro shock and industry. The relation is negative given a productivity shock whereas positive given a money supply shock. However, the magnitude and sign of the relation differ across industries. The findings also suggest that industry specific features do affect dispersion of stock returns. For instance, in case of a monetary shock, size effect is negative and statistically significant indicating that industries with bigger-sized firms are affected more than industries having smaller firms.

Appendix

INDUSTRY CLASSIFICATIONS

A. FIVE INDUSTRY CLASSIFICATION

1 Cnsmr: Consumer Durables, NonDurables, Wholesale, Retail, and Some Services (Laundries, Repair Shops)

0100-0999, 2000-2399, 2700-2749, 2770-2799, 3100-3199, 3940-3989, 2500-2519, 2590-2599 3630-3659, 3710-3711, 3714-3714, 3716-3716, 3750-3751, 3792-3792, 3900-3939, 3990-3999 5000-5999, 7200-7299, 7600-7699

2 Manuf: Manufacturing, Energy, and Utilities

2520-2589, 2600-2699, 2750-2769, 2800-2829, 2840-2899, 3000-3099, 3200-3569, 3580-3621 3623-3629, 3700-3709, 3712-3713, 3715-3715, 3717-3749, 3752-3791, 3793-3799, 3860-3899 1200-1399, 2900-2999, 4900-4949

3 HiTec: Business Equipment, Telephone and Television Transmission

3570-3579, 3660-3692, 3694-3699, 3810-3839, 4800-4899, 3622-3622, 7370-7379, 7391-7391, 8730-8734

4 Hlth: Healthcare, Medical Equipment, and Drugs

2830-2839, 3693-3693, 3840-3859, 8000-8099

5 Other: Other – Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment, Finance

B. THIRTY INDUSTRY CLASSIFICATION

1 Food: Food Products

0100-0299, 0700-0799, 0910-0919, 2000-2046, 2048-2048, 2050-2068, 2070-2079, 2086-2087 2090-2092, 2095-2099

2 Beer: Beer & Liquor

2080-2080, 2082-2085

3 Smoke: Tobacco Products

2100-2199

4 Games: Recreation

0920-0999, 3650-3652, 3732-3732, 3930-3931, 3940-3949, 7800-7833, 7840-7841, 7900-7900 7910-7911, 7920-7933, 7940-7949, 7980-7980, 7990-7999

5 Books: Printing and Publishing

2700-2759, 2770-2771, 2780-2799, 3993-3993

6 Hshld: Consumer Goods

2047-2047, 2391-2392, 2510-2519, 2590-2599, 2840-2844, 3160-3161, 3170-3172, 3190-3199 3229-3229, 3260-3260, 3262-3263, 3269-3269, 3230-3231, 3630-3639, 3750-3751, 3800-3800 3860-3861, 3870-3873, 3910-3911, 3914-3915, 3960-3962, 3991-3991, 3995-3995

7 Clths: Apparel

2300-2390, 3020-3021, 3100-3111, 3130-3131, 3140-3151, 3963-3965

8 Hlth: Healthcare, Medical Equipment, Pharmaceutical Products

2830-2831, 2833-2836, 3693-3693, 3840-3851, 8000-8099

9 Chems: Chemicals

2800-2829, 2850-2879, 2890-2899

10 Txtls: Textiles

2200-2284, 2290-2295, 2297-2299, 2393-2395, 2397-2399

11 Cnstr: Construction and Construction Materials

0800-0899, 1500-1511, 1520-1549, 1600-1799, 2400-2439, 2450-2459, 2490-2499, 2660-2661
2950-2952, 3200-3200, 3210-3211, 3240-3241, 3250-3259, 3261-3261, 3264-3264, 3270-3275
3280-3281, 3290-3293, 3295-3299, 3420-3433, 3440-3442, 3446-3446, 3448-3452, 3490-3499
3996-3996

12 Steel: Steel Works Etc

3300-3300, 3310-3317, 3320-3325, 3330-3341, 3350-3357, 3360-3379, 3390-3399

13 FabPr: Fabricated Products and Machinery

3400-3400, 3443-3444, 3460-3479, 3510-3536, 3538-3538, 3540-3569, 3580-3582, 3585-3586
3589-3599

14 ElcEq: Electrical Equipment

3600-3600, 3610-3613, 3620-3621, 3623-3629, 3640-3646, 3648-3649, 3660-3660, 3690-3692

3699-3699

15 Autos: Automobiles and Trucks

2296-2296, 2396-2396, 3010-3011, 3537-3537, 3647-3647, 3694-3694, 3700-3700, 3710-3711 3713-3716, 3790-3792, 3799-3799

16 Carry: Aircraft, ships, and railroad equipment

3720-3725, 3728-3731, 3740-3743

17 Mines: Precious Metals, Non-Metallic, and Industrial Metal Mining

1000-1119, 1400-1499

18 Coal: Coal

1200-1299

19 Oil: Petroleum and Natural Gas

1300-1300, 1310-1339, 1370-1382, 1389-1389, 2900-2912, 2990-2999

20 Util: Utilities

4900-4900, 4910-4911, 4920-4925, 4930-4932, 4939-4942

21 Telcm: Communication

4800-4800, 4810-4813, 4820-4822, 4830-4841, 4880-4892, 4899-4899

22 Servs: Personal and Business Services

7020-7021, 7030-7033, 7200-7200, 7210-7212, 7214-7221, 7230-7231, 7240-7241, 7250-7251 7260-7300, 7310-7342, 7349-7353, 7359-7372, 7374-7385, 7389-7397, 7399-7399, 7500-7500

7510-7549, 7600-7600, 7620-7620, 7622-7623, 7629-7631, 7640-7641, 7690-7699, 8100-8499 8600-8700, 8710-8713, 8720-8721, 8730-8734, 8740-8748, 8800-8911, 8920-8999

23 BusEq: Business Equipment

3570-3579, 3622-3622, 3661-3666, 3669-3689, 3695-3695, 3810-3812 3820-3839, 7373-7373

24 Paper: Business Supplies and Shipping Containers

2440-2449, 2520-2549, 2600-2659, 2670-2699, 2760-2761, 3220-3221, 3410-3412, 3950-3955

25 Trans: Transportation

4000-4013, 4040-4049, 4100-4100, 4110-4121, 4130-4131, 4140-4142, 4150-4151, 4170-4173 4190-4200, 4210-4231, 4240-4249, 4400-4700, 4710-4712, 4720-4749, 4780-4780, 4782-4785, 4789-4789

26 Whlsl: Wholesale

5000-5000, 5010-5015, 5020-5023, 5030-5060, 5063-5065, 5070-5078, 5080-5094, 5099-5099 5110-5113, 5120-5122, 5130-5172, 5180-5182, 5190-5199

27 Rtail: Retail

5200-5200, 5210-5231, 5250-5251, 5260-5261, 5270-5271, 5300-5300, 5310-5311, 5320-5320 5330-5331, 5334-5334, 5340-5349, 5390-5400, 5410-5412, 5420-5500, 5510-5579, 5590-5700 5710-5722, 5730-5736, 5750-5799, 5900-5900, 5910-5912, 5920-5932, 5940-5990, 5992-5995, 5999-5999

28 Meals: Restaurants, Hotels, Motels

5800-5829, 5890-5899, 7000-7000, 7010-7019, 7040-7049, 7213-7213

29 Fin: Banking, Insurance, Real Estate, Trading

6000-6000, 6010-6036, 6040-6062, 6080-6082, 6090-6100, 6110-6113, 6120-6179
6190-6300, 6310-6331, 6350-6351, 6360-6361, 6370-6379, 6390-6411, 6500-6500
6510-6510, 6512-6515, 6517-6532, 6540-6541, 6550-6553, 6590-6599, 6610-6611
6700-6700, 6710-6726, 6730-6733, 6740-6779, 6790-6795, 6798-6799

30 Other: Everything Else

4950-4961, 4970-4971, 4990-4991

C. FORTY-NINE INDUSTRY CLASSIFICATION

1 Agric: Agriculture

0100-0299, 0700-0799, 0910-0919, 2048-2048

2 Food: Food Products

2000-2046, 2050-2063, 2070-2079, 2090-2092, 2095-2095, 2098-2099

3 Soda: Candy & Soda

2064-2068, 2086-2087, 2096-2097

4 Beer: Beer & Liquor

2080-2080, 2082-2085

5 Smoke: Tobacco Products

2100-2199

6 Toys: Recreation

0920-0999, 3650-3652, 3732-3732, 3930-3931, 3940-3949 Toys

7 Fun: Entertainment

7800-7833, 7840-7841, 7900-7900, 7910-7911, 7920-7933, 7940-7949, 7980-7980, 7990-7999

8 Books: Printing and Publishing

2700-2749, 2770-2771, 2780-2799

9 Hshld: Consumer Goods

2047-2047, 2391-2392, 2510-2519, 2590-2599, 2840-2844, 3160-3161, 3170-3172, 3190-3199
3229-3229, 3260-3260, 3262-3263, 3269-3269, 3230-3231, 3630-3639, 3750-3751, 3800-3800
3860-3861, 3870-3873, 3910-3911, 3914-3915, 3960-3962, 3991-3991, 3995-3995

10 Clths: Apparel

2300-2390, 3020-3021, 3100-3111, 3130-3131, 3140-3149, 3150-3151, 3963-3965

11 Hlth: Healthcare

8000-8099

12 MedEq: Medical Equipment

3693-3693, 3840-3851

13 Drugs: Pharmaceutical Products

2830-2831, 2833-836

14 Chems: Chemicals

2800-2829, 2850-2879, 2890-2899

15 Rubbr: Rubber and Plastic Products

3031-3031, 3041-3041, 3050-3053, 3060-3099

16 Txtls: Textiles

2200-22284, 2290-2295, 2297-2299, 2393-2395, 2397-2399

17 BldMt: Construction Materials

0800-0899, 2400-2439, 2450-2459, 2490-2499, 2660-2661, 2950-2952, 3200-3200, 3210-3211
3240-3241, 3250-3259, 3261-3261, 3264-3264, 3270-3275, 3280-3281, 3290-3293, 3295-3299
3420-3433, 3440-3442, 3446-3446, 3448-3452, 3490-3499, 3996-3996

18 Cnstr: Construction

1500-1511, 1520-1549, 1600-1799

19 Steel: Steel Works Etc

3300-3300, 3310-3317, 3320-3325, 3330-3341, 3350-3357, 3360-3379, 3390-3399

20 FabPr: Fabricated Products

3400-3400, 3443-3444, 3460-3479

21 Mach: Machinery

3510-3536, 3538-3538, 3540-3569, 3580-3582, 3585-3586, 3589-3599

22 ElcEq: Electrical Equipment

3600-3600, 3610-3613, 3620-3621, 3623-3629, 3640-3646, 3648-3649, 3660-3660
3690-3692, 3699-3699

23 Autos: Automobiles and Trucks

2296-2296, 2396-2396, 3010-3011, 3537-3537, 3647-3647, 3694-3694, 3700-3700
3710-3711, 3713-3716, 3790-3792, 3799-3799

24 Aero: Aircraft

3720-3725, 3728-3729

25 Ships: Shipbuilding, Railroad Equipment

3730-3731, 3740-3743

26 Guns: Defense

3760-3769, 3795-3795, 3480-3489

27 Gold: Precious Metals

1040-1049

28 Mines: Non-Metallic and Industrial Metal Mining

1000-1039, 1050-1119, 1400-1499

29 Coal: Coal

1200-1299

30 Oil: Petroleum and Natural Gas

1300-1300, 1310-1339, 1370-1382, 1389-1389, 2900-2912, 2990-2999

31 Util: Utilities

4900-4900, 4910-4911, 4920-4925, 4930-4932, 4939-4942

32 Telcm: Communication

4800-4800, 4810-4813, 4820-4822, 4830-4841, 4880-4892, 4899-4899

33 PerSv: Personal Services

7020-7021, 7030-7033, 7200-7200, 7210-7212, 7214-7217, 7219-7221, 7230-7231, 7240-7241 7250-7251, 7260-7299, 7395-7395, 7500-7500, 7520-7529, 7530-7549, 7600-7600, 7620-7620 7622-7623, 7629-7631, 7640-7641, 7690-7699, 8100-8499, 8600-8699, 8800-8899, 7510-7515

34 BusSv: Business Services

2750-2759, 3993-3993, 7218-7218, 7300-7300, 7310-7342, 7349-7353, 7359-7369, 7374-7374 7376-7385, 7389-7394, 7396-7397, 7399-7399, 7519-7519, 8700-8700, 8710-8713, 8720-8721 8730-8734, 8740-8748, 8900-8911, 8920-8999, 4220-4229

35 Hardw: Computers

3570-3579, 3680-3689, 3695-3695

36 Softw: Computer Software

7370-7373, 7375-7375

37 Chips: Electronic Equipment

3622-3622, 3661-3666, 3669-3679, 3810-3810, 3812-3812

38 LabEq: Measuring and Control Equipment

3811-3811, 3820-3839

39 Paper: Business Supplies

2520-2549, 2600-2639, 2670-2699, 2760-2761, 3950-3955

40 Boxes: Shipping Containers

2440-2449, 2640-2659, 3220-3221, 3410-3412

41 Trans: Transportation

4000-4013, 4040-4049, 4100-4100, 4110-4121, 4130-4131, 4140-4142, 4150-4151
4170-4173, 4190-4199, 4200-4200, 4210-4219, 4230-4231, 4240-4249, 4400-4700
4710-4712, 4720-4749, 4780-4780, 4782-4785, 4789-4789

42 Whlsl: Wholesale

5000-5000, 5010-5015, 5020-5023, 5030-5060, 5063-5065, 5070-5078, 5080-5088, 5090-5094
5099-5100, 5110-5113, 5120-5122, 5130-5172, 5180-5182, 5190-5199

43 Rtail: Retail

5200-5200, 5210-5231, 5250-5251, 5260-5261, 5270-5271, 5300-5300, 5310-5311, 5320-5320
5330-5331, 5334-5334, 5340-5349, 5390-5400, 5410-5412, 5420-5469, 5490-5500, 5510-5529
5530-5579, 5590-5700, 5710-5722, 5730-5736, 5750-5799, 5900-5900, 5910-5912, 5920-5932
5940-5990, 5992-5995, 5999-5999

44 Meals: Restaurants, Hotels, Motels

5800-5829, 5890-5899, 7000-7000, 7010-7019, 7040-7049, 7213-7213

45 Banks: Banking

6000-6000, 6010-6036, 6040-6062, 6080-6082, 6090-6099, 6100-6100, 6110-6113, 6120-6179, 6190-6199

46 Insur: Insurance

6300-6300, 6310-6331, 6350-6351, 6360-6361, 6370-6379, 6390-6411

47 RlEst: Real Estate

6500-6500, 6510-6510, 6512-6515, 6517-6532, 6540-6541, 6550-6553, 6590-6599, 6610-6611

48 Fin: Trading

6200-6299, 6700-6700, 6710-6726, 6730-6733, 6740-6779, 6790-6795, 6798-6799

49 Other: Almost Nothing

4950-4959, 4960-4961, 4970-4971, 4990-4991