Econometric Modelling in a Mixed-Frequency and Data-Rich Environment

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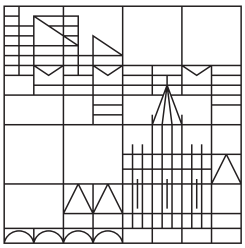

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To my late grandfather

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Summary

Thanks to technological progress, the availability of time series data is constantly increasing over time. Such data is usually not only available at a single common frequency but rather on a wide range of different frequencies. Economic and financial time series are no exception where data is available in large datasets and at different frequencies. For instance, some financial observations can be easily collected and thus their time series can be constructed at very high frequencies. On the contrary, for some economic variables, collecting data can be a challenging and time consuming process and as a result these variables can only be sampled at low frequencies. Although data availability represents a very useful source for information that can potentially help us better understand the world we live in, it also provides a challenging problem. Namely, how to extract and make use of relevant information available in large datasets and at different frequencies. This thesis attempts to provide empirical methods that can deal with this issue.

Time series data can help us understand the dynamic relationship between different important economic variables. For example, a main objective of central banks is to understand how monetary policy affects other macroeconomic variables. The effect of monetary policy on macroeconomic variables such as inflation and unemployment is rather indirect and can only be observed with a delay; however, the effect of monetary policy on the financial markets is direct and immediate and provides different channels through which monetary policy affects other macroeconomic indicators. In the *first chapter* we investigate the dynamic response of stocks' volatilities to monetary policy shocks. To deal with the large availability of stocks and sectors in the financial market, we propose different methodologies based on a suitable dynamic factor model (DFM) as well as Bayesian estimation to help us understand how the various stocks and sectors respond differently to monetary policy shocks.

Extracting relevant information from data can possibly enhance the forecasting accuracy of the forecasts obtained from econometric models. Forecasting economic time series is not just an interesting topic for academic research, but rather a topic of crucial importance to policy makers and financial market participants alike. The *second* and *third chapters* focus primarily on extending existing time series models used in forecasting

quarterly gross domestic product (GDP) by means of monthly economic indicators. The *second chapter* suggests improvements to the univariate mixed-frequency models to allow them to deal with different business cycle patterns commonly observed in economic time series. Moreover, it combines this approach with a DFM used to extract few statistical factors summarizing information from a large dataset. These factors are then used as predictors in the forecasting equation. The *third chapter* extends existing multivariate mixed-frequency models to provide density forecasts in addition to point forecasts. Both a bootstrap approach as well as a Bayesian approach are outlined describing how density forecasts can be obtained from the multivariate mixed-frequency model used in forecasting. The forecasting performance of the models proposed in this thesis is compared to other models previously suggested and used in the literature by means of both Monte Carlo simulations as well as empirical studies. In general, the results are promising suggesting possible forecast gains which can be achieved when the models proposed in this thesis are used.

The *first chapter* investigates the response of stock market volatility to a monetary policy shock using a structural factor-augmented Bayesian vector autoregressive (FAVAR) model. We construct a monthly dataset of realized volatilities of the constituents of the S&P500 index and extract volatility factors from this dataset using a suitable DFM. The volatility factors are included in a structural FAVAR model where the dynamic response of stock market volatility to a monetary policy shock is analyzed. In addition, we also use a large Bayesian vector autoregressive (BVAR) model to examine the responses of stocks' volatilities to a monetary policy shock. Unlike existing literature, the methodologies used in this paper do not only allow us to study the dynamic response of the aggregate market volatility, but also the dynamic responses of all the volatilities of the single stocks and the different sectors included in the dataset. In general, the results show that the stock market returns decrease and the stock market volatility increases following a monetary policy tightening. Although the magnitude of the volatility response to monetary policy shocks varies between the different stocks and sectors, the dynamics of the response do not differ widely. Both the magnitude and dynamics of the volatility response depend on the sample period examined.

The *second chapter* is a joint work with Sandra Stankiewicz, and was published in *International Journal of Forecasting* in 2015. In this chapter we investigate the in- and out-of-sample performance of mixed-frequency models of the MIDAS class with switching regimes for US macroeconomic data. For modeling mixed-frequency data with business cycle pattern we introduce the Markov-switching MIDAS model with unrestricted lag polynomial (MS-U-MIDAS). Usually models of the MIDAS class use lag polynomials of a specific function which impose some structure on the weights of the regressors included

in the model. This may deteriorate the predictive power of the model if the imposed structure differs from the data generating process. When the difference between the available data frequencies is small and there is no risk of parameter proliferation, using an unrestricted lag polynomial might not only simplify the model estimation, but also improve its forecasting performance. We allow the parameters of the MIDAS model with unrestricted lag polynomial to change according to a Markov-switching scheme in order to account for the business cycle pattern observed in many macroeconomic variables. Thus we combine the unrestricted MIDAS with a Markov-switching approach and propose a new Markov-switching MIDAS model with unrestricted lag polynomial (MS-U-MIDAS). We apply this model to a large dataset with the help of factor analysis. Monte Carlo experiments and an empirical forecasting comparison carried out for the US GDP growth show that the models of the MS-U-MIDAS class exhibit similar or better nowcasting and forecasting performance than their counterparts with restricted lag polynomials.

The *third chapter* compares the forecasting performance of the unrestricted mixed-frequency VAR (MF-VAR) model to the more commonly used VAR (LF-VAR) model sampled at a common low-frequency. The literature so far has successfully documented the forecast gains that can be obtained from using high-frequency variables in forecasting a lower frequency variable in a univariate mixed-frequency setting. These forecast gains are usually attributed to the ability of the mixed-frequency models to nowcast. More recently, the usage of mixed-frequency variables in a VAR framework has been introduced to the literature. In this paper we assess the forecasting and nowcasting performance of the MF-VAR, however, we do not impose any restrictions on the parameters of the models. Although the unrestricted version is more flexible, it suffers from parameter proliferation and is therefore only suitable when the difference between the low- and high-frequency variables is small (i.e. quarterly and monthly frequencies). Unlike previous work, our interest is not only limited to evaluating the out-of-sample performance in terms of point forecasts but also density forecasts. Thus, we suggest a parametric bootstrap approach as well as a Bayesian approach to compute density forecasts. Moreover, we show how the nowcasts can be obtained using both direct and iterative forecasting methods. We use both Monte Carlo simulation experiments and an empirical study for the US to compare the forecasting performance of both the MF-VAR model and the LF-VAR model. The results highlight the point and density forecasts gains that can be achieved by the MF-VAR model.

Zusammenfassung

Dank des technologischen Fortschritts, nimmt die Verfügbarkeit von Zeitreihendaten ständig zu. Solche Daten sind in der Regel nicht nur an einer einzigen gemeinsamen Frequenz, sondern über eine größere Reichweite an unterschiedlichen Frequenzen erhältlich. Wirtschafts- und Finanzzeitreihen bilden in diesem Fall keine Ausnahme, wo Daten sowohl in großen Datenmengen als auch über verschiedene Frequenzen hinweg verfügbar sind. Zum Beispiel lassen sich einige Finanzbeobachtungen leicht erheben, und somit kann deren Zeitreihe z.T. bei sehr hohen Frequenzen erstellt werden. Anders ist es bei anderen wirtschaftlichen Reihen, wo das Erheben von Daten ein schwieriger und zeitaufwendiger Vorgang ist und daraus folgt, dass eine Stichprobe von diesen Variablen nur bei sehr niedrigen Frequenzen gezogen werden kann. Obwohl die Datenverfügbarkeit eine sehr nützliche Informationsquelle darstellt, die uns möglicherweise dabei helfen kann, unsere Welt besser zu verstehen, bietet sie gleichzeitig ein anspruchsvolles Problem. Und zwar, wie die relevanten Informationen von großen Datenmengen und bei verschiedenen Frequenzen am besten zu extrahieren und zu nutzen sind. Diese Dissertation hat zum Ziel, empirische Methoden zu stellen, mithilfe deren man diese Problematik angehen kann.

Zeitreihendaten können uns helfen, die dynamische Beziehung zwischen verschiedenen, wichtigen, ökonomischen Variablen zu verstehen. Beispielsweise ist es ein Hauptziel der Zentralbanken zu verstehen, wie sich die Geldpolitik auf andere makroökonomische Variablen auswirkt. Die Wirkung der Geldpolitik auf makroökonomische Variablen wie Inflation und Arbeitslosigkeit ist eher indirekt und somit nur mit einer Verzögerung beobachtbar. Andererseits ist die Wirkung der Geldpolitik auf die Finanzmärkte direkt und unmittelbar und bietet verschiedene Kanäle, über die Geldpolitik auf andere makroökonomische Indikatoren einwirkt. Im ersten Kapitel wird die dynamische Reaktion der Aktienvolatilität auf geldpolitische Schocks untersucht. Um mit dem großen Bestand an Aktien und Sektoren im Finanzmarkt umzugehen, bieten wir verschiedene Methoden auf der Grundlage eines geeigneten dynamischen Faktoren-Modell (DFM) sowie einer Bayesschen-Schätzung, die uns helfen zu verstehen, wie die verschiedenen Aktien und Sektoren unterschiedlich auf geldpolitische Schocks reagieren.

Das Extrahieren von relevanten Informationen aus den Daten kann möglicherweise zur Verbesserung der Prognosegenauigkeit der von ökonometrischen Modellen erhaltenen Prognosen beitragen. Prognose ökonomischer Zeitreihen ist nicht nur ein interessantes Thema für die akademische Forschung, sondern auch von entscheidender Bedeutung für politische Entscheidungsträger und Akteure im Finanzmarkt gleichermaßen. Das zweite und das dritte Kapitel konzentrieren sich in erster Linie auf die Erweiterung bestehender Zeitreihenmodelle, die mithilfe monatlicher Wirtschafsindikatoren das vierteljährliche Bruttoindlandsprodukt (BIP) prognostizieren. Das zweite Kapitel stellt Verbesserungsvorschläge für univariate Mischfrequenz-Modelle, um ihnen zu erlauben, an unterschieliche Konjunkturzyklus-Mustern heranzugehen, die in ökonomischen Zeitreihen häufig zu beobachten sind. Darüber hinaus kombiniert es diesen Ansatz mit einem DFM, das dazu verwendet wird, einige Faktoren zu extrahieren, die Informationen aus einer großen Datenmenge zusammenfassen. Diese Faktoren werden dann als Prädiktoren in der Prognosegleichung verwendet. Das dritte Kapitel erweitert bestehende multivariate Mischfrequenz-Modelle, um neben den Dichteprognosen auch Punktprognosen zu liefern. Es werden sowohl ein Bootstrap-Ansatz sowie ein Bayesscher Ansatz dargestellt, die beschreiben, wie Dichteprognosen aus dem multivariaten Mischfrequenzmodell gewonnen werden, das in der Prognose verwendet wird. Die Prognoseleistung der in dieser Arbeit vorgeschlagenen Modelle wird mithilfe der Monte Carlo Simulationen sowie einer Reihe empirischer Studien mit anderen Modellen verglichen, die in der Literatur bisher verwendet und vorgeschlagen worden sind. Im Allgemeinen sind die Ergebnisse vielversprechend und deuten auf mögliche Prognosegewinne hin, die durch die Verwendung der hier vorgeschlagenen Modelle erreicht werden könnten.

Das erste Kapitel untersucht die Reaktion der Aktienmarktvolatilität auf einen geldpolitischen Schock mithilfe eines strukturellen faktor-erweiterten Bayesschen Vektor autoregressiven (Favar) Modells. Wir konstruieren einen monatlichen Datensatz von realisierten Volatilitäten der Bestandteile des SP500-Index und extrahieren Volatilitätsfaktoren aus diesem Datensatz unter Verwendung eines geeigneten DFMs. Die Volatilitätsfaktoren sind in einem strukturellen FAVAR Modell einbezogen, wo die Dynamik der Aktienmarktvolatilität auf einen geldpolitischen Schock analysiert wird. Darüber hinaus verwenden wir auch einen großen Bayesschen Vektor autoregressiven (BVAR) Modell, um die Reaktionen der Aktienvolatilität auf einen geldpolitischen Schock zu untersuchen. Im Gegensatz zu bestehender Literatur, erlauben uns die in dieser Arbeit verwendeten Methoden nicht nur, die dynamische Reaktion der Aggregatmarktvolatilität, aber auch die dynamischen Reaktionen aller Volatilitäten der einzelnen Aktien und der verschiedenen Sektoren im Datenbestand, zu analysieren. Im Allgemeinen zeigen die Ergebnisse, dass infolge einer Straffung der Geldpolitik der Aktienmarktumsatz sinkt und die Aktienmarktvolatilität steigt. Obwohl das Ausmaß der Volatilitätsreaktion auf geldpolitische Schocks

zwischen den verschiedenen Aktien und Sektoren variiert, weist die Dynamik der Reaktion keine erheblichen Unterschiede auf. Sowohl die Größe als auch die Dynamik der Volatilitätreaktion hängt vom Stichprobenzeitraum ab.

Das zweite Kapitel ist eine gemeinsame Arbeit mit Sandra Stankiewicz und wurde 2015 im International Journal of Forecasting veröffentlicht. In diesem Kapitel untersuchen wir die In-und Out-of-Sample-Mischfrequenz-Modelle der MIDAS-Klasse mit schaltenden Regimes für US-makroökonomische Daten. Zur Modellierung von Mischfrequenz-Daten mit Konjunkturzyklusmuster führen wir das Markov-Switching-MIDAS-Modell mit uneingeschränkten Lag Polynom (MS-U-MIDAS) ein. Normalerweise verwenden Modelle der MIDAS-Klasse Lag Polynome einer spezifischen Funktion, die eine gewisse Struktur auf den Gewichten der im Modell einbezogenen Regressoren auferlegen. Dies kann die Vorhersagekraft des Modells senken, wenn sich diese Struktur vom Datengenerierungsprozess unterscheidet. Wenn die Differenz zwischen den verfügbaren Datenfrequenzen klein ist, und keine Gefahr von Parameterproliferation besteht, dient die Verwendung eines uneingeschränkten Lag Polynoms nicht nur der Verinfachung, sondern sogar der Verbesserung der Prognoseleistung. Wir lassen die Parameter des MIDAS-Modells mit einem unbeschränkten Lag-Polynom (U-MIDAS) gemäß einem Markov-Switching-Prinzip variieren, um das Konjunkturzyklusmuster zu berücksichtigen, was in vielen makroökonomischen Variablen zu beobachten ist. So kombinieren wir das uneingeschränkte MIDAS mit einem Markov-Switching-Ansatz und schlagen ein neues Markov-Switching-MIDAS-Modell mit uneingeschränktem Lag Polynom (MS-U-MIDAS) vor. Wir wenden dieses Modell bei einem großen Datensatz mithilfe der Faktorenanalyse an. Monte-Carlo-Experimente und ein durchgeführter empirischer Prognosevergleich für das Wachstum des US-BIP zeigen, dass die Modelle der MS-U-MIDAS-Klasse ähnliche oder bessere Nowcasting- und Prognoseleistung aufweisen, als ihre Gegenüber mit eingeschränkten Lag Polynomen.

Das dritte Kapitel vergleicht die Vorhersageleistung des uneingeschränkten Mischfrequenz-VAR (MF-VAR) Modells mit der des häufiger verwendeten VAR (LF-VAR) Modells, das anand einer gemeinsamen niedrigen Frequenz gezogen wird. Die Literatur hat bisher erfolgreich die Prognosegewinne dokumentiert, die aus der Verwendung einer Hochfrequenz-Variable für die Prognose einer Variablen einer niederigeren Frequenz, in einer Mischfrequenz-Einstellung, gezogen werden können. Diese Prognosegewinne werden in der Regel auf die Nowcast-Fähigkeit der Mischfrequenz-Modelle zurückgeführt. Neuerdings wurde die Verwendung der Mischfrequenz-Variablen in einem VAR Rahmen in die Literatur eingeführt. In dieser Arbeit bewerten wir die Vorhersage- und Nowcasting-Leistung des MF-VAR, allerdings werden von uns keine Einschränkungen der Parameter der Modelle auferlegt. Obwohl die uneingeschränkte

Version flexibler ist, leidet sie unter Parameterproliferation und ist daher nur geeignet, wenn die Differenz zwischen den Niedrig- und Hochfrequenz-Variablen klein ist (d.h. vierteljährliche und monatliche Frequenzen). Im Gegensatz zu früheren Arbeiten, interessieren wir uns nicht ausschließlich für die Evaluation der Out-of-Sample-Leistung in Bezug auf Punktprognosen, sondern auch Dichteprognosen. Daher schlagen wir einen parametrischen Bootstrap-Ansatz sowie einen Bayesschen-Ansatz vor, um die Dichteprognosen zu berechnen. Darüber hinaus zeigen wir, wie die Nowcasts mit direkten und iterativen Prognoseverfahren gewonnen werden können. Wir verwenden sowohl Monte-Carlo-Simulation Experimente als auch eine empirische Studie für die USA, um die Vorhersageleistung des MF-VAR-Modells und des LF-VAR-Modells zu vergleichen. Die Ergebnisse unterstreichen die Gewinne bei den Punkt- und Dichteprognosen, die durch das MF-VAR Modell erreicht werden können.

CHAPTER 1

The Effects of Monetary Policy Shocks on a Panel of Stock Market Volatilities: A Factor-Augmented Bayesian VAR Approach

1.1 Introduction

Understanding the dynamic relationship between monetary policy and the financial stock market is of large interest to both political decision makers and market participants. Although the main targets of monetary policy are related to macroeconomic variables such as employment, inflation, and output, monetary policy tools only have indirect effects on these variables. On the other hand, the effect of monetary policy on financial markets is direct and immediate. Policy makers use actions such as a change in the federal funds rate to affect financial markets in order to achieve their macroeconomic targets through different channels. In addition, from the investors' perspective, recognizing the reaction of stock markets to monetary policy shocks can lead to more profitable trading. Thus, it is crucial to understand the magnitude and dynamics of the stock market's reaction to monetary policy.

In general, two branches of existing literature tried to investigate the effect of monetary policy on financial market variables, but only a smaller number of those papers focused on the responses of stock market volatilities. The first group of these papers uses univariate regression models to understand how the magnitude of financial market volatility is affected by monetary policy (see e.g. Chuliá et al. (2010), Andersson (2010), Gospodinov and Jamali (2012a), among others). This approach, however, only allows the researcher to assess the magnitude of the response, but not its dynamics. Although the main focus of this literature is on the responses of aggregate market volatility, some attention is also given to the responses of the volatilities at both the sectoral and stock level. On the other hand, fewer papers use multivariate models to analyze both the magnitude and the dynamics of the responses of the market's volatility to monetary policy shocks (see e.g. Gospodinov and Jamali (2012b)). Due to the large dimensionality of multivariate models, those papers only consider the responses of aggregate measures of the market's volatility. To contribute to this literature, we propose different methodologies based on dynamic factor models and Bayesian vector autoregressive models that allow us to investigate both the magnitude and dynamics of the responses of the volatility, not only at the aggregate level but also for the different stocks and sectors. In this paper we model a large dataset of monthly volatilities and include them together with other macroeconomic variables and stock returns in a structural VAR to analyze the dynamic response of the stocks' volatilities to monetary policy shocks using impulse response functions. Moreover, we also examine volatility responses in different policy regimes and assess whether the responses depend on the period examined or not.

Theory suggests that following an expansionary monetary policy, interest rates decrease leading to a higher demand on stocks compared to bonds and hence, stock prices increase. There are, however, different channels through which monetary policy can affect the econ-

omy using asset prices[1]. According to Tobin (1969), movements in stock prices can affect the economy through the investment channel. An increase in stock prices makes it cheaper for firms to invest because each issued share produces more funds. This means that buying facilities and equipments is cheaper for the firm. Therefore, a rise in stock prices leads to a lower cost of capital and as a result investments and output increase. As highlighted in Bernanke and Gertler (1995), asymmetric information problems present in credit markets serve as another transmission mechanism for monetary policy through asset prices. In the literature such a mechanism is usually referred to as the balance sheet or credit view channel. When the net worth of business firms becomes lower, lending problems to these firms related to adverse selection and moral hazards become more severe. A rise in stock prices reduces both adverse selection and moral hazard problems leading to an increase in lending. Consequently, investment spending and aggregate spending increase. Alternatively, monetary policy transmission can also take place through the household's balance sheet, specifically through household wealth effect. In the life cycle model of Modigliani (1971), the lifetime resources of consumers determine their consumption. Stocks are a main component of financial wealth which is an important part of consumers' lifetime resources. An increase in stock prices raises household wealth; accordingly, the lifetime resources of consumers increase resulting in a rise in consumption. Using US data, Lettau et al. (2002) show empirically that the household wealth channel plays a minor role in influencing consumption.

The response of the stock market to monetary policy is not only limited to stock market returns, but also extends to stock market volatility through different channels. Since monetary policy tightening can be viewed as new information in the market, investors try to rebalance their portfolios between equities and bonds more actively following a monetary policy tightening. Such behavior spurs an increase in trading volume translating into an increase in volatility because of the well documented strong positive correlation between trading volume and volatility in the literature[2]. Declining stock prices are usually accompanied by rising volatility, and vice versa. Although a sizable literature has documented the negative correlation between stock returns and volatility, there is less agreement on the direction of the causality. The early work of Black (1976) and Christie (1982) attributes the asymmetric relation between stock returns and volatility to changes in debt-to-equity ratio. This asymmetric return-volatility relationship is known in the literature as the leverage effect. In the leverage effect hypothesis, when asset prices go down, the relative value of the companies' debt increases compared to their equity. Therefore, when stock prices decline, companies become riskier and more volatile. Another explanation advocated by French et al. (1987) and Campbell and Hentschel (1992) that illustrates the asymmetric relation between stock returns and volatility is referred to as the volatility feedback hy-

[1] Mishkin (2007) surveys how monetary policy affects the economy through asset prices.

[2] See e.g. Karpoff (1987) for a survey of this literature.

pothesis. In the volatility feedback hypothesis monetary policy can exert direct influence on volatility through the risk premium. If volatility is priced, an expected increase in volatility requires a higher rate of return. As a result, immediate stock prices decline in order to allow for higher future returns. Thus, negative news can increase future volatility and expected returns while decreasing contemporaneous returns. In sum, the causality in the leverage effect runs from prices to volatility as opposed to the volatility feedback which depends on the reverse causal relationship. However, at lower frequencies, the relationship between returns and volatility may appear immediate and the two explanations become indistinguishable.

Since the effect of monetary policy on stock market variables is of large interest in both financial and monetary economics, there is a large literature in both fields. In finance, many papers focus on the effects of the announcements of federal open market committee (FOMC) related to the federal funds target rate on financial variables. Most of the literature related to the effect of monetary policy on asset prices follows the work of Cook and Hahn (1989). In this paper, the authors measure the impact of monetary policy on the bond market by regressing changes in returns on changes in the federal funds target rate. Using a similar line of research, Reinhart and Simin (1997), Bernanke and Kuttner (2005), Gürkaynak et al. (2005), Zebedee et al. (2008), among many others investigate the impact of monetary policy announcements on stock returns. In these studies both daily and high frequency data are used. Although an increase in federal funds rate lowers stock returns, the magnitude of the change depends on the data, the sample period, and the method used in each study. More recently, Chuliá et al. (2010), Andersson (2010), Gospodinov and Jamali (2012a), among others analyze the effects of monetary policy announcements on stock market volatility. Although the main focus of the literature is on the stock market as a whole, Chuliá et al. (2010) examine the response across the different stocks and sectors to monetary policy announcements. Adopting a different methodology, Flannery and Protopapadakis (2002) and Bomfim (2003) use generalized autoregressive conditional heteroskedasticity (GARCH) models to estimate the effects of monetary policy on the volatility of different assets.

Although the previously mentioned literature focuses intensively on the effects of monetary policy on the stock market, the univariate regression framework used does not, however, assess the dynamic relationship between the variables of interest. Since the pioneering work of Sims (1980), vector autoregressive (VAR) models have became very popular in modeling multivariate time series used in macroeconomics. In VARs, the dynamic response of the variables in the system to an impulse in another variable can be examined by means of impulse response analysis. Thorbecke (1997), Millard and Wells (2003), Bjørnland and Leitemo (2009), among others use structural VARs to analyze the effects of monetary policy shocks on stock market returns. They include different monthly macroeconomic variables along with federal funds rate and stock market returns index in

a structural VAR to investigate the response of the stock market returns to an identified monetary policy shock using impulse response functions. Gospodinov and Jamali (2012b) expand this framework by including a stock market volatility index in a structural VAR. They analyze the dynamic response of the stock market volatility to a monetary policy shock.

In this paper we construct a large dimensional panel of financial stocks and we compute monthly realized volatilities for the whole dataset. We propose three approaches to analyze the response of the panel of volatilities to monetary policy shocks. In the first approach, to reduce the large dimension, we extract a volatility factor from the realized volatilities dataset using the DFM of Luciani and Veredas (2015). This DFM allows us to extract volatility factors while accounting for the stylized facts in the realized volatilities. Then we follow Bernanke et al. (2005) and augment the estimated factor in a structural factor-augmented vector autoregressive (FAVAR) model where we employ a recursive identification scheme. Impulse responses are used to investigate the response of the volatility factor to a monetary policy shock. In a similar fashion as Blaes (2009), we can use the DFM equation to obtain the impulse responses of all the series included in the dataset from which the volatility factor is extracted. Different tests and information criteria suggest the use of one volatility factor to summarize the variation in the whole dataset; this means that the responses of the different stocks will only vary in magnitude or direction but not in dynamics. In the second approach the dataset is divided into 9 different sectors. A volatility factor is estimated from each sector and then the 9 estimated volatility factors are included together in a structural FAVAR where impulse responses are used to analyze the response of the different sectors' volatilities. The responses of the stocks from each sector are obtained using the DFM equation. This approach allows the dynamics of the volatilities responses to vary across the different sectors, but within each sector the volatilities of the single stocks only vary in magnitude or direction and not in dynamics. Instead of using a DFM, in the third approach we include a number of stocks' volatilities directly in a structural VAR and examine their responses using impulse response functions. Due to the large dimensionality of this structural VAR, we estimate the model using the Bayesian method implemented by Banbura et al. (2010). This approach does not impose any restrictions on the dynamics or magnitude of the responses of the stocks' volatilities included in the structural VAR; however, in this approach, a limited number of stocks can be included in the structural VAR[3]. In order to allow for a fair comparison between all the three different approaches, in the first and the second approach we estimate the structural FAVAR model using the same Bayesian technique used in the third approach.

The results obtained from the impulse responses show that the stock market returns de-

[3]For instance, Banbura et al. (2010) included up to 131 variables in a structural VAR. To do so, they used a high degree of shrinkage.

crease and the volatility increases following a contractionary monetary policy shock. In general, the impulse responses suggest a strong negative correlation between the dynamic responses of the stock returns and the volatility. The magnitude of the volatility responses varies between the different sectors and stocks. For instance, a monetary policy shock has a stronger impact on the financial sector as opposed to other sectors. In addition, the magnitude of the responses of the companies which have large market capitalization (market cap) tends to be stronger. Both the magnitude and the dynamics of the responses of the variables in the system vary across the different policy regimes. In particular, starting from Greenspan's chairmanship of the Federal Reserve, the effect of monetary policy shocks on stock market variables is stronger compared to previous periods.
The rest of the paper is organized as follows. In Section 1.2 we analyze the financial dataset, present the DFM, and extract volatility factors. Section 1.3 introduces the structural VAR model and summarizes its Bayesian estimation. The results are presented in Section 1.4. Section 1.5 concludes.

1.2 Data description and factors extraction

The financial dataset[4] consists of 213 daily price series and covers the period from 02/01/1973 to 31/07/2012. It contains US companies that are part of the S&P500 index for the whole duration of the sample. The data represents 9 different sectors[5], namely, industrials (IND), financials (FIN), health care (HC), consumer discretionary (CD), information technology and telecommunications services (ITTS), utilities (UT), materials (MAT), energy (EN), and consumer staples (CS). Daily returns for each of the 213 series are computed as:

$$R^i_{n,t} = \log(P^i_{n,t}) - \log(P^i_{n-1,t}), \tag{1.1}$$

where $P^i_{n,t}$ is the closing price on day n and month t for variable i. Although a lot of work has been done recently to compare different methods for estimating daily volatility, few papers focused on comparing monthly volatility measures (see e.g. Liu and Tse (2013)). Using the GARCH model of Bollerslev (1986) and its extensions to estimate monthly volatility is not uncommon. The use of squared daily stock returns over a month as a measure for monthly volatility has become popular since French et al. (1987) and Schwert (1989). Later such measure was called realized volatility by Andersen et al. (2001) when

[4]All the series in the financial dataset are obtained from Datastream. A complete description of the dataset can be found in Table 1.A.1 in Appendix 1.A.

[5]IND includes 34 series, FIN includes 28 series, HC includes 16 series, CD includes 32 series, ITTS includes 17 series, UT includes 28 series, MAT includes 16 series, EN includes 17 series, and CS includes 25 series. The S&P500 index includes one sector for information technology and another sector for telecommunication services. Since there are only 3 series from the telecommunications services that cover the whole sample, we include the telecommunications services along with information technology in one sector.

applied to high frequency data to obtain daily measure for volatility[6]. In this paper we adopt the realized volatility as a measure of monthly volatility. Following French et al. (1987) and Schwert (1989), monthly realized volatility for each series is estimated as:

$$RV_t^i = \sqrt{\sum_{n=1}^{N} \left(R_{n,t}^i - \overline{R}_t^i\right)^2}, \tag{1.2}$$

where N is the number of trading days in month t and $\overline{R}_t^i$ is the average daily return of stock i in month t. From now on, we denote the log of realized volatility as realized volatility[7]. Accordingly, a monthly panel of realized volatility is constructed from January 1973 to July 2012. The monthly panel of realized volatilities is analyzed in Table 1.2.1 in a similar way as Luciani and Veredas (2015) analyze their daily panel of realized volatilities[8]. The daily panel of realized volatilities used in Luciani and Veredas (2015), however, is constructed from 02/01/2001 to 31/12/2008 and consists of 90 US equity companies that are part of S&P100 index.

Many studies document the long memory behavior observed in daily realized volatility. In order to capture the long memory found in daily realized volatility, Andersen et al. (2003) propose the use of an ARFIMA (p, d, q) model[9]. The fractional integration parameter, denoted by d, measures the value of differencing required to provide the long memory processes short memory. So the realized volatility, RV_t^i, is fractionally integrated of order d_i if $(1-L)^{d_i} RV_t^i$ is integrated of order zero, $I(0)$. Usually the values of d_i range between 0 and 1, and values closer to 1 refer to more persistent processes. Values of d_i between 0 and 0.5 refer to mean reverting and finite variance processes while values of d_i between 0.5 and 1 only imply variance stationarity. The first panel in Table 1.2.1 reports values for d_i estimated from ARFIMA$(1, d, 0)$ models[10]. The median value for the estimated d parameter in the whole dataset is 0.48 suggesting the presence of long memory; however, the degree of long memory is smaller than a value of 0.55 obtained by Luciani and Veredas (2015) from their daily dataset[11]. Such result might cautiously suggest that daily realized volatility has a higher degree of long memory compared to monthly volatility. Observing the first panel in more depth, one can notice that the difference between

[6] It is also possible to use high frequency data to obtain monthly realized volatility; however, we do not use such method due to the unavailability of the data. In this paper we use daily observations to calculate monthly measure of realized volatility.

[7] Similar to the measure Luciani and Veredas (2015) have used.

[8] This dataset is originally used in Barigozzi et al. (2010).

[9] See e.g. Palma (2007) for surveying time series models with long memory.

[10] The ARFIMA$(1, d, 0)$ model is estimated using the nonlinear least square method in Ox by Doornik (2009). This method was preferred since it does not restrict the d parameter to be less than 0.5 like the maximum likelihood method. Other ARFIMA (p, d, q) model specifications are also examined; however the results do not vary largely.

[11] In general, one should note that different estimation methods for the ARFIMA(p, d, q) results in different estimates for the the d parameter.

Table 1.2.1: Descriptive statistics for realized volatilities

		ALL	IND	FIN	HC	CD	ITTS	UT	MAT	EN	CS
						ARFIMA $(1, d, 0)$					
	max.	0.64	0.61	0.55	0.60	0.60	0.53	0.62	0.56	0.58	0.64
d	med.	0.48	0.51	0.47	0.47	0.50	0.47	0.49	0.46	0.44	0.48
	min.	0.32	0.41	0.39	0.41	0.32	0.40	0.39	0.42	0.37	0.33
						Autocorrelation					
	max.	0.81	0.75	0.69	0.79	0.76	0.64	0.71	0.73	0.70	0.81
Lag 1	med.	0.58	0.60	0.57	0.59	0.63	0.55	0.58	0.54	0.56	0.59
	min.	0.33	0.42	0.45	0.41	0.42	0.39	0.47	0.45	0.33	0.44
	max.	0.69	0.57	0.49	0.64	0.59	0.48	0.58	0.60	0.56	0.69
Lag 6	med.	0.38	0.38	0.38	0.36	0.41	0.37	0.38	0.34	0.37	0.39
	min.	0.17	0.24	0.23	0.24	0.23	0.24	0.26	0.17	0.20	0.19
	max.	0.59	0.48	0.39	0.56	0.49	0.37	0.48	0.47	0.46	0.59
Lag 12	med.	0.28	0.28	0.26	0.27	0.29	0.25	0.27	0.25	0.29	0.29
	min.	0.03	0.15	0.09	0.12	0.11	0.08	0.12	0.03	0.10	0.12
						Autocorrelation squares					
	max.	0.84	0.78	0.73	0.79	0.78	0.69	0.81	0.69	0.68	0.84
Lag 1	med.	0.51	0.53	0.48	0.56	0.58	0.54	0.46	0.50	0.48	0.48
	min.	0.13	0.13	0.31	0.33	0.19	0.22	0.22	0.40	0.26	0.33
	max.	0.70	0.61	0.44	0.59	0.54	0.52	0.53	0.47	0.54	0.70
Lag 6	med.	0.27	0.25	0.26	0.28	0.29	0.28	0.24	0.27	0.29	0.26
	min.	0.00	0.00	0.06	0.09	0.00	0.07	0.00	0.14	0.00	0.13
						Autocorrelation absolute values					
	max.	0.82	0.75	0.67	0.79	0.73	0.64	0.71	0.64	0.65	0.82
Lag 1	med.	0.54	0.51	0.49	0.56	0.56	0.54	0.50	0.51	0.53	0.52
	min.	0.24	0.29	0.31	0.36	0.37	0.29	0.24	0.43	0.29	0.31
	max.	0.69	0.58	0.47	0.64	0.57	0.48	0.54	0.48	0.54	0.69
Lag 6	med.	0.34	0.32	0.31	0.33	0.35	0.34	0.29	0.31	0.36	0.31
	min.	0.00	0.03	0.14	0.15	0.04	0.12	0.02	0.14	0.00	0.14
						Skewness					
	max.	1.43	1.43	1.07	0.82	1.33	0.80	1.32	0.74	1.11	1.04
	med.	0.42	0.52	0.30	0.50	0.41	0.40	0.49	0.37	0.28	0.34
	min.	-2.52	-1.67	-0.19	-0.24	-0.88	-0.33	-2.37	-0.01	-1.43	-2.52
						Kurtosis					
	max.	17.37	10.07	6.19	4.53	6.46	7.48	17.37	5.17	9.99	11.58
	med.	3.72	4.06	3.59	3.60	3.72	3.87	3.93	3.58	3.64	3.64
	min.	2.56	2.81	2.64	2.56	2.86	3.05	3.01	2.96	2.92	2.69

Descriptive statistics for the monthly realized volatility for (ALL) 213 companies from S&P 500 in the period between January 1973 and July 2012 representing 9 sectors: industrials (IND), financials (FIN), health care (HC), consumer discretionary (CD), information technology and telecommunications services (ITTS), utilities (UT), materials (MAT), energy (EN), and Consumer staples (CS). The first panel shows the fractional integration parameter d estimated from ARFIMA$(1, d, 0)$, the second panel presents autocorrelations for lags 1, 6, and 12, the third and fourth panels show the autocorrelations for squared and absolute realized volatilities respectively for lags 1 and 6, and the fifth and sixth panels show skewness and kurtosis respectively. All panels present maximum (max.), median (med.), and minimum (min.) values.

the maximum and minimum values for d in the panel as well as within each sector is quite substantial. On the other hand, the median values across the sectors are very close to each other. While the degree of long memory is heterogeneous among all the assets, it is quite similar across the different sectors indicating that long memory can be a market feature.
Long memory processes are usually characterized by a slow decay in the sample autocorrelation functions. The second panel in Table 1.2.1 reports the sample autocorrelation functions for all the sectors for lags 1, 6, and 12. Similar to the fractional integration parameter, we observe large differences between maximum and minimum values within the sectors, but median values across the different sectors are very similar. One observes that the median for lag 1 is 0.58 , for lag 6 is 0.38, and for lag 12 is 0.28. This persistence in autocorrelations is a feature of long memory processes. Again, although the autocorrelations of the monthly realized volatilities are persistent, they are not as persistent as daily realized volatility.
The third and fourth panels in Table 1.2.1 show the autocorrelations for both the squares and absolute values of the monthly realized volatilities; both are measures of the volatility of realized volatility. The dependence observed in both these two measures is evidence of conditional dynamics in realized volatility. The last two panels in Table 1.2.1 report both skewness and kurtosis. The results suggest that although both skewness and kurtosis are different among assets and across sectors, both are present in the monthly realized volatility. So, in general, monthly realized volatilities are skewed and show heavy tails.
In addition, in Table 1.A.2 in Appendix 1.A, we report a similar descriptive statistics table for the annualized realized volatilities calculated without taking the logs. In this table we present results across industry groups as well as the for each sector separately. Although the results are very similar to Table 1.2.1, one can observe that both skewness and kurtosis are more pronounced in Table 1.A.2 compared to Table 1.2.1. One can also notice that in Table 1.A.2 there is a higher degree of long memory in the financials sector compared to other sectors.
Since the previous analysis show that the monthly realized volatilities share the same stylized facts observed in the daily realized volatilities as shown in Luciani and Veredas (2015), we follow their proposed dynamic factor model to extract factors from the monthly panel of realized volatilities. Following the notation of Luciani and Veredas (2015), the dynamic factor model can be written as:

$$\mathbf{RV_t} = \mathbf{\Lambda F_t} + \xi_\mathbf{t}, \tag{1.3}$$

$$\mathbf{D}(L)\mathbf{F_t} = \mathbf{C}(L)\mathbf{H_t^{1/2}}\mu_\mathbf{t}, \tag{1.4}$$

$$(1-L)^{\delta_i}\xi_{it} = G_i(L)\epsilon_{it}. \tag{1.5}$$

$\mathbf{RV_t}$ is the $N \times 1$ vector of realized volatilities, $\mathbf{\Lambda}$ is the $N \times r$ loading matrix, $\mathbf{F_t}$ are the $r \ll N$ common factors, and $\xi_\mathbf{t}$ is the $N \times 1$ vector of idiosyncratic components

which captures the firm's specific dynamics. The common factors evolve according to a VARFIMA model with conditional heteroskedasticity as shown in equation (1.4) where $\mathbf{D}(L)$ is a diagonal matrix of polynomials of fractional integration, $\mathbf{C}(L)$ is the pure MA representation of a VARMA model for $\mathbf{D}(L)\mathbf{F_t}$, and the variance covariance of realized volatilities is captured by $\mathbf{H_t^{1/2}}$. The orthogonal common shocks, $\mu_\mathbf{t}$, follow a standardized distribution $\mathcal{D}$ that is allowed to have skewness and heavy tails. In equation (1.5), ARFIMA processes are used to model the idiosyncratic components, where δ_i measures the degree of fractional integration of the i^{th} idiosyncratic component and $G_i(L)$ is the pure MA representation of an ARMA model for $(1-L)^{\delta_i}\xi_{it}$. The idiosyncratic shock, ϵ_{it}, follows a zero-location distribution $\mathcal{D}$ which allows for both skewness and heavy tails.

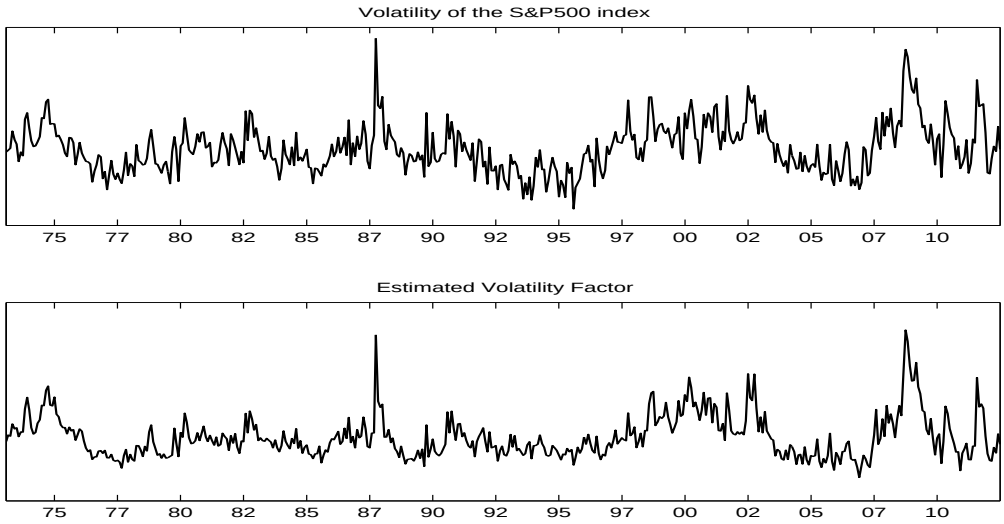
The model of Luciani and Veredas (2015) relates to fractional cointegration in a similar way as the model of Bai and Ng (2004) is related to cointegration. Luciani and Veredas (2015) document the usefulness of their model in estimating factors from a large dataset where long memory is present using both a Monte Carlo study and an empirical application. Using a theoretical proof, Bai and Ng (2004)[12] show that the factors can be estimated consistently using the principal components method on the first differenced data. In general, the method of principal components only provides consistent estimates of the factors when the error terms are stationary. When the variables of interest are cointegrated or fractionally cointegrated, the estimates of the factors obtained using principal components are not consistent since the error terms are not guaranteed to be stationary. Applying the principle components method to the first differenced data allows for consistent estimation of the factors and the error terms regardless to their dynamic properties. More formally, define $\mathbf{rv_t} = \Delta\mathbf{RV_t}$, $\mathbf{f_t} = \Delta\mathbf{F_t}$, and $\mathbf{z_t} = \Delta\xi_\mathbf{t}$ for $t = 2, \ldots, T$. By first differencing equation (1.3), we get $\mathbf{rv_t} = \mathbf{\Lambda f_t} + \mathbf{z_t}$. The principal components method can be used to obtain the estimates $\widehat{\mathbf{f}}_t$, $\widehat{\mathbf{\Lambda}}$, and $\widehat{\mathbf{z}}_t$. Consistent estimates $\widehat{\mathbf{F}}_t$ and $\widehat{\xi}_t$ are obtained by cumulating $\widehat{\mathbf{f}}_t$ and $\widehat{\mathbf{z}}_t$ i.e. $\widehat{\mathbf{F}}_t = \sum_{t=2}^{t} \widehat{\mathbf{f_t}}$ and $\widehat{\xi}_t = \sum_{t=2}^{t} \widehat{\mathbf{z}}_t$.

In order to estimate the model in (1.3)-(1.5), one should first determine the number of factors to be used. Since the number of factors is unknown, we use the Bai and Ng (2002) information criteria to determine it. The information criteria point to only one factor. As a robustness check, we also look at the percentage of variation explained by each factor; it turns out that the first factor explains 22% of the variation in the data, the second factor explains 2.77% and each of the other factors explains less than 2% of the variation in the data. Such a result also suggests the suitability of using one factor in the analysis. This is in line with both Luciani and Veredas (2015) and Barigozzi et al. (2010) and also supports the hypothesis of the co-movement of the monthly realized volatilities. The estimated first factor shows a high degree of long memory. The fractional integration parameter of the estimated first factor is 0.64; higher than any single series in the panel

[12]This result is also valid for the model of Luciani and Veredas (2015) since none of their assumptions violate the assumptions of Bai and Ng (2004) and so a proof is not needed.

of monthly realized volatilities from which the factor was extracted. This is due to the fact that the estimated factor is a linear combination which smoothes out the temporary volatility shocks in the single firms. Such a result holds for all aggregates in general. The estimated factor, $\hat{F}_t$, also correlates highly with the monthly realized volatility of the S&P500 index with a correlation coefficient of 0.90[13]. It can be observed from the plots of the monthly volatility of the S&P500 index and the estiamated volatility factor in Figure 1.2.1 that they are highly correlated; this is important to ensure that the response of the volatility factor to monetary policy shocks behaves in a similar way as the volatility of the S&P500 index.

Figure 1.2.1: Plots for the volatility of the S&P 500 index and the estimated volatility factor



Plots of the monthly volatility of the S&P 500 index and the estimated volatility factor from the whole dataset in the period between February 1973 and July 2012.

In addition, we also divide the dataset into 9 different sectors. Following the above procedure, we estimate volatility factors from each sector. Table 1.2.2 shows the percentage of variation explained by the first 5 factors extracted from each sector. With the exception of the first factor estimated from each sector, all the other factors summarize a small percentage of the variation within each sector. This result suggests that the first factor largely summarizes the variation in each sector. The correlation coefficients between the estimated volatility factors are shown in Table 1.A.3 in Appendix 1.A. Figure 1.A.1 in

[13] Although the dataset used here only contains the 213 assets that are part of S&P500 index for the whole duration used in this paper, the estimated factor from this panel still correlates highly with the realized volatility of the S&P500 index. We also tried to divide the sample into two periods, and compare the estimated factor from each period with the corresponding realized volatility of the S&P500 index. It turns out that the correlation coefficient for the first period is 0.93 while the coefficient for the more recent period is 0.88. This might be because the dataset does not include many of the American companies in both the Information technology and telecommunication services sectors that only became part of the S&P500 index more recently.

Appendix 1.A shows the plots of the first factors estimated from each sector. From the plots, one can observe high correlations between the different sectors. All the sectors' estimated volatility factor capture the high volatility during the Black Monday, the dot-com bubble, and the recent financial crises. However, the magnitude of the spikes during crises periods differs between the different sectors.

Table 1.2.2: Percentage of variation explained by the factors

	1	2	3	4	5
ALL	22.04	2.77	1.55	1.46	1.33
IND	29.30	3.74	3.40	3.35	3.22
FIN	28.22	4.98	4.31	4.19	4.03
HC	28.75	7.03	6.46	6.04	5.79
CD	22.30	4.50	4.04	3.85	3.61
ITTS	29.15	7.24	6.41	6.15	5.20
UT	35.56	6.05	4.30	3.52	3.45
MAT	33.92	6.43	5.97	5.75	5.56
EN	34.10	6.54	6.23	5.50	5.22
CS	25.24	5.24	4.81	4.47	4.25

The percentage of the overall variation explained by the first 5 factors from each sector and the whole dataset.

Within each sector, the estimated factor loading for each company is shown in Table 1.A.1 in Appendix 1.A. This shows how the estimated first volatility factor for each sector loads on the monthly realized volatility of each company that belong to the sector. Although the differences between the factor loadings of the companies in each sector is small, companies with large market cap tend to have larger factor loadings compared to other companies within their sectors. For example, the sectors' estimated volatility factor load highly on companies such as Bank of America, Chevron Corp., Dow Chemical, Exxon Mobil Corp., General Electric, IBM, Johnson & Johnson, and Procter & Gamble.
Without any further restrictions, when the number of factors is larger than one, the method of principal components estimates the space spanned by the latent factors[14]. Thus, principal components estimate the factors and the factor loadings up to a rotation. When the interest is in forecasting, for instance, the identification of the factors and the factor loadings is not an issue. On the other hand, in this paper we are interested in the factor loadings in order to relate the response of the estimated factor to the response of the variables. Therefore, it is important to estimate the identified factors and factor loadings. However, given that one factor is enough to capture the variation in the data, i.e. $r = 1$, identification is no longer problematic since the factors and factor loadings are identified up to a sign.
To sum up, in this section we construct a monthly dataset of realized volatilities of the con-

[14]Bai and Ng (2013) study the conditions for identifying the static factors when principal components are used in estimation.

stituents of the S&P500 index and its different sectors. The analysis of the dataset shows that the monthly realized volatilities have features, such as long memory, co-movement, conditional volatility, skewness, and heavy tails. To account for the stylized facts in the monthly realized volatilities, we use the DFM of Luciani and Veredas (2015) to consistently estimate the identified factors and their corresponding identified factor loadings from the different datasets. In the following sections, we include the estimated volatility factor(s) in a structural FAVAR model and analyze the response of the estimated volatility factor(s) to monetary policy shocks. From the response of the estimated volatility factor, we obtain the response of the different series from which the factor is extracted through equation (1.3). This is, however, not possible if we use the volatility of the S&P500 index instead of the volatility factor.

1.3 Structural VAR model

Since the seminal work of Sims (1980), VAR models have been the workhorse of empirical macroeconomics in both forecasting and structural analysis. In contrast to dynamic simultaneous equation models, VARs do not impose restrictions on the parameters; as a result, they allow for more general representation of the relationships in the data. Structural VARs are very useful in empirical analysis because they have different applications, such as impulse responses, forecast error variance decompositions, and historical decompositions. Impulse responses, which are of main interest in this paper, can be used to examine the expected response of the variables in the model to a structural shock. As a starting point, following the standard VAR literature, we define a VAR with an intercept in the reduced form as:

$$y_t = v + A_1 y_{t-1} + \ldots + A_p y_{t-p} + u_t, \tag{1.6}$$

where v is a $k \times 1$ vector of intercepts, y_t is a $k \times 1$ vector of endogenous variables, u_t is a $k \times 1$ vector of innovations with $E(u_t) = 0$ and $E(u_t u_t') = \Psi$, $A_1, \ldots, A_p$ are the $k \times k$ coefficient matrices, and p is the lag order.

1.3.1 Bayesian estimation

Due to the large dimensionality used in some approaches[15] in this paper, we use a Bayesian VAR (BVAR). The estimation of the BVAR follows the approach of Banbura

[15] Although the relatively parsimonious first approach can be estimated using classical methods, the second and the third approaches are of larger dimensions. In order to allow for fair comparison between all the three different approaches used in this paper, we use the same Bayesian estimation method for all the three approaches. In addition, the use of Bayesian techniques allows us to study the model using shorter sample periods.

et al. (2010) which is based on the earlier work of Litterman (1986), Kadiyala and Karlsson (1997), and Sims and Zha (1998). Following the idea of the Minnesota prior suggested by Litterman (1986) and the notation used by Banbura et al. (2010), we set the following moments for the coefficients' prior distribution:

$$E[(A_l)_{ij}] = \begin{cases} \pi_i, & i = j \ , \ l = 1 \\ 0, & \text{otherwise} \end{cases} , \tag{1.7}$$

$$V[(A_l)_{ij}] = \begin{cases} \dfrac{\lambda^2}{l^2}, & i = j \\ \dfrac{\lambda^2}{l^2}\dfrac{\sigma_i^2}{\sigma_j^2}, & \text{otherwise} \end{cases} , \tag{1.8}$$

where $(A_l)_{ij}$ is the ij-th coefficient of A_l. π_i reflects the researcher's belief about the persistence of variable i. For stationary variables, π_i should be close to 0, while for variables in levels, π_i is usually set to 1. The overall tightness of the prior distribution is controlled by the hyperparameter λ; for $\lambda = \infty$ the posterior expectations and the ordinary least squares estimates coincide, but if $\lambda = 0$, the posterior is equal to the prior. As has been shown in De Mol et al. (2008), when the number of variables in the system increases, the shrinkage should also increase in order to avoid over-fitting. In practice, σ_i^2 is usually replaced by the OLS estimate of the error variance from a univariate autoregressive model of order p in the i^{th} equation.

The Minnesota prior is an automatic way of choosing the coefficients' expectations and variances in which a distinction is made between own lags and lags of other dependent variables. In the Minnesota prior, with the exception of the coefficients of the dependent variable's first own lag, the prior's expectation of all the coefficients is zero. Since closer lags are expected to be more relevant, the factor $1/l^2$ allows the coefficients to be shrunk more as the lag length increases. The term σ_i^2/σ_j^2 addresses the difference in scaling and variability in the data. In the original Minnesota prior the coefficients are assumed to be normally and independently distributed, while the variance covariance matrix, Ψ, is assumed to be diagonal, fixed, and equal to Σ, where $\Sigma = \text{diag}(\sigma_1^2, \cdots, \sigma_k^2)$. Since the focus of this paper is in structural analysis, it is important to take into account the possible correlations between the residuals of the different variables. Therefore, the assumption of a diagonal covariance matrix is not reasonable. In order to avoid this implausible assumption, we follow Kadiyala and Karlsson (1997) and use a Normal inverted Wishart prior while maintaining the properties of the Minnesota prior. For clarity, we use a VAR in matrix form:

$$Y = XA + U, \tag{1.9}$$

where $Y = (y_1, \cdots, y_T)'$ is a $T \times k$ matrix of endogenous variables, $X = (x_1, \cdots, x_T)'$ and $x_t = (1, y'_{t-1}, \cdots, y'_{t-p})'$ is a $T \times m$ matrix of ones and lagged endogenous variables,

and $U = (u_1, \cdots, u_T)'$ is a $T \times k$ matrix of innovations. $A = (v, A_1, \cdots, A_p)'$ is a $m \times k$ matrix of coefficients, where $m = kp + 1$. The normal inverted Wishart prior can be written as:

$$\text{vec}(A)|\Psi \sim N(\text{vec}(A_0), \Psi \otimes \Omega_0) \quad \text{and} \quad \Psi \sim iW(S_0, a_0). \tag{1.10}$$

We choose the prior parameters A_0, Ω_0, S_0, and a_0 to allow the prior expectations and variances to match those implied by equations (1.7) and (1.8), and the expectation of Ψ to coincide with Σ of the Minnesota prior. The prior is implemented by adding dummy observations Y_d and X_d to the VAR in equation (1.9). The following T_d observations are added to the system:

$$Y_d = \begin{pmatrix} \text{diag}(\delta_1\sigma_1, \cdots, \delta_k\sigma_k)/\lambda \\ 0_{k(p-1)\times k} \\ \cdots\cdots\cdots\cdots\cdots\cdots \\ \text{diag}(\sigma_1, \cdots, \sigma_k) \\ \cdots\cdots\cdots\cdots\cdots\cdots \\ 0_{1\times k} \end{pmatrix} \quad X_d = \begin{pmatrix} 0_{kp\times 1} & J_p \otimes (\sigma_1, \cdots, \sigma_k)/\lambda \\ & \cdots\cdots\cdots\cdots\cdots\cdots \\ 0_{k\times 1} & 0_{k\times kp} \\ & \cdots\cdots\cdots\cdots\cdots\cdots \\ \kappa & 0_{1\times kp} \end{pmatrix},$$

where κ is a very small number reflecting the uninformative prior for the intercept and $J_p = \text{diag}(1, \cdots, p)$. Including the above set of dummy observations is similar to setting the normal inverted Wishart prior using $A_0 = (X_d'X_d)^{-1}X_d'Y_d$, $\Omega_0 = (X_d'X_d)^{-1}$, $S_0 = (Y_d - X_dA_0)'(Y_d - X_dA_0)$, and $a_0 = T_d - m$. The VAR in matrix form after augmenting the dummy observations to the VAR in equation (1.9):

$$Y_* = X_*A + U_*, \tag{1.11}$$

where $Y_* = (Y', Y_d')'$, $X_* = (X', X_d')'$, and $U_* = (U', U_d')'$. Defining $\tilde{A} = (X_*'X_*)^{-1}X_*'Y_*$ and $\tilde{\Sigma} = (Y_* - X_*\tilde{A})'(Y_* - X_*\tilde{A})$, the normal inverted Wishart posterior has the form:

$$\text{vec}(A)|\Psi, Y \sim N(\text{vec}(\tilde{A}), \Psi \otimes (X_*'X_*)^{-1}) \quad \text{and} \quad \Psi|Y \sim iW(\tilde{\Sigma}, T + k + 2). \tag{1.12}$$

Using the above formulation, the posterior expectation of the coefficients obtained from both the normal inverted Wishart and the Minnesota setups coincides with the OLS estimates obtained from the regression in equation (1.11).

1.3.2 Structural analysis

In the previous subsection we introduced the reduced form VAR model in order to allow for estimation; however, the main interest is in the structural shocks and not just the

reduced form shocks. To identify a monetary policy shock, we include in the monthly structural VAR the log of personal consumption expenditure (PCE)[16] as a measure of inflation, the log of industrial production (IP) as a measure of aggregate economic activity, and federal funds rate (FFR) as a monetary policy instrument. IP, PCE, and FFR are the minimum set of variables required to identify a monetary policy shock (see e.g. Christiano et al. (1999)). We also include the log of intermediate materials (COM)[17] as a forward looking variable in order to mitigate a possible price puzzle. To analyze the effects of a monetary policy shock on the stock market, we also include S&P500 returns (RET) in addition to measure(s) of volatility (VOL) in the structural VAR.

The variance covariance matrix of the reduced form VAR in equation (1.6) can be decomposed into $\Psi = W\Sigma_e W'$, where W is a lower triangular matrix with unit diagonal and Σ_e is a diagonal variance covariance matrix of the structural shocks. Using the Cholesky decomposition $\Psi = CC'$, we define $W = CD^{-1}$ where D is a diagonal matrix with the same elements as the main diagonal of C. Premultiplying the reduced form VAR by $B = W^{-1}$ gives the structural VAR:

$$By_t = \nu + B_1 y_{t-1} + \ldots + B_p y_{t-p} + e_t, \tag{1.13}$$

where $\nu = Bv$, $B_i = BA_i$ for $i = 1, \ldots, p$, and $e_t = Bu_t$ is a $K \times 1$ vector of structural shocks. In the literature different identifying assumptions could be imposed on the contemporaneous matrix B. Here we opt for the commonly used recursive ordering assumption which implies that B is a lower triangular matrix and hence provides enough restrictions to recover the structural shocks from the reduced form innovations. The variables in the structural VAR are ordered as follows:

$$y_t = (\text{COM}_t, \quad \text{PCE}_t, \quad \text{IP}_t, \quad \text{FFR}_t, \quad \text{RET}_t, \quad \text{VOL}_t{}')'. \tag{1.14}$$

This ordering scheme suggests that macroeconomic variables respond with a time lag to monetary policy shocks while stock market variables respond contemporaneously to all the variables in the system. FFR responds contemporaneously to all macroeconomic variables but responds with a time lag to financial stock market variables. This ordering scheme is suggested in many papers in the literature such as Christiano et al. (1999), Bernanke et al. (2005), among many others. The structural shock, e_t^{FFR}, from the FFR equation in equation (1.13) is identified as a monetary policy shock. The impulse responses to a structural monetary policy shock can be obtained from the infinite order moving average (MA) representation of equation (1.13). Since the model is exactly iden-

[16] We also tried to use consumer price index (CPI) as a measure of inflation: however, PCE provides a less pronounced price puzzle.

[17] COM was the best forward looking variable in mitigating the price puzzle among many variables that we tried.

tified, we compute the impulse responses and their error bands following Canova (1991) and Gordon and Leeper (1994). In this procedure, draws are first made from the posterior of the reduced form parameters and then structural parameters are computed for each draw.

1.4 Results

In this section we present the results for the three approaches used to analyze the effects of a monetary policy shock on the stock market volatility. In order to capture the long memory in the realized volatility we estimate all the structural VAR models using 6 lags. The results obtained from the Bayesian estimation are based on 20,000 draws. As suggested by Sims and Zha (1999), we use probability bands corresponding to 68%. To avoid misleading cancellation of the long run relationship between the variables, all the variables are included in levels with the exception of returns[18]. COM, PCE, IP, Ret and VOL are included in logs multiplied by 100; therefore, the impulse responses are percentage changes compared to the initial level. In all the studys we increase the federal funds rate by 100 basis points. To avoid over-fitting, parameters are shrunk more when the number of variables in the system increases or when the sample period is shorter. For the variables COM, PCE, IP,and FFR we set $\pi_i = 1$, for RET we set $\pi_i = 0$, while for VOL we use $\pi_i = 0.3$[19].

1.4.1 One factor structural FAVAR

In this approach we augment the estimated volatility factor from the whole panel of realized volatilities in a structural FAVAR model, i.e., in equation (1.14), $\text{VOL}_t \equiv \hat{F}_t$. This parsimonious approach allows us to analyze the response of the aggregate market volatility to a monetary policy shock[20]. In addition, using equation (1.3), impulse responses of each single stock to a monetary policy shock can be obtained by multiplying the impulse responses of the volatility factor by the corresponding factor loading. Since the whole variation of the panel of volatilities is summarized by only one factor, the responses of the single stocks only vary in magnitude[21] but not in dynamics.
The impulse responses of the variables in the system estimated using the sample between February 1973 and July 2012 are shown in Figure 1.4.1. The results show that industrial

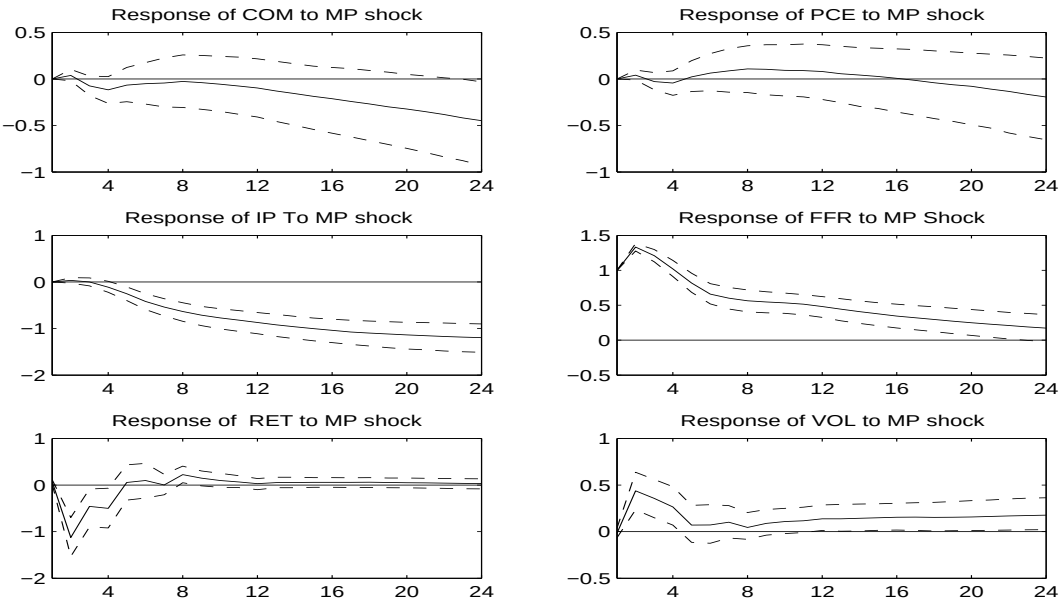
[18] As a robustness check, we also included the macroeconomic variables in growth rates; the results, however, do not vary.

[19] We also used different sets of sensible values for π_i; However, the results are robust to the different choices.

[20] For robustness, a similar exercise is conducted while substituting the volatility factor with the volatility of the S&P500 index. The results obtained are quite similar; this validates our usage of a volatility factor in the analysis instead of including a volatility of an index.

[21] Although in this approach the responses of the stocks are allowed to vary in magnitude and direction, the factor loadings are positive in 211 out of 213 stocks included in the panel of volatilities.

Figure 1.4.1: Impulse responses for the macroeconomic and financial variables



Responses of the variables included in the FAVAR to a contractionary monetary policy shock. The dashed lines are the 16^{th} and 84^{th} quantiles from the posterior draws, and thus corresponds to a one standard deviation posterior probability band under normality. The model is estimated using the sample between February 1973 and July 2012.

production significantly goes down 4 months following a monetary policy shock; this is in line with theory. The response of the personal consumption expenditure is, however, not significant. Although, according to theory, inflation should go down following a contractionary monetary policy shock, a large literature documents a price puzzle in structural VARs (see e.g. Hanson (2004)). Stock market returns decrease by more than 1% while the volatility factor increases by more than 0.4% after the shock. The stock market returns reach their lowest level one month after the shock and then start to increase reaching a positive value after 7 periods and then return to their initial value. Similarly, the estimated volatility factor attains its highest level after one month and tapers back to its original state after 4 months. In accordance with the theory, the results show that the stock markets returns decrease while the volatility increases following a tightening monetary policy. In addition, a strong negative correlation between stock market returns and volatility is quite obvious from the impulse responses.

Assuming that the parameters of the model remain constant in a long sample period might not be appropriate. Therefore, in order to have a better understanding of the dynamic response of the stock market variables to a monetary policy shock, we estimate the model over shorter sample periods[22]. In the first sample we estimate the model in the period

[22]Alternatively one can estimate the model in a long sample period using either a structural time-varying parameter VAR (TVP-VAR) or Markov-switching VAR (MS-VAR). In the TVP-VAR, the underlying assumption is that the parameters of the model vary smoothly between consecutive periods. On the other

between February 1973 and January 1978. This sample represents the period when the Federal Reserve was under the chairmanship of Arthur F. Burns. Although Arthur F. Burns was the chairman from February 1970 to January 1978, the starting date of our sample is determined by the availability of the data. The results of the impulse responses for this sample period is shown in Figure 1.A.3 in Appendix 1.A. Following a monetary policy shock, industrial production significantly goes down while personal consumption expenditure moves slightly up. It is worth noting here that according to Taylor (1999), the Federal Reserve accommodated inflation to a larger degree before the 1980s. The stock returns fall down by less than 3% after one period and returns back to their original position after 2 periods. In the long run, we can also observe positivie slight changes in stock returns which only last for short periods. In this sample period the monetary policy has a strong effect on the stock returns in terms of magnitude, but these effects only last for short durations. On the other hand, the response of the volatility during this period is insignificant.

The second sample period used is August 1979 to July 1987. Paul Volcker, who is accredited of ending the high inflation during the early 1980s, was the chairman of the Federal Reserve during this period. Figure 1.A.4 in Appendix 1.A shows the impulse responses of the system under the chairmanship of Paul Volcker. The industrial production starts to decrease 4 months after the monetary policy shock. Eight months after the monetary policy shock, the personal consumption expenditure falls significantly. The stock market returns decrease by more than 0.6% two months after the shock, while the volatility increases by less than 0.2% immediately after the shock and then starts to return back to its original state after two months. According to these results, a monetary policy shock of a similar size has a stronger impact on inflation during Volcker's period compared to Burn's period. On the other hand, the response of the stock market returns to a monetary policy shock is stronger and faster during Burn's period. In both periods, the responses of the stock market volatility are minimal.

In the third experiment, we examine the period between August 1987 and January 2006 when Alan Greenspan was the chairman of the Federal Reserve. During Greenspan's chairmanship of the Federal Reserve, the financial markets experienced both the Black Monday and the dot-com bubble. Since the financial market has strong effects on the economy, one should expect the Federal Reserve to use its own tools to influence the financial market in order to achieve its macroeconomic targets. The results of the impulse responses are shown in Figure 1.A.5 in Appendix 1.A. Industrial production initially increases for three periods following a contractionary monetary policy shock and then begins to decrease. Although this contradicts the theory, this result is not uncommon in the

hand, the MS-VAR assumes that all growth periods as well as all recession periods are similar in different times. However, since we have 6 variables in the system, the estimation of both models is exhaustive and a lot of shrinkage should be applied to allow for estimation. Therefore, we prefer to estimate the model at meaningful shorter sample periods.

literature (see e.g. Brissimis and Magginas (2006)). In this sample period, we can also observe a strong price puzzle which lasts for more than 6 months. The responses of stock market variables are quite pronounced during Greenspan's period. Stock returns decrease by around 5% one period after the shock and then start to increase again reaching their original state after 5 months. The volatility factor increases by around 0.8% following the shock and then starts decreasing immediately. These results might suggest that the decisions made by the Federal Reserve during this period had a strong influence on the financial market, specially during financial crises periods.
The last sample covers the period between February 2006 and July 2012. This represents the period under the chairmanship of Ben Bernanke. Analyzing this period is quite difficult because it is mainly covered by the recent financial crises. In addition, in a large part of the sample the federal funds rate is close to zero and the Federal Reserve is using quantitative easing. Although it might be inappropriate to use our methodology to identify a monetary policy shock in this sample period, we include the results for completeness[23]. The impulse responses are shown in Figure 1.A.6 in Appendix 1.A. Both industrial production and personal consumption expenditure decrease following the shock. The stock market returns decrease by around 6% one period after the shock and remain at this level for three periods and then start to increase again afterwards. After one period, the volatility factor starts increasing for three periods by 5% and then decreases to its initial value. In general, the responses of the variables to a monetary policy shock are stronger in magnitude and more persistent in this sample period compared to previous periods.

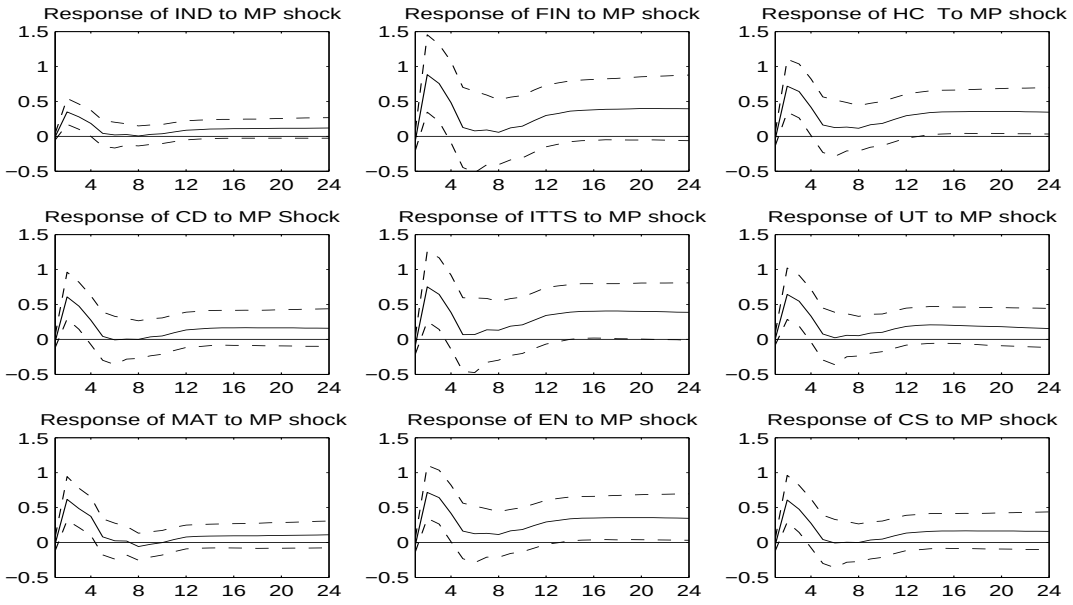
1.4.2 Sectors structural FAVAR

The assumption implied by the first approach is that the dynamics of the impulse responses of the single stocks' volatilities do not vary. This might be too restrictive. In order to relax this assumption, we include the volatility factors estimated from each sector in the FAVAR instead of including only one factor representing all stocks. Therefore, in this approach, we use $\text{VOL}_t \equiv \hat{F}_{t,sectors}$ in equation (1.14), where $\hat{F}_{t,sectors}$ is a 9×1 vector of the estimated volatility factors from each of the 9 different sectors. This approach allows us to investigate the responses of the different sectors to a monetary policy shock; both the magnitude and the dynamics of the sectors' responses are allowed to vary. Within each sector, the impulse response of each stock's volatility to a monetary policy shock can be obtained by multiplying the impulse response of the sector's volatility by the corresponding factor loading of the stock. Since only one factor summarizes the variation within each sector, the impulse responses of the different stocks in each sector only vary in magnitude. Given that companies which have large market cap tend to have larger

[23]We also estimate the model in the period between February 2006 and November 2008 to avoid the period where the federal funds rate is close to zero; the results are similar to the ones reported.

factor loadings compared to other companies within the same sector as shown in Table 1.A.1 in Appendix 1.A, the magnitude of the volatility responses of the large market cap companies is in general stronger. In other words, since the volatility factors of the different sectors load more on large market cap companies, the volatility responses of these companies are, in general, more affected by the responses of the volatility factors.

Figure 1.4.2: Impulse responses for the different sectors



Responses of the volatilities of the different sectors included in the FAVAR to a contractionary monetary policy shock. The dashed lines are the 16^{th} and 84^{th} quantiles from the posterior draws, and thus corresponds to a one standard deviation posterior probability band under normality. The model is estimated using the sample between February 1973 and July 2012.

The impulse responses of the different sectors to a monetary policy shock using the sample period between February 1973 and July 2012 are shown in Figure 1.4.2. The magnitude of the responses vary between the sectors. The results show that the response of the financials sector to a monetary policy shock is stronger than other sectors; this result confirms the findings of Chuliá et al. (2010). On the other hand, the response of the industrials sector is less sensitive to monetary policy shocks compared to other sectors. The dynamics of the responses of the different sectors look very similar; the volatility increases one period after the shock and then starts tapering to its original value. The results obtained from this approach imply that there is a dynamic common factor which leads the co-movement of the different sectors.

1.4.3 Structural VAR for volatilities

Instead of using a structural FAVAR model, in this approach we include realized volatilities of different stocks directly in a structural VAR. This approach allows us to analyze

the response of the volatilities of the different stocks to monetary policy shocks without any restrictions on their magnitude or dynamics. However, due to the large dimensionality of this structural VAR, the number of realized volatilities that can be included in the structural VAR is restricted. Following the large BVAR approach of Banbura et al. (2010), we use $\text{VOL}_t \equiv RV_{t,all}$ in equation (1.14), where $RV_{t,all}$ is a 54×1 vector of realized volatilities of 54 stocks from the volatilities dataset, so we include 6 stocks from each of the 9 sectors included in the dataset. Due to the very large dimensionality of this model, a lot of shrinkage should be imposed in order to avoid over-fitting[24]. The responses of the 54 volatility series to a monetary policy shock are shown in Figures 1.A.7, 1.A.8, and 1.A.9 in Appendix 1.A. In these figures we do not observe positive responses from the volatility series and most of the responses are not significant, possibly due the large amount of shrinkage used in estimation. Therefore, to avoid the massive shrinkage used in the very large dimensional VARs, we propose the use of approximately 20 volatility series in the structural VAR, this is equivalent to the medium VAR used in Banbura et al. (2010)[25]. So we proceed by including volatility series from each sector separately to the structural VAR.

Figures 1.A.10 and 1.A.11 in Appendix 1.A show the responses of the realized volatilities of the stocks in both the energy and materials sectors to a monetary policy shock in the period between February 1973 and July 2012. For the energy sector in Figure 1.A.10, we include $\text{VOL}_t \equiv RV_{t,energy}$ in equation (1.14), where $RV_{t,energy}$ is a 17×1 vector of the realized volatilities of the stocks in the energy sector. And for the materials sector in Figure 1.A.11, we include $\text{VOL}_t \equiv RV_{t,materials}$ in equation (1.14), where $RV_{t,materials}$ is a 16×1 vector of the realized volatilities of the stocks in the materials sector. In both figures the dynamics of the responses of the different realized volatilities look very similar; however, the magnitude and the significance of the responses vary between the different stocks. In Figure 1.A.10, we observe that the responses of both Chevron Corp. and Exxon Mobil Corp. have strong magnitude compared to other companies in the energy sector; both companies have large factor loadings as shown in Table 1.A.1 in Appendix 1.A and have large market cap. In Figure 1.A.11, we notice that Dow Chemical, which has a large factor loading and large market cap, shows a response with strong magnitude.

Although this approach allows the dynamics of the responses to be different, the variation between the dynamics of the responses of the realized volatilities is minimal. The results of the impulse responses obtained from this totally unrestricted approach justify our results from the first and the second approach. In addition, we highlight that companies with large market cap are more likely to have larger factor loadings and stronger responses to monetary policy shocks in terms of magnitude. The results might suggest

[24] See Banbura et al. (2010) for details on how the shrinkage parameter should be chosen.

[25] Banbura et al. (2010) suggest that including 20 variables in a structural VAR is sufficient to capture the relevant shocks and information.

that the monetary policy shocks affect the dynamic common volatility factor of the stock market, and as a result the companies which are highly loaded on by the volatility factor are the ones that are more affected by the shocks.

1.5 Conclusion

In this paper we study the responses of the aggregate market volatility, the sectors' volatilities, and the stocks' volatilities to monetary policy shocks. First, we construct a monthly dataset of realized volatilities which consists of the components of the S&P500 index. The monthly dataset is analyzed and the presence of long memory, conditional heteroskedasticity, skewness, and heavy tails is evident in the monthly realized volatilities. In order to account for the aforementioned stylized facts present in the data, we follow Luciani and Veredas (2015) and estimate the volatility factors by applying the principle components method on the differenced data. It is shown that only one volatility factor is enough to appropriately summarize the variation in the data suggesting that there is a dynamic common factor leading the co-movement of the different stocks in the market.

In the second estimation step, we augment a VAR with macroeconomic variables with the estimated volatility factor to form a structural FAVAR model. The FAVAR is used to analyze the response of the stock market volatility to a contractionary monetary policy shock. The approaches used in this paper allow us to examine the volatility response of the different sectors and the individual stocks. The results of the impulse responses suggest that the stock market returns decrease while the volatility increases following a monetary policy tightening; a strong negative correlation between returns and volatility can be observed from their dynamic responses. Although the dynamics do not vary widely between the responses of the different stocks and sectors, the magnitude of the responses differs. For instance, the response of the financials sector to a monetary policy shock is stronger in magnitude than other sectors. Moreover, companies with large market cap are more likely to exhibit responses with stronger magnitude. In addition, we analyze the responses of the variables in the system at different policy regimes. According to the results, starting from Greenspan's chairmanship of the Federal Reserve, the responses of stock market variables to monetary policy shocks become more pronounced compared to earlier periods.

The results are important for both investors and policy makers. From investors' perspective, an investor can make profitable trades if he successfully anticipates policy actions. From the policy point of view, understanding the magnitude and dynamics of the response of the stock market variables to policy actions is very important because this response can influence the real economy through different channels.

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1.A Appendix

Table 1.A.1: Dataset for financial stocks

	Name	Code	Sector	$\hat{\Lambda}$
1	3M	902172(P)	IND	0.17
2	ABBOTT LABORATORIES	916328(P)	HC	0.29
3	ADVANCED MICRO DEVC.	936365(P)	ITTS	0.27
4	AGL RESOURCES	906820(P)	UT	0.23
5	AIR PRDS.& CHEMS.	905271(P)	MAT	0.30
6	ALCOA	905113(P)	MAT	0.26
7	ALTRIA GROUP	904853(P)	CS	0.18
8	AMER.ELEC.PWR.	905425(P)	UT	0.15
9	AMERICAN EXPRESS	906156(P)	FIN	0.20
10	AMERICAN INTL.GP.	916305(P)	FIN	0.25
11	ANALOG DEVICES	905276(P)	ITTS	0.24
12	APACHE	921983(P)	EN	0.26
13	APPLIED MATS.	905296(P)	ITTS	0.21
14	ARCHER-DANLS.-MIDL.	921093(P)	CS	0.18
15	AUTOMATIC DATA PROC.	912669(P)	ITTS	0.24
16	AVERY DENNISON	921161(P)	IND	0.21
17	AVON PRODUCTS	905793(P)	CS	0.21
18	BALL	932060(P)	MAT	0.26
19	BANK OF AMERICA	923937(P)	FIN	0.22
20	BANK OF NEW YORK MELLON	905840(P)	FIN	0.22
21	C R BARD	905592(P)	HC	0.22
22	BAXTER INTL.	916365(P)	HC	0.28
23	BB&T	992305(P)	FIN	0.12
24	BEAM	904259(P)	CD	0.19
25	BECTON DICKINSON	905876(P)	HC	0.26
26	BEMIS	912125(P)	MAT	0.24
27	H&R BLOCK	905596(P)	CD	0.15
28	BOEING	904818(P)	IND	0.18
29	BRISTOL MYERS SQUIBB	905080(P)	HC	0.30
30	BROWN-FORMAN 'B'	912216(P)	CS	0.16
31	CAMPBELL SOUP	905075(P)	CS	0.21
32	CATERPILLAR	902224(P)	IND	0.19
33	CENTERPOINT EN.	904842(P)	UT	0.20
34	CENTURYLINK	906838(P)	ITTS	0.16

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Table 1.A.1 – *Continued from previous page*

	Name	**Code**	**Sector**	$\hat{\Lambda}$
35	CHEVRON	905024(P)	EN	0.29
36	CHUBB	916790(P)	FIN	0.21
37	CINCINNATI FINL.	951545(P)	FIN	0.16
38	CLIFFS NATURAL RESOURCES	912420(P)	MAT	0.19
39	CLOROX	916125(P)	CS	0.17
40	CMS ENERGY	901686(P)	UT	0.15
41	COCA COLA	904282(P)	CS	0.24
42	COLGATE-PALM.	906148(P)	CS	0.23
43	COMCAST 'A'	981550(P)	CD	0.11
44	COMERICA	922964(P)	FIN	0.19
45	COMPUTER SCIS.	916091(P)	ITTS	0.17
46	CONAGRA FOODS	929814(P)	CS	0.21
47	CONOCOPHILLIPS	901666(P)	EN	0.25
48	CONSOLIDATED EDISON	902288(P)	UT	0.21
49	COOPER INDUSTRIES	912568(P)	IND	0.16
50	CORNING	912273(P)	IND	0.16
51	CUMMINS	905966(P)	IND	0.16
52	CVS CAREMARK	912635(P)	CS	0.19
53	DEERE	906189(P)	IND	0.15
54	R R DONNELLEY & SONS	905047(P)	IND	0.17
55	DOVER	904830(P)	IND	0.20
56	DOW CHEMICAL	905114(P)	MAT	0.29
57	DTE ENERGY	905214(P)	UT	0.18
58	E I DU PONT DE NEMOURS	902199(P)	MAT	0.31
59	DUKE ENERGY	904383(P)	UT	0.21
60	EATON	903749(P)	IND	0.21
61	ECOLAB	921268(P)	MAT	0.20
62	EDISON INTL.	902324(P)	UT	0.19
63	EMERSON ELECTRIC	905115(P)	IND	0.16
64	ENTERGY	902306(P)	UT	0.18
65	EQT	904390(P)	UT	0.13
66	EQUIFAX	906194(P)	FIN	0.15
67	EXELON	902317(P)	UT	0.18
68	EXXON MOBIL	905039(P)	EN	0.31
69	FAMILY DOLLAR STORES	923755(P)	CD	0.14
70	FIRST HORIZON NATIONAL	905780(P)	FIN	0.15

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Table 1.A.1 – *Continued from previous page*

	Name	**Code**	**Sector**	$\hat{\Lambda}$
71	FIRSTENERGY	905159(P)	UT	0.17
72	FLOWSERVE	905755(P)	IND	0.13
73	FMC	905082(P)	MAT	0.22
74	FORD MOTOR	902230(P)	CD	0.21
75	FOREST LABS.	921276(P)	HC	0.22
76	FRONTIER COMMUNICATIONS	922301(P)	ITTS	0.08
77	GANNETT	923449(P)	CD	0.23
78	GENERAL DYNAMICS	907652(P)	IND	0.17
79	GENERAL ELECTRIC	906150(P)	IND	0.21
80	GENERAL MILLS	905801(P)	CS	0.23
81	GENUINE PARTS	906511(P)	CD	0.20
82	GOODYEAR TIRE & RUB.	904837(P)	CD	0.19
83	WW GRAINGER	905898(P)	IND	0.18
84	HALLIBURTON	904678(P)	EN	0.28
85	HARRIS	905409(P)	ITTS	0.26
86	HASBRO	912030(P)	CD	0.17
87	HJ HEINZ	902262(P)	CS	0.23
88	HELMERICH & PAYNE	921049(P)	EN	0.26
89	HESS	905802(P)	EN	0.26
90	HEWLETT-PACKARD	905277(P)	ITTS	0.21
91	HORMEL FOODS	921051(P)	CS	0.13
92	HOST HOTELS & RESORTS	912588(P)	FIN	0.18
93	HUMANA	916860(P)	HC	0.22
94	INTERNATIONAL BUS.MCHS.	906187(P)	ITTS	0.31
95	HUNTINGTON BCSH.	951068(P)	FIN	0.17
96	ILLINOIS TOOL WORKS	905052(P)	IND	0.20
97	INGERSOLL-RAND	905446(P)	IND	0.20
98	INTEGRYS ENERGY GROUP	902336(P)	UT	0.21
99	INTEL	922726(P)	ITTS	0.30
100	INTL.PAPER	904069(P)	MAT	0.30
101	INTERPUBLIC GP.	923465(P)	CD	0.16
102	JACOBS ENGR.	912142(P)	IND	0.14
103	JOHNSON & JOHNSON	912212(P)	HC	0.33
104	JOHNSON CONTROLS	907677(P)	CD	0.20
105	JP MORGAN CHASE & CO.	902242(P)	FIN	0.23
106	KELLOGG	905922(P)	CS	0.25

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Table 1.A.1 – *Continued from previous page*

	Name	**Code**	**Sector**	$\hat{\Lambda}$
107	KIMBERLY-CLARK	902354(P)	CS	0.18
108	KROGER	912134(P)	CS	0.16
109	LEGGETT&PLATT	906487(P)	CD	0.15
110	LENNAR 'A'	912219(P)	CD	0.14
111	LEUCADIA NATIONAL	921925(P)	FIN	0.15
112	ELI LILLY	921290(P)	HC	0.28
113	LIMITED BRANDS	937343(P)	CD	-0.03
114	LINCOLN NAT.	912402(P)	FIN	0.21
115	LOEWS	922418(P)	FIN	0.19
116	LOWE'S COMPANIES	905620(P)	CD	0.16
117	M&T BK.	951503(P)	FIN	0.17
118	MARSH & MCLENNAN	904780(P)	FIN	0.21
119	MASCO	905624(P)	IND	0.16
120	MATTEL	912811(P)	CD	0.17
121	MCCORMICK & CO NV.	510493(P)	CS	0.14
122	MCDONALDS	921910(P)	CD	0.19
123	MCGRAW-HILL	905414(P)	CD	0.19
124	MEADWESTVACO	905806(P)	MAT	0.27
125	MEDTRONIC	906496(P)	HC	0.21
126	MOLEX	929635(P)	ITTS	0.24
127	MOTOROLA SOLUTIONS	904878(P)	ITTS	0.30
128	MURPHY OIL	906404(P)	EN	0.25
129	MYLAN	906931(P)	HC	0.00
130	NABORS INDS.	916532(P)	EN	-0.05
131	NEWELL RUBBERMAID	906933(P)	CD	0.16
132	NEWMONT MINING	912160(P)	MAT	0.18
133	NEXTERA ENERGY	905016(P)	UT	0.20
134	NISOURCE	906176(P)	UT	0.17
135	NOBLE ENERGY	906557(P)	EN	0.25
136	NORDSTROM	906560(P)	CD	0.17
137	NORTHEAST UTILITIES	921999(P)	UT	0.20
138	NORTHERN TRUST	905861(P)	FIN	0.17
139	NORTHROP GRUMMAN	905809(P)	IND	0.15
140	NUCOR	921482(P)	MAT	0.24
141	OCCIDENTAL PTL.	905102(P)	EN	0.26
142	OMNICOM GP.	932913(P)	CD	0.17

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Table 1.A.1 – *Continued from previous page*

	Name	**Code**	**Sector**	$\hat{\Lambda}$
143	ONEOK	904480(P)	UT	0.14
144	PACCAR	921757(P)	IND	0.15
145	PALL	921484(P)	IND	0.12
146	PARKER-HANNIFIN	905150(P)	IND	0.20
147	PENNEY JC	912781(P)	CD	0.18
148	PEPCO HOLDINGS	904509(P)	UT	0.20
149	PEPSICO	905677(P)	CS	0.24
150	PERKINELMER	912157(P)	HC	0.26
151	PFIZER	904030(P)	HC	0.29
152	PG&E	902314(P)	UT	0.20
153	PINNACLE WEST CAP.	902607(P)	UT	0.17
154	PITNEY-BOWES	905118(P)	IND	0.16
155	PNC FINL.SVS.GP.	944175(P)	FIN	0.22
156	PPG INDUSTRIES	901897(P)	MAT	0.29
157	PPL	902107(P)	UT	0.17
158	PREC.CASTPARTS	997350(P)	IND	0.06
159	PROCTER & GAMBLE	912228(P)	CS	0.28
160	PROGRESSIVE OHIO	936324(P)	FIN	0.18
161	PUB.SER.ENTER.GP.	902321(P)	UT	0.21
162	RAYTHEON 'B'	912633(P)	IND	0.19
163	REGIONS FINL.NEW	951051(P)	FIN	0.12
164	ROBERT HALF INTL.	923649(P)	IND	0.13
165	ROCKWELL AUTOMATION	902233(P)	IND	0.18
166	ROWAN COMPANIES CL.A	907620(P)	EN	0.27
167	RYDER SYSTEM	906284(P)	IND	0.19
168	SCANA	904539(P)	UT	0.20
169	SCHLUMBERGER	912090(P)	EN	0.30
170	SEALED AIR	923036(P)	MAT	0.18
171	SEMPRA EN.	902103(P)	UT	0.19
172	SHERWIN-WILLIAMS	905361(P)	CD	0.18
173	J M SMUCKER	912441(P)	CS	0.16
174	SNAP-ON	906400(P)	CD	0.20
175	SOUTHERN	902325(P)	UT	0.20
176	SOUTHWEST AIRLINES	905647(P)	IND	0.15
177	SOUTHWESTERN ENERGY	930551(P)	EN	0.11
178	SPRINT NEXTEL	904864(P)	ITTS	0.18

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Table 1.A.1 – *Continued from previous page*

	Name	**Code**	**Sector**	$\hat{\Lambda}$
179	STANLEY BLACK & DECKER	921503(P)	CD	0.20
180	STARWOOD HTLS.& RSTS.	514950(P)	CD	0.17
181	STATE STREET	951052(P)	FIN	0.21
182	SUNOCO	905255(P)	EN	0.22
183	SYSCO	916079(P)	CS	0.21
184	TARGET	923425(P)	CD	0.20
185	TECO ENERGY	905454(P)	UT	0.19
186	TENET HLTHCR.	912969(P)	HC	0.16
187	TERADYNE	912744(P)	ITTS	0.29
188	TESORO	912052(P)	EN	0.15
189	TEXAS INSTS.	905061(P)	ITTS	0.26
190	TEXTRON	921649(P)	IND	0.19
191	THE HERSHEY COMPANY	905077(P)	CS	0.19
192	TRAVELERS COS.	933974(P)	FIN	0.21
193	THERMO FISHER SCIENTIFIC	906394(P)	HC	0.24
194	TJX COS.	921855(P)	CD	0.17
195	TORCHMARK	993394(P)	FIN	0.20
196	TYSON FOODS 'A'	906643(P)	CS	0.13
197	UNION PACIFIC	905105(P)	IND	0.19
198	UNITED TECHNOLOGIES	905122(P)	IND	0.19
199	V F	901892(P)	CD	0.19
200	VARIAN MED.SYS.	906220(P)	HC	0.26
201	VORNADO REALTY TST.	912146(P)	FIN	0.12
202	VULCAN MATERIALS	905816(P)	MAT	0.20
203	WAL MART STORES	916548(P)	CS	0.22
204	WALGREEN	904866(P)	CS	0.18
205	WALT DISNEY	921964(P)	CD	0.20
206	WASHINGTON PST.'B'	922079(P)	CD	0.15
207	WEYERHAEUSER	905818(P)	FIN	0.19
208	WHIRLPOOL	904869(P)	CD	0.21
209	WILLIAMS COS.	922407(P)	EN	0.21
210	WISCONSIN ENERGY	902335(P)	UT	0.21
211	XCEL ENERGY	905010(P)	UT	0.21
212	XEROX	905284(P)	ITTS	0.28
213	ZIONS BANCORP.	951584(P)	FIN	0.18

The table contains a list of the companies that are part of the S&P500 index and cover the period from 02/01/1973 to 31/07/2012. The data, obtained from Datastream, represents 9 different sectors, namely, industrials (IND), financials (FIN), health care (HC), consumer discretionary (CD), information technology and telecommunications services (ITTS), utilities (UT), materials (MAT), energy (EN), and consumer staples (CS). The names and codes are similar to the ones used by Datastream. The factor loading, Λ, obtained from the dynamic factor model, shows how the estimated first volatility factor for each sector loads on the monthly realized volatility of each company within the sector.

Table 1.A.2: Descriptive statistics for annualized realized volatilities (without taking the logs)

		ALL	IND	FIN	HC	CD	ITTS	UT	MAT	EN	CS
						ARFIMA $(1, d, 0)$					
	max.	0.80	0.66	0.80	0.54	0.69	0.61	0.59	0.61	0.62	0.53
d	med.	0.48	0.48	0.63	0.43	0.50	0.48	0.45	0.50	0.47	0.48
	min.	0.30	0.33	0.42	0.30	0.32	0.38	0.33	0.36	0.35	0.38
						Autocorrelation					
	max.	0.85	0.77	0.82	0.66	0.85	0.75	0.72	0.78	0.75	0.66
Lag 1	med.	0.60	0.58	0.72	0.56	0.62	0.61	0.58	0.63	0.65	0.56
	min.	0.37	0.41	0.46	0.37	0.44	0.40	0.45	0.51	0.56	0.40
	max.	0.72	0.54	0.63	0.56	0.72	0.54	0.47	0.57	0.50	0.50
Lag 6	med.	0.36	0.34	0.46	0.34	0.37	0.40	0.31	0.33	0.35	0.33
	min.	0.16	0.20	0.24	0.17	0.20	0.23	0.16	0.20	0.21	0.17
	max.	0.62	0.49	0.48	0.48	0.62	0.42	0.35	0.42	0.43	0.40
Lag 12	med.	0.23	0.22	0.25	0.27	0.24	0.32	0.21	0.19	0.22	0.23
	min.	0.01	0.03	0.17	0.14	0.14	0.13	0.01	0.07	0.09	0.04
						Autocorrelation squares					
	max.	0.83	0.75	0.83	0.64	0.82	0.76	0.72	0.81	0.78	0.63
Lag 1	med.	0.59	0.57	0.72	0.52	0.61	0.56	0.56	0.62	0.63	0.59
	min.	0.35	0.36	0.43	0.37	0.38	0.35	0.44	0.42	0.57	0.35
	max.	0.65	0.52	0.59	0.52	0.65	0.48	0.36	0.45	0.37	0.48
Lag 6	med.	0.28	0.28	0.40	0.23	0.30	0.34	0.22	0.27	0.26	0.25
	min.	0.07	0.12	0.16	0.09	0.14	0.14	0.10	0.10	0.12	0.07
						Skewness					
	max.	3.60	2.67	3.60	2.37	2.34	2.29	3.12	2.70	3.60	1.77
	med.	1.69	1.61	2.00	1.32	1.56	1.40	2.04	1.76	1.94	1.34
	min.	0.78	0.78	1.22	0.78	1.03	1.06	1.64	1.23	1.49	0.86
						Kurtosis					
	max.	21.51	13.05	20.51	11.95	10.42	10.40	17.57	14.03	21.51	8.34
	med.	7.46	6.92	9.50	5.44	6.27	5.59	9.33	7.84	9.92	5.76
	min.	3.59	3.59	4.88	3.71	4.09	4.30	6.87	5.37	7.12	3.66

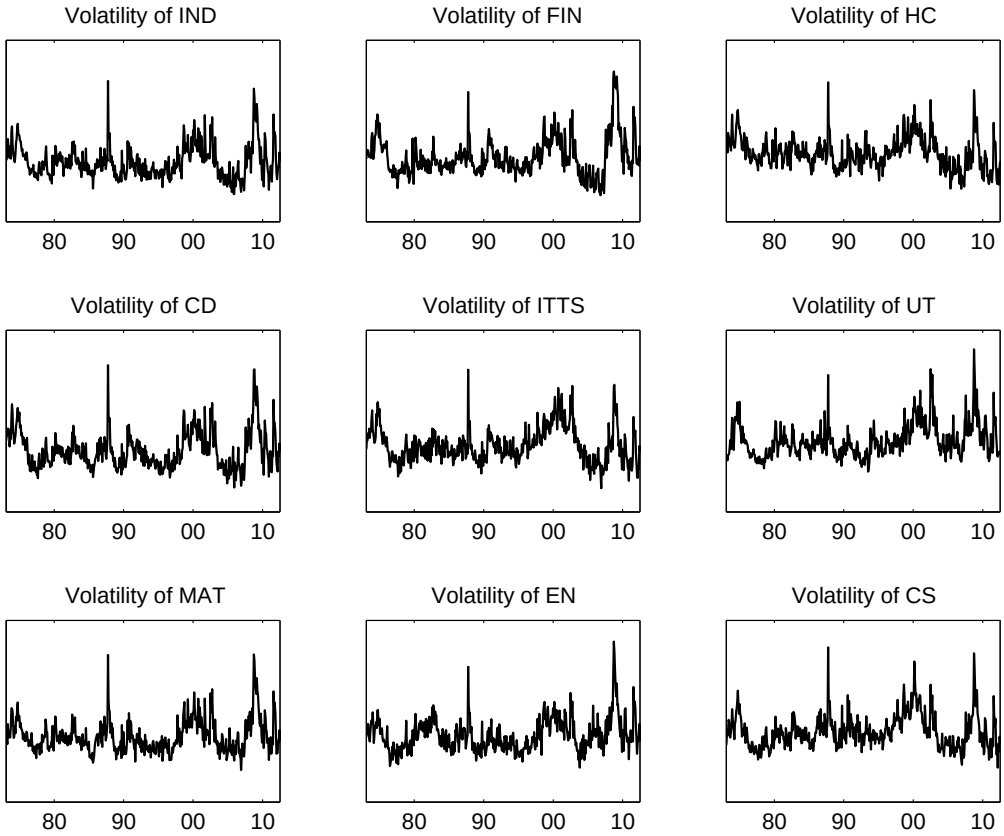
Descriptive statistics for the annualized monthly realized volatilities (caluclated without taking the logs as: $RV_t^i = \sqrt{12 \times \sum_{n=1}^{N} \left(R_{n,t}^i - \overline{R}_t^i\right)^2}$) for (ALL) 213 companies from S&P 500 in the period between January 1973 and July 2012 representing 9 sectors: industrials (IND), financials (FIN), health care (HC), consumer discretionary (CD), information technology and telecommunications services (ITTS), utilities (UT), materials (MAT), energy (EN), and Consumer staples (CS). The first panel shows the fractional integration parameter d estimated from ARFIMA$(1, d, 0)$, the second panel presents autocorrelations for lags 1, 6, and 12, the third panel shows the autocorrelations for squared volatilities for lags 1 and 6, and the fourth and fifth panels show skewness and kurtosis respectively. All panels present maximum (max.), median (med.), and minimum (min.) values.

Table 1.A.3: Correlations between different volatility factors

	S&P	ALL	IND	FIN	HC	CD	ITTS	UT	MAT	EN	CS
S&P500	1	0.90	0.89	0.84	0.72	0.87	0.77	0.77	0.88	0.81	0.80
ALL		1	0.97	0.93	0.85	0.96	0.89	0.85	0.95	0.86	0.91
IND			1	0.90	0.84	0.95	0.86	0.75	0.94	0.82	0.85
FIN				1	0.72	0.91	0.76	0.75	0.88	0.77	0.81
HC					1	0.80	0.86	0.64	0.76	0.66	0.84
CD						1	0.83	0.75	0.93	0.82	0.84
ITTS							1	0.72	0.79	0.68	0.86
UT								1	0.77	0.75	0.74
MAT									1	0.85	0.82
EN										1	0.74
CS											1

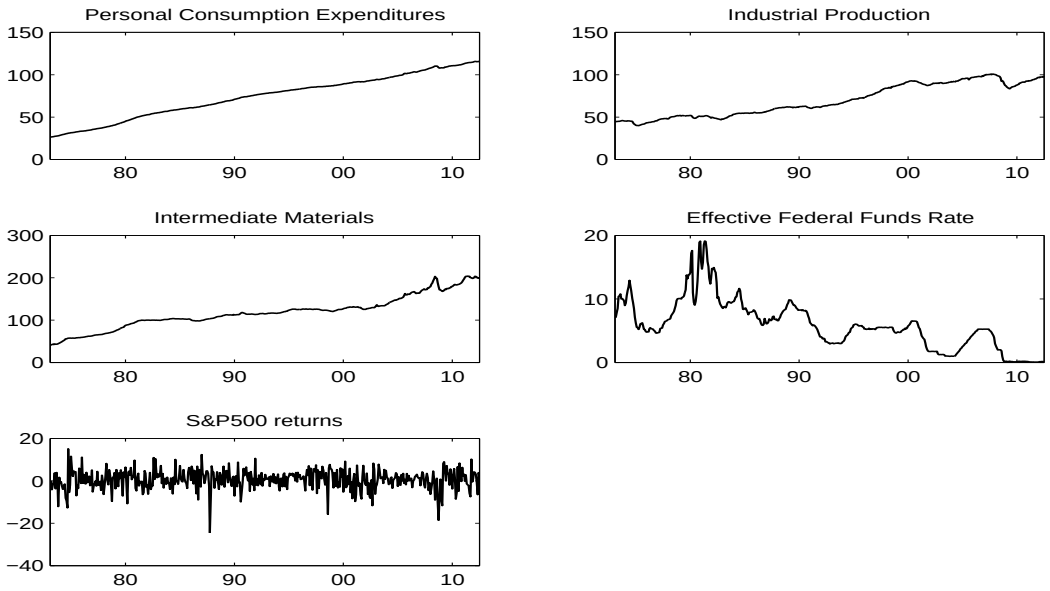
Correlation coefficients between the monthly volatility of the S&P500 index and the estimated volatility factors from the different sectors and the whole dataset.

Figure 1.A.1: Volatility plots of the different sectors



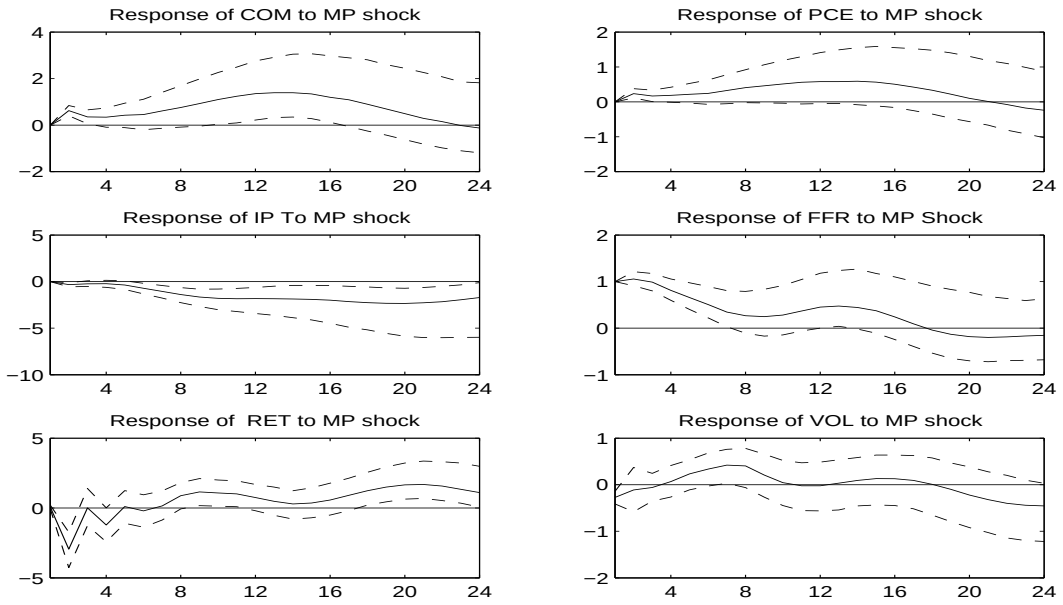
The estimated monthly volatility factor for each sector in the period between February 1973 and July 2012.

Figure 1.A.2: Monthly variables plots



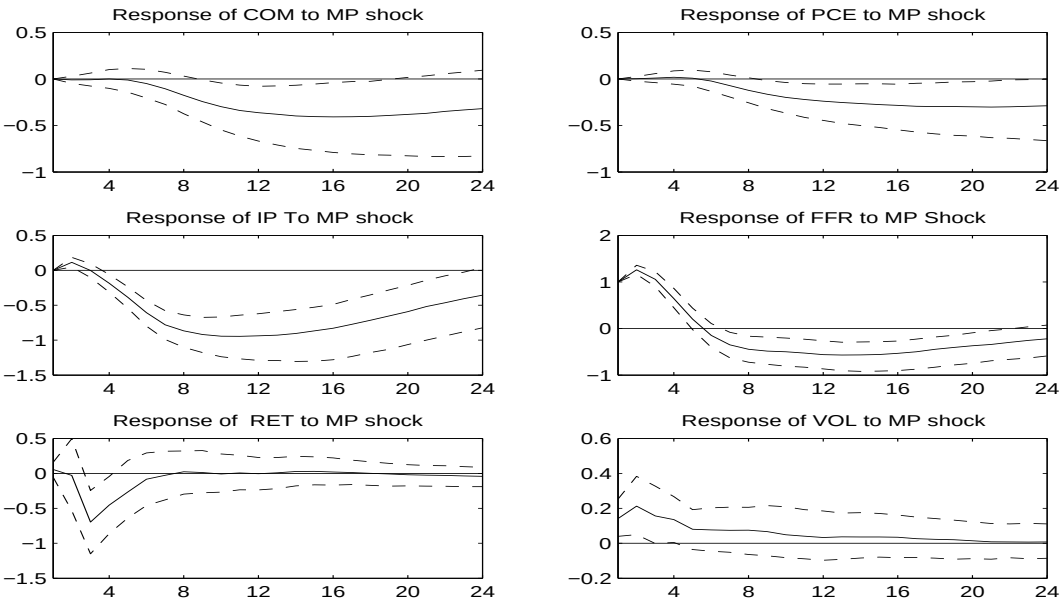
The monthly time series plots of the macroeconomic variables and the returns of the S&P500 index in the period between February 1973 and July 2012.

Figure 1.A.3: Impulse responses during Burns' chairmanship



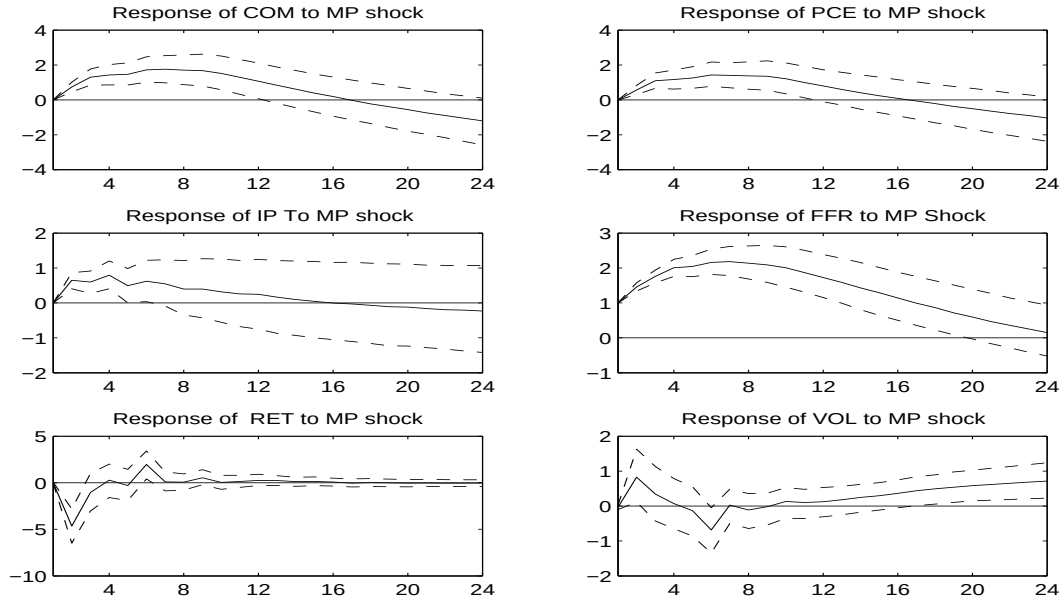
Responses of the variables included in the FAVAR to a contractionary monetary policy shock. The dashed lines are the 16^{th} and 84^{th} quantiles from the posterior draws, and thus corresponds to a one standard deviation posterior probability band under normality. The model is estimated using the sample between February 1973 and January 1978.

Figure 1.A.4: Impulse responses during Volcker's chairmanship



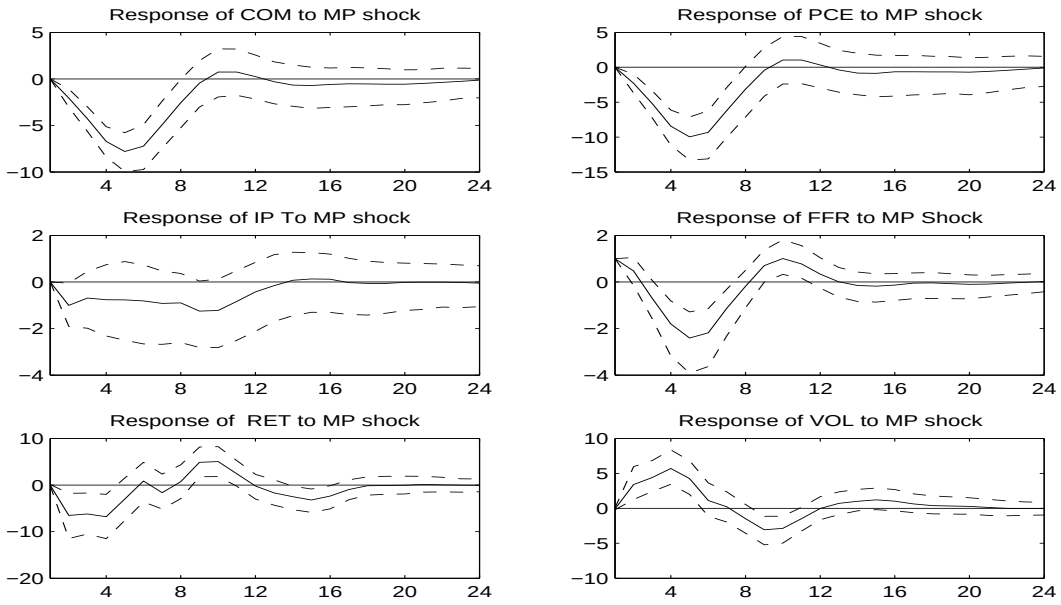
Responses of the variables included in the FAVAR to a contractionary monetary policy shock. The dashed lines are the 16^{th} and 84^{th} quantiles from the posterior draws, and thus corresponds to a one standard deviation posterior probability band under normality. The model is estimated using the sample between August 1979 and July 1987.

Figure 1.A.5: Impulse responses during Greenspan's chairmanship



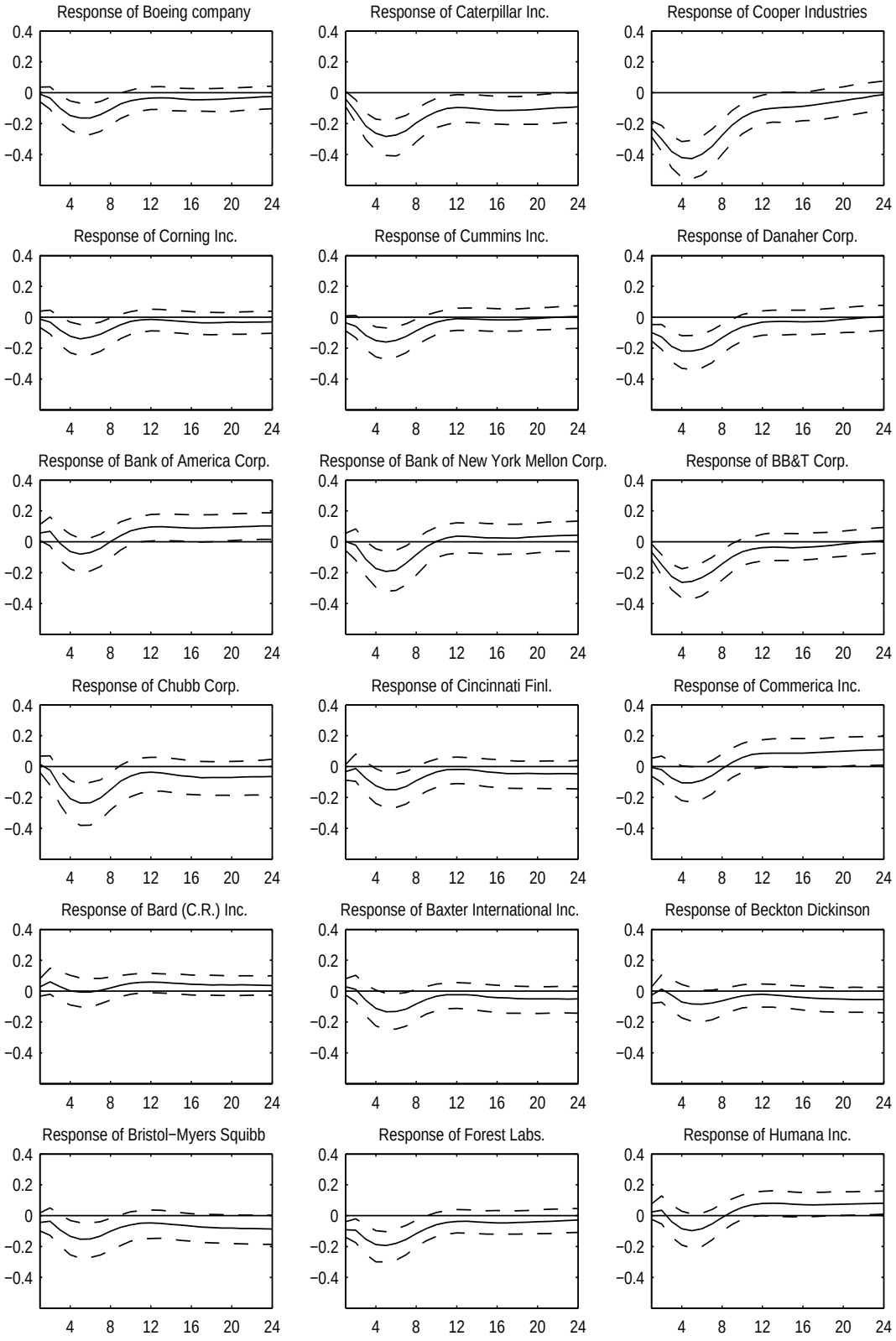
Responses of the variables included in the FAVAR to a contractionary monetary policy shock. The dashed lines are the 16^{th} and 84^{th} quantiles from the posterior draws, and thus corresponds to a one standard deviation posterior probability band under normality. The model is estimated using the sample between August 1987 and January 2006.

Figure 1.A.6: Impulse responses during Bernanke's chairmanship



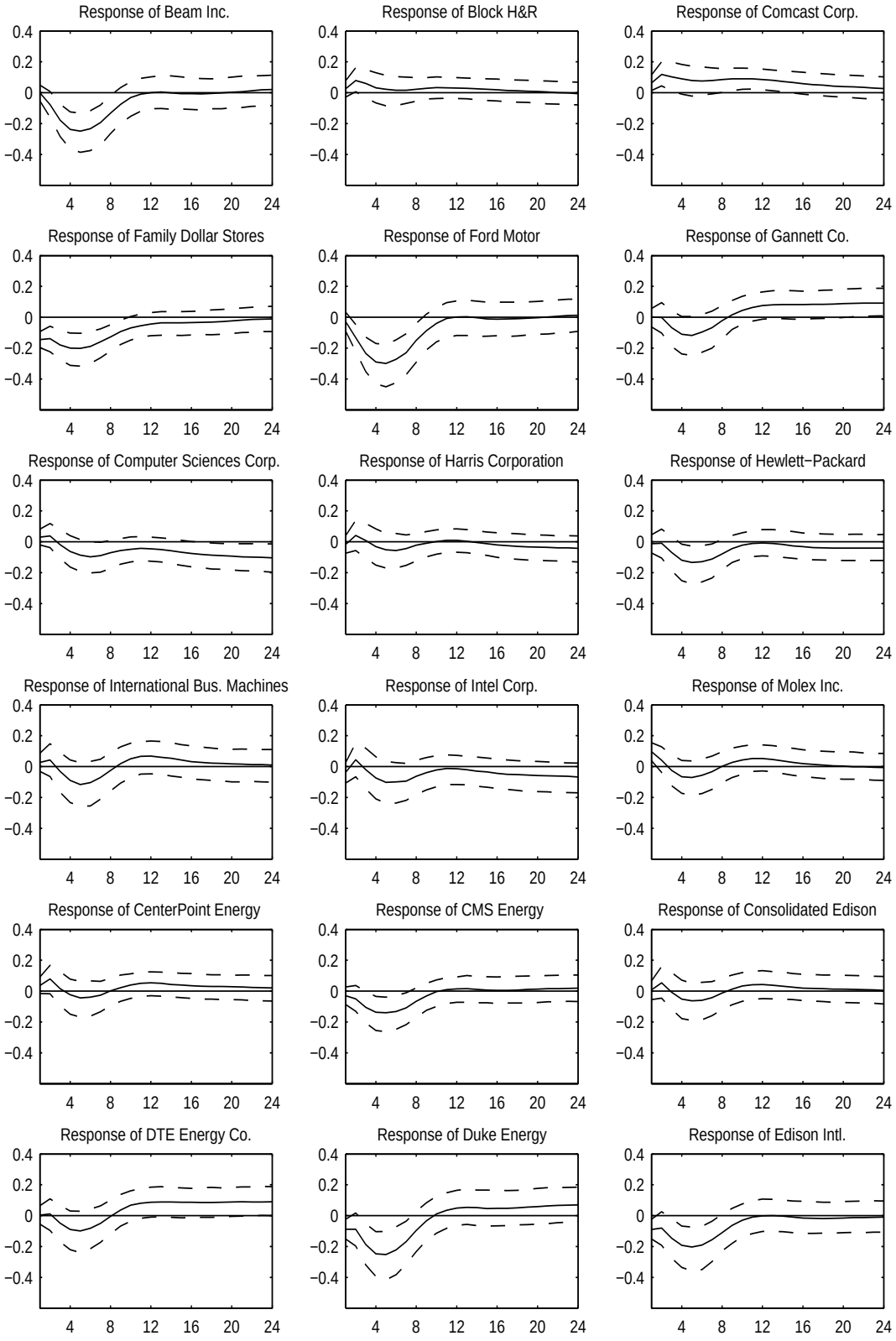
Responses of the variables included in the FAVAR to a contractionary monetary policy shock. The dashed lines are the 16^{th} and 84^{th} quantiles from the posterior draws, and thus corresponds to a one standard deviation posterior probability band under normality. The model is estimated using the sample between February 2006 and July 2012.

Figure 1.A.7: Impulse responses for companies from different sectors



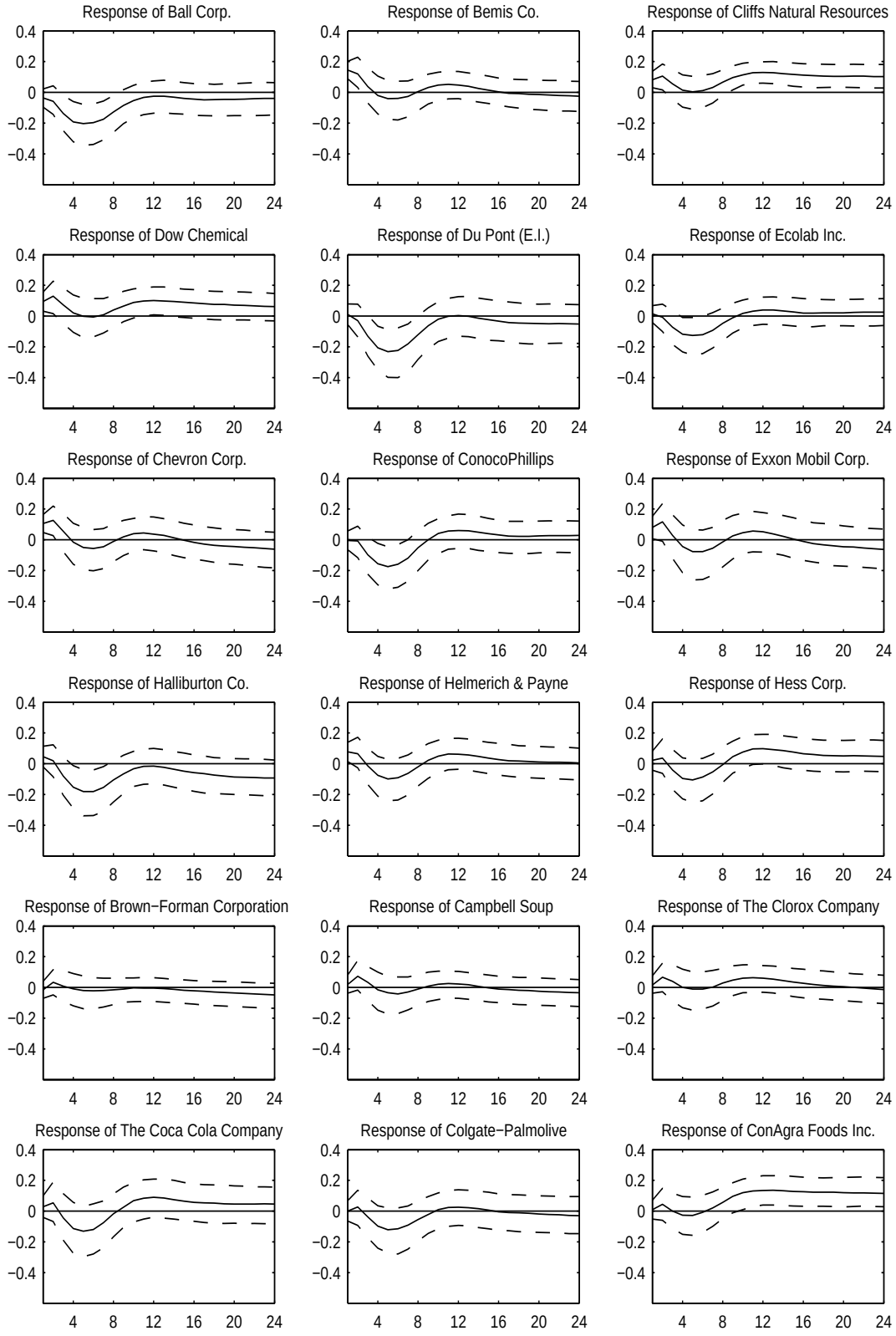
Responses of the realized volatilities of companies in different sectors included in a large structural VAR (59 variables) to a contractionary monetary policy shock. The dashed lines are the 16^{th} and 84^{th} quantiles from the posterior draws, and thus corresponds to a one standard deviation posterior probability band under normality. The model is estimated using the sample between February 1973 and July 2012.

Figure 1.A.8: Impulse responses for companies from different sectors



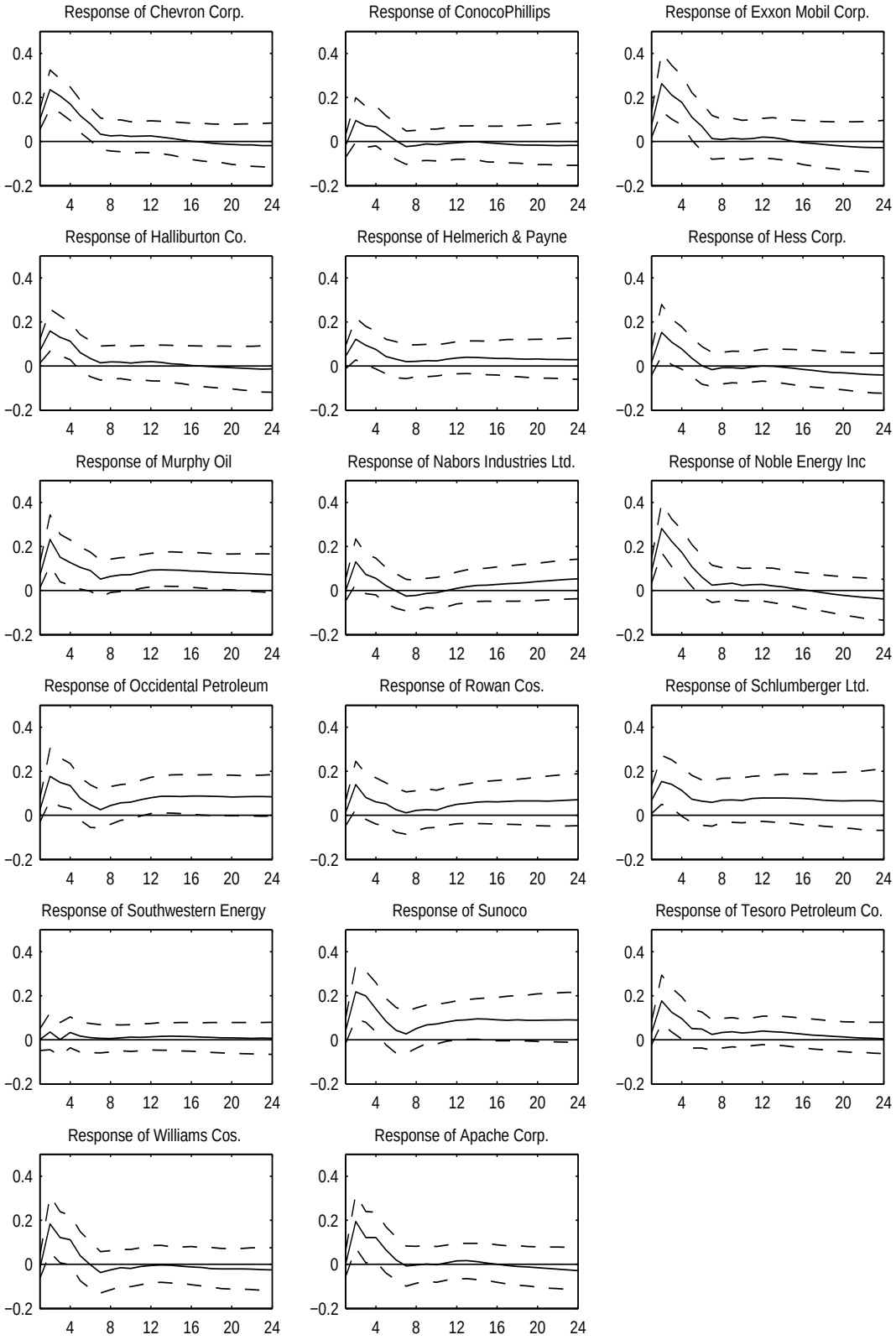
Responses of the realized volatilities of companies in different sectors included in a large structural VAR (59 variables) to a contractionary monetary policy shock. The dashed lines are the 16^{th} and 84^{th} quantiles from the posterior draws, and thus corresponds to a one standard deviation posterior probability band under normality. The model is estimated using the sample between February 1973 and July 2012.

Figure 1.A.9: Impulse responses for companies from different sectors



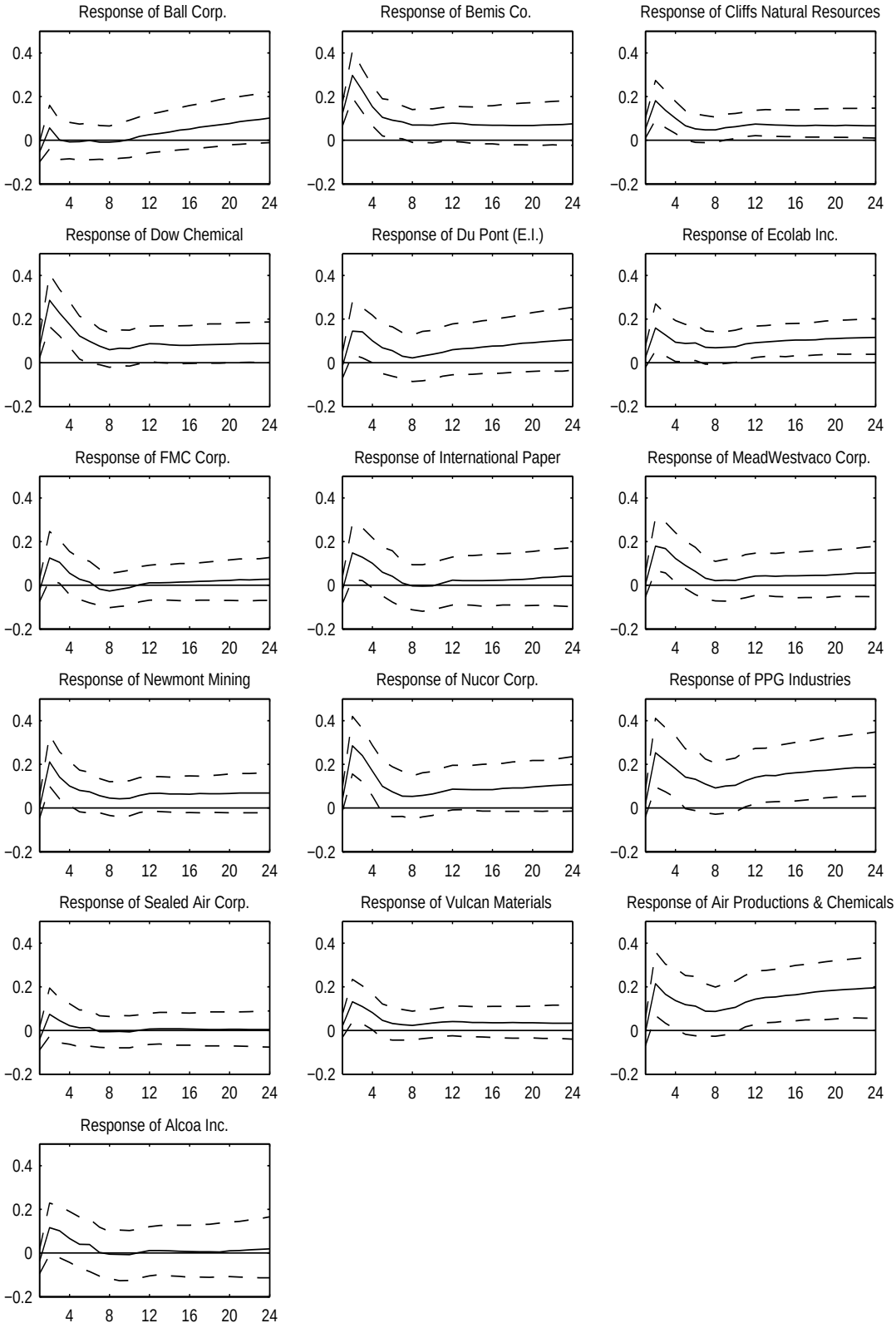
Responses of the realized volatilities of companies in different sectors included in a large structural VAR (59 variables) to a contractionary monetary policy shock. The dashed lines are the 16^{th} and 84^{th} quantiles from the posterior draws, and thus corresponds to a one standard deviation posterior probability band under normality. The model is estimated using the sample between February 1973 and July 2012.

Figure 1.A.10: Impulse responses for the companies in the energy sector



Responses of the realized volatilities of the companies in the energy sector included in the structural VAR to a contractionary monetary policy shock. The dashed lines are the 16^{th} and 84^{th} quantiles from the posterior draws, and thus corresponds to a one standard deviation posterior probability band under normality. The model is estimated using the sample between February 1973 and July 2012.

Figure 1.A.11: Impulse responses for the companies in the materials sector



Responses of the realized volatilities of the companies in the materials sector included in the structural VAR to a contractionary monetary policy shock. The dashed lines are the 16^{th} and 84^{th} quantiles from the posterior draws, and thus corresponds to a one standard deviation posterior probability band under normality. The model is estimated using the sample between February 1973 and July 2012.

CHAPTER 2

Forecasting GDP Growth Using Mixed-Frequency Models With Switching Regimes

2.1 Introduction

Forecasting GDP growth is important for the decision making process both on the central administrative level (central bank, government) and for the industry. Due to the difficulties in the measurement of GDP, it is published with a delay of a couple of months and repeatedly revised. This creates an obstacle for the policy makers and market participants who need to be ahead of or at least quickly adjust to the changes in the economy. Thus, reliable predictions are badly needed, but most of the existing forecasting models do not perform satisfactorily. This might be due to the fact that these models often ignore the non-linearities in the data (e.g. business cycle patterns) and/or fail to explore the informational content of the data published more frequently or with a shorter lag than the GDP. In addition, many models fail to make use of the informational content of large datasets due to the problem of parameter proliferation.

Many approaches fail to account for the fact that macroeconomic variables often behave differently in different phases of the business cycle. Thus, a model with constant parameters might not reflect the present situation well, yet alone be useful for forecasting. Furthermore, most models cannot include time series of different frequencies within the same regression. Instead, they require the data to be transformed (through aggregation or interpolation), so that left- and right-hand side variables are of the same frequency. That, however, might lead to loss of information. In addition, many models are not suitable to deal with large datasets, which forces the forecaster to limit the number of explanatory variables and ignore useful information from other potential regressors. Finally, in most models it is not possible to include the most recent observations of the higher-frequency variable when the corresponding data on the dependent variable is not yet available. Thus, these models cannot be used for nowcasting. This is a major drawback, as higher-frequency variables are useful indicators of the current state of the economy. They are also published relatively often and with a small delay, which makes them potentially very useful in forecasting lower-frequency variables, such as GDP growth.

Some approaches can be used to solve the above-mentioned problems. Among these are regime-switching models, introduced by Hamilton (1989), Mixed Data Sampling Regressions (MIDAS), recently developed by Ghysels, Santa-Clara, and Valkanov (2002), and dynamic factor analysis (see e.g. Stock and Watson (2002a)). Regime-switching models allow the parameters of the model to change according to the current state of the economy (e.g. different parameters for the expansion and recession periods), and accounting for business cycle patterns in macroeconomic variables might improve the forecasting performance of the model. MIDAS models, on the other hand, can include time series of different frequencies in the same regression without transforming them through aggregation or interpolation. They are also very useful in nowcasting (MIDAS with leads), as they can make use of the observations of higher-frequency variables even if the data on lower-

frequency variables for the corresponding period is not available yet.[1] Finally, dynamic factor analysis helps to exploit the informational content of large datasets by summarizing the variation of the observed variables by just a few unobserved factors. Thus, using a single factor that explains a large part of the dataset variation, instead of a single observed variable, may capture more information from the available dataset and ensure parsimony of the model.

A vast literature is available on Markov-switching models, usually in the context of modeling business cycle patterns of macroeconomic data. Anas, Billio, Ferrara, and Duca (2007) explore multivariate Markov-switching models for analyzing the relationship between the phases of the business cycle in the United States and Euro zone. Krolzig (2000) investigates the forecasting performance of the multivariate Markov-switching processes through Monte Carlo experiments and an empirical application for the United States business cycle. Also Clements and Krolzig (1998) study the forecasting performance of Markov-switching models through Monte Carlo simulations and an empirical study for the US GNP. Lahiri and Wang (1994) use the Markov-switching framework to predict the turning points in the US business cycle. Frömmel, MacDonald, and Menkhoff (2005), Cheung and Erlandsson (2005), and Engel (1994) apply Markov-switching models to explain and predict the fluctuations in exchange rates, whereas Pagliacci and Barraez (2010), Evans and Wachtel (1993), and Simon (1996) use the Markov-switching framework to analyze the past dynamics of inflation in Venezuela, the United States and Australia respectively.

MIDAS models, recently introduced to the literature, have already found a number of interesting applications in both macroeconomics and finance. Kuzin, Marcellino, and Schumacher (2011) investigate the performance of the MIDAS model for nowcasting and forecasting GDP in the Euro area in comparison to a mixed-frequency VAR (with missing values of the lower frequency variables interpolated by Kalman filter). They conclude that both approaches seem to be complementary, as MIDAS performs better for short forecast horizons, whereas mixed-frequency VAR for longer ones. A similar study is performed by Marcellino and Schumacher (2010), who investigate factor MIDAS models versus state space factor models in forecasting German GDP. They find that factor MIDAS models usually outperform their state-space counterparts in forecasting and that the most parsimonious MIDAS regression performs best overall.

Bai, Ghysels, and Wright (2013) investigate MIDAS regressions versus state space models through Monte Carlo simulations and an empirical exercise on predicting the GDP growth of the United States. They conclude that both approaches are comparable in terms of forecasting performance. Clements and Galvão (2008, 2009) use MIDAS regressions of monthly and quarterly data for forecasting the GDP growth of the United

[1] This feature makes MIDAS models also useful for dealing with ragged-edge data (out of the scope of this paper).

States and obtain promising results, especially for MIDAS with leads. Andreou, Ghysels, and Kourtellos (2013) test the suitability of using MIDAS factor models with leads for forecasting quarterly GDP growth of the United States with a large dataset of daily financial and quarterly macroeconomic indicators. They find relatively good performance of those kind of models, especially in the crisis periods. Barsoum (2011) carries out a similar analysis for the United Kingdom, comparing MIDAS and factor-augmented MIDAS (both with and without leads) with a bunch of benchmark models. He obtains mixed results on the performance of MIDAS models in general, but promising results for MIDAS with leads.

Although useful, Markov-switching and MIDAS models can only address one problem at a time: either the issue of business cycle patterns or the difference in frequencies of the data. Therefore, Guérin and Marcellino (2013) combine both approaches, introducing a Markov-switching Mixed Data Sampling model (MS-MIDAS).[2] They assess its forecasting performance through Monte Carlo simulations and carry out empirical studies on forecasting GDP growth of the United States and the United Kingdom, showing that MS-MIDAS is a useful approach. In their version of the model Guérin and Marcellino (2013) use the so-called restricted lag polynomial, which is based on a specific function (e.g. exponential function). Depending on this function, a particular structure is imposed on the weights of the regressors in the model. This prevents parameter proliferation, but at the same time restricts the values that those weights can take. Although quite flexible, this approach might not fully reflect the data generating process, possibly deteriorating the forecasting performance of the model. Foroni, Marcellino, and Schumacher (2015) compare the forecasting performance of MIDAS with U-MIDAS (a MIDAS model with unrestricted lag polynomial weights) by means of Monte Carlo simulations. They show that for small differences in frequencies of the analyzed variables the U-MIDAS performs better than restricted MIDAS for most of the examined cases. For the rest of the cases the models perform comparably both in-sample and out-of-sample. For most macroeconomic applications quarterly and monthly data are used, so the difference in frequencies of the variables is small and parameter proliferation is not a serious problem. Thus, the unrestricted version of MIDAS might be very useful for forecasting such variables as GDP growth. Since accounting for business cycle pattern in macroeconomic data might improve the forecasting performance of the model, we extend the U-MIDAS approach by incorporating it into a Markov-switching framework in order to allow for changes in parameters according to the business cycle state of the economy. Thus, we combine the MS-MIDAS of Guérin and Marcellino (2013), and U-MIDAS of Foroni et al. (2015), proposing a Markov-switching Mixed Data Sampling model with unrestricted lag polynomial (MS-U-MIDAS).

[2] More recently Bessec and Bouabdallah (2015) use a factor-augmented MS-MIDAS model in forecasting.

We evaluate the usefulness of the MS-U-MIDAS model by a Monte Carlo study and an empirical forecasting comparison. We first investigate the qualities of the MS-U-MIDAS with autoregressive dynamics (MS-U-MIDAS-AR) through Monte Carlo experiments. For different data generating processes (DGPs) we compare the in-sample and out-of-sample performance of the MS-U-MIDAS-AR model to its restricted counterparts (MS-MIDAS-AR and MS-ADL-MIDAS) in terms of Root Mean Squared Error (RMSE) and Quadratic Probability Score (QPS). For the in-sample analysis in terms of both the RMSE and QPS we find that MS-U-MIDAS-AR performs on average better than its counterparts. For the out-of-sample analysis all three models perform comparably in terms of RMSE, although MS-U-MIDAS-AR beats MS-MIDAS-AR in the case when the simulated data are highly persistent, which is a result consistent with the findings of Foroni et al. (2015). In terms of predicting the true regime, however, the MS-U-MIDAS-AR performs on average better than its restricted counterparts.

In our empirical forecast comparison, we apply the MS-U-MIDAS model to forecast GDP growth of the United States using a large dataset of monthly macroeconomic and financial indicators. To reduce the dimension of the data and at the same time efficiently use the available information, we extract factors from the dataset using principal component analysis (PCA). These factors are then used as regressors for forecasting the GDP growth. First, we investigate the in-sample properties of the MS-U-MIDAS model. Then the out-of-sample forecasting performance of the MS-U-MIDAS class of models is compared with the performance of a wide range of models of Markov-switching and MIDAS type, as well as benchmark models such as the random walk (RW), autoregressive (AR) and (autoregressive) distributed lag models ((A)DL). As already mentioned, the construction of the MIDAS-class of models makes it easy to include data of higher frequencies, even if the corresponding data of lower frequency is not available. Thus one can use these models for nowcasting by including data on monthly variables corresponding to the quarter for which the forecast of a lower frequency variable (such as GDP growth) is made. That quality makes these models a very useful forecasting tool for policy makers and we explore this feature in our analysis, using models with leads whenever it is possible. We find that in most analyzed cases the forecasting performance of the MS-U-MIDAS class of models is comparable or better than that of their restricted counterparts, which is probably due to the fact that the former model does not impose any structure on the weights of the regressors and thus has more flexibility in adjusting to the true data generating process.

The paper is structured as follows. Section 2.2 presents the class of MIDAS models used in the analysis. Section 2.3 describes the design and results of Monte Carlo simulations. In Section 2.4 we apply the MS-U-MIDAS model for predicting the US GDP growth and present the results of our forecasting comparison. Section 2.5 concludes.

2.2 Forecasting models

2.2.1 The MIDAS model

The MIDAS model has been recently introduced to the literature by Ghysels et al. (2002). The basic version of the MIDAS regression used to obtain an $h-$step ahead forecast can be written using the notation based on Clements and Galvão (2008):

$$y_t^Q = \beta_0 + \beta_1 B(L^{1/m}; \boldsymbol{\theta}) x_{t-h}^M + \varepsilon_t, \tag{2.1}$$

where $B(L^{1/m}; \boldsymbol{\theta}) = \sum_{k=1}^{K} b(k; \boldsymbol{\theta}) L^{(k-1)/m}$ is the sum of weights assigned to K lags of the independent variable (the lag polynomial). $b(k; \boldsymbol{\theta})$ is the k^{th} weight of the K-lag polynomial, shaped by a certain function of $\boldsymbol{\theta}$ parameters (as e.g. exponential function described below). L denotes the lag operator such that $L^{s/m} x_{t-h}^M = x_{t-h-s/m}^M$. t is the time index for the lower frequency variable y, whereas m is the time index for the higher frequency variable x. Q describes variables observed on a quarterly and M on a monthly basis.

MIDAS models are useful for nowcasting, as they allow for the inclusion of available data of higher-frequency when the corresponding observations of the lower-frequency variable are yet unknown. In this case one can include the most recent observations of the explanatory variable in the lag polynomial of equation (2.1).

There are a couple of different lag polynomials used in MIDAS regressions (e.g. Beta and Almon lag polynomials). We focus on the most commonly used function for the lag polynomial in MIDAS models - the exponential function. The so-called Exponential Almon lag polynomial parametrizes $b(k; \boldsymbol{\theta})$ according to the following scheme:

$$b(k; \boldsymbol{\theta}) = \frac{\exp(\theta_1 k + \theta_2 k^2 + ... + \theta_Q k^Q)}{\sum_{k=1}^{K} \exp(\theta_1 k + \theta_2 k^2 + ... + \theta_Q k^Q)}. \tag{2.2}$$

This specification ensures that the lag coefficients are positive and sum up to one, which is the necessary condition for the identification of the parameters of the model. The parameter estimation is done by non-linear least squares method. Empirical applications are usually based on two parameters of the above-described function, thus $\boldsymbol{\theta} = (\theta_1, \theta_2)'$, which simplifies the model, but still ensures flexibility in the specification of the shape of the polynomial. A wide variety of shapes of lag coefficients can be obtained, ranging from equal weights for all lags, through weights declining at a given pace, to weights forming a hump shape.

2.2.2 Unrestricted MIDAS

In some cases the shape of the lag polynomial determined by e.g. the function (2.2) may not reflect the underlying data generating process well. Therefore a model without restrictions on the weights of the lag polynomial was introduced by Foroni et al. (2015) and denoted as the unrestricted MIDAS (U-MIDAS):

$$y_t^Q = \beta_0 + \sum_{j=0}^{J-1} \beta_{j+1} x_{t-h-j/m}^M + \varepsilon_t.$$

The notation is consistent with equation (2.1).
What distinguishes the above regression from equation (2.1) is the fact that no structure is imposed on the shape of the weights of the lag polynomial. That means that all $J+1$ parameters of this model need to be estimated, whereas in the case of the restricted MIDAS model the number of the parameters to be estimated is by construction limited to four: β_0, β_1, θ_1 and θ_1. However, when the difference in frequencies of the analyzed data is small, as is the case in many macroeconomic applications, the issue of parameter proliferation due to the use of the U-MIDAS model is not especially problematic. In a series of Monte Carlo experiments Foroni et al. (2015) show that the U-MIDAS model performs comparably or better than the restricted MIDAS both in-sample and out-of-sample, when the difference in frequencies between the dependent and independent variable is small (e.g. quarterly versus monthly data). In addition, the U-MIDAS model can be estimated by ordinary least squares, which simplifies the estimation in comparison to the MIDAS model. The drawback of the U-MIDAS is that its performance declines dramatically due to parameter proliferation, when the difference in frequencies between the variables in the model is large. Thus this approach is not suitable for all kinds of analyses. However, for many macroeconomic applications the use of functional lag polynomials in MIDAS does not seem to be necessary and using the U-MIDAS model instead may be beneficial.

2.2.3 Markov-switching U-MIDAS

Macroeconomic data often exhibit a business cycle pattern. Therefore, it is reasonable to assume that the parameters of the model change according to the business cycle phase of the economy. One possible way to account for this data behavior is the use of the Markov-switching model of Hamilton (1989). The parameters of this model depend on the current economic regime (e.g. parameters differ in the recession and expansion phase). Guérin and Marcellino (2013) combined Markov-switching approach with the MIDAS framework and introduced Markov-switching MIDAS regression (MS-MIDAS):

$$y_t^Q = \beta_0(S_t) + \beta_1(S_t) B(L^{1/m}; \boldsymbol{\theta}) x_{t-h}^M + \varepsilon_t(S_t),$$

where $\varepsilon_t|S_t \sim NID(0, \sigma^2(S_t))$, that is, the error terms are normally and identically distributed with mean zero and variance $\sigma^2(S_t)$, which varies with changing states of the world. $S_t = \{1, ..., R\}$ denotes different states of the world (regimes) present in the data generating process. The MS-MIDAS model is in a way similar to equation (2.1). However, S_t in the brackets indicates the parameters that change according to different regimes. In the above regression the intercept β_0, the slope parameter β_1 and the variance of the error term $\sigma^2(S_t)$ are allowed to change.
The probability of transition from the current regime a to regime b is defined as follows:

$$p_{ab} = Pr(S_{t+1} = b|S_t = a).$$

All possible transition probabilities form a matrix P with probabilities of staying in the same regime in the next period at the diagonal, and the probabilities of switching to another state in the next period below and above the diagonal. E.g. for two regimes a and b:

$$P = \begin{pmatrix} p_{aa} & p_{ab} \\ p_{ba} & p_{bb} \end{pmatrix}. \tag{2.3}$$

p_{ab} is the probability of switching from state a to state b in the next period, p_{ba} the probability of changing from regime b to a in the following period, whereas p_{aa} and p_{bb} are the probabilities of staying in the same regime in the next period. The sums of probabilities in each row add up to one. Thus, in the case of two regimes it is sufficient to determine e.g. p_{aa} and p_{bb} to obtain the whole matrix. We assume that the transition probabilities stay constant over time, which is a standard approach in the Markov-switching applications.
As explained above, MIDAS models with lag polynomials restricted by some specific function might not be flexible enough to reflect the true data generating process well. That applies also to the Markov-switching version of the model that was introduced by Guérin and Marcellino (2013). As Foroni et al. (2015) found that using the unrestricted version of the model might improve its forecasting performance, we incorporate the unrestricted lag polynomial into the Markov-switching framework and introduce the unrestricted Markov-switching MIDAS model (MS-U-MIDAS):

$$y_t^Q = \beta_0(S_t) + \sum_{j=0}^{J-1} \beta_{j+1}(S_t) x_{t-h-j/m}^M + \varepsilon_t(S_t).$$

To account for the business cycle pattern of the data, the parameters of the above equation, that is, the intercept β_0, the slope parameters β_{j+1} and the variance of the error term σ_ε^2 can change according to different regimes. Note that while in the MS-MIDAS of Guérin and Marcellino (2013) the parameters $\boldsymbol{\theta}$ stay fixed at their estimated values, all the parameters in the MS-U-MIDAS may switch, giving the latter model more flexibility. With the help of information criteria one can decide on the number of regimes present in the data

generating process and on the parameters that are allowed to switch. One can e.g. take into consideration a model with all the above-mentioned parameters switching or consider a model with e.g. only the intercept and/or the variance of the error term switching. Thus, the above presented model offers great flexibility in modeling the available data and may be very useful for forecasting purposes.

All variations of the Markov-switching models presented in this paper, are estimated by the Maximum-Likelihood method. Thus, an assumption about the normality of the error terms is required. Following the procedure described by Hamilton (1994) we maximize the following log-likelihood function:

$$L = \sum_{t=1}^{T} \log f(y_t^Q | \Omega_{t-1}),$$

where $f(y_t^Q|\Omega_{t-1})$ denotes the density of y_t^Q conditional on Ω_{t-1} - the information given up to time $t-1$. The conditional density $f(y_t^Q|\Omega_{t-1})$ can be rewritten as:

$$f(y_t^Q|\Omega_{t-1}) = \sum_{i=1}^{R} P(S_t = i|\Omega_{t-1}) f(y_t^Q|S_t = i, \Omega_{t-1}).$$

The maximization of the log-likelihood function is carried out with the help of the Expectation Maximization algorithm, as described in Hamilton (1994). We use MATLAB for all computations.[3]

2.2.4 MIDAS models with autoregressive dynamics

Many empirical studies show that adding an autoregressive term to a model significantly improves its forecasting performance. Therefore, we also include autoregressive dynamics in the models considered in this paper.

Andreou et al. (2013) introduce autoregressive dynamics into the MIDAS regression in a straightforward way, calling their model an ADL-MIDAS:

$$y_t^Q = \beta_0 + \sum_{i=0}^{p-1} \lambda_{i+1} y_{t-d-i}^Q + \beta_1 B(L^{1/m}; \boldsymbol{\theta}) x_{t-h}^M + \varepsilon_t. \tag{2.4}$$

When h is an integer, $d = h$, but when some information on the regressors is available for the quarter for which the forecast is calculated, e.g. when $h = 1/3$ (data on two months within the quarter is available), then $d = 1$.

[3]We gratefully acknowledge the help of Pierre Guérin who provided us with his GAUSS code for the MS-MIDAS estimation as a robustness check for our code. For the estimation of MS-U-MIDAS class of models we modified the Toolbox for Markov-switching models of Perlin (2011), available at the website: http://www.mathworks.com/matlabcentral/fileexchange/authors/21596.

Clements and Galvão (2008) propose a different solution, introducing the autoregressive term into the MIDAS model as a common factor, so that the response of y to x remains non-seasonal. Their model is called MIDAS-AR:

$$y_t^Q = \beta_0 + \lambda y_{t-d}^Q + \beta_1 B(L^{1/m}; \boldsymbol{\theta})(1 - \lambda L^d) x_{t-h}^M + \varepsilon_t. \tag{2.5}$$

The introduction of the autoregressive dynamics into the U-MIDAS model (U-MIDAS-AR) is straightforward and the model is given by:

$$y_t^Q = \beta_0 + \sum_{i=0}^{p-1} \lambda_{i+1} y_{t-d-i}^Q + \sum_{j=0}^{J-1} \beta_{j+1} x_{t-h-j/m}^M + \varepsilon_t.$$

The Markov-switching versions of MIDAS-AR, ADL-MIDAS and U-MIDAS-AR used for h-step ahead forecasts are given by:

$$\text{MS-MIDAS-AR: } y_t^Q = \beta_0(S_t) + \lambda y_{t-d}^Q + \beta_1(S_t) B(L^{1/m}; \boldsymbol{\theta})(1 - \lambda L^d) x_{t-h}^M + \varepsilon_t(S_t), \tag{2.6}$$

$$\text{MS-ADL-MIDAS: } y_t^Q = \beta_0(S_t) + \sum_{i=0}^{p-1} \lambda_{i+1} y_{t-d-i}^Q + \beta_1(S_t) B(L^{1/m}; \boldsymbol{\theta}) x_{t-h}^M + \varepsilon_t(S_t), \tag{2.7}$$

and

$$\text{MS-U-MIDAS-AR: } y_t^Q = \beta_0(S_t) + \sum_{i=0}^{p-1} \lambda_{i+1} y_{t-d-i}^Q + \sum_{j=0}^{J-1} \beta_{j+1}(S_t) x_{t-h-j/m}^M + \varepsilon_t(S_t). \tag{2.8}$$

2.3 Monte Carlo experiment

We investigate the in-sample fit and forecasting performance of MS-U-MIDAS with autoregressive dynamics through Monte Carlo experiments for different data generating processes (DGPs). The first DGP is an extended version of the process used by Foroni et al. (2015), and is given as a bivariate Markov-switching VAR(1):

$$\begin{pmatrix} y_t \\ x_t \end{pmatrix} = \begin{pmatrix} \rho & \delta_l(S_t) \\ \delta_h & \rho \end{pmatrix} \begin{pmatrix} y_{t-1} \\ x_{t-1} \end{pmatrix} + \begin{pmatrix} e_{y,t}(S_t) \\ e_{x,t}(S_t) \end{pmatrix}. \tag{2.9}$$

We assume a business cycle pattern in the DGP by allowing some of the parameters of the above-described model to switch between regimes. In our simulations we allow for two regimes. We assume that y_t depends on x_t, but y_t has no influence on x_t. Thus we set the parameter δ_h to zero.

For the sake of comparison, we use similar set of possible parameter values as Foroni

et al. (2015). We run the simulations for various values of the parameter ρ to account for different possible degrees of persistence of y_t and x_t : $\rho = \{0.1; 0.5; 0.9\}$. We assume that the degree of persistence of the variables stays constant across regimes, which is an assumption consistent with the models presented in Section 2.4. Unlike ρ, the parameter δ_l, determining how strong x_t influences y_t, can take different values for different regimes: $\delta_l(S_t = 1) = \{0.1; 0.5\}$ and $\delta_l(S_t = 2) = 1$. The error terms also change their characteristics across the regimes. We assume that $e_{y,t}$ and $e_{x,t}$ are independently and normally distributed with mean zero. Their variances switch between regimes and are chosen in such a way that the unconditional variance of y_t equals 1 in the first and 2 in the second regime. Similarly, we also consider a bivariate MS-VAR(4) as a DGP. The exact details are shown in equation (2.11) in Appendix 2.A.

The second DGP we consider for the out-of-sample analysis is an autoregressive Markov-switching MIDAS process (MS-MIDAS-AR) given by equation (2.6). The high-frequency variable x_t is generated according to equation (2.10). We use 6 lags of the high-frequency variable in the DGP. We also use an exponential Almon lag polynomial specified in (2.2) with $\boldsymbol{\theta} = (\theta_1, \theta_2)'$. We account for two regimes and allow the intercept β_0, the slope parameter β_1 and the variance of the error term σ^2 to switch between the regimes. The parameters $\boldsymbol{\theta}$ and the autoregressive parameter λ stay constant across the regimes. We make the experiment for two different sets of parameters, whose exact values are given in Table 2.3.5. The parameter values are chosen according to Foroni et al. (2015) and the estimation results for our dataset.

For both DGPs we assume two different possible matrices of transition probabilities. For the first case $p_{11} = 0.95$ and $p_{22} = 0.85$, whereas for the second case $p_{11} = p_{22} = 0.95$. The high probabilities of staying in the same regime in the next period reflect the high persistence of the business cycle regimes observed in reality. As for both DGPs we only allow for two regimes, the above-described probabilities fully specify the matrix P given in (2.3).

We compare the in-sample and forecasting performance of the MS-U-MIDAS-AR relative to MS-MIDAS-AR and MS-ADL-MIDAS in order to see which of them performs better for the different DGPs. In all simulations we account for the start-up effect, that is, we delete the first 100 simulated values of the variables y_t and x_t. During estimation the Akaike criterion (AIC) is used to determine the lag order at each simulation. Up to 6 lags of the high frequency variable are used for the estimation.

2.3.1 In-sample analysis

Our main focus is the out-of-sample performance of the MS-U-MIDAS model. Thus for the in-sample analysis we only consider the first DGP, that is a bivariate Markov-switching VAR (MS-VAR). We generate 600 observations of y_t and x_t, following (2.9). This can

Table 2.3.1: In-sample Root Mean Squared Error of MS-U-MIDAS-AR relative to MS-MIDAS-AR and MS-ADL-MIDAS (DGP is a bivariate MS-VAR(1) with two regimes)

					RMSE (25th, 50th and 75th percentiles)					
	δ_l		transition probabilities		MS-U-MIDAS-AR vs. MS-MIDAS-AR			MS-U-MIDAS-AR vs. MS-ADL-MIDAS		
ρ	$S_t = 1$	$S_t = 2$	p_{11}	p_{22}	25^{th}	50^{th}	75^{th}	25^{th}	50^{th}	75^{th}
0.1	0.1	1	0.95	0.85	0.95	0.98	1.01	0.97	0.99	1.00
0.1	0.5	1	0.95	0.85	0.95	0.98	1.01	0.97	0.99	1.00
0.5	0.1	1	0.95	0.85	0.95	0.98	1.01	0.96	0.98	1.00
0.5	0.5	1	0.95	0.85	0.93	0.96	0.99	0.94	0.96	0.99
0.9	0.1	1	0.95	0.85	0.79	0.85	0.91	0.96	1.00	1.04
0.9	0.5	1	0.95	0.85	0.43	0.50	0.55	0.95	0.99	1.02
0.1	0.1	1	0.95	0.95	0.96	0.99	1.01	0.97	0.99	1.00
0.1	0.5	1	0.95	0.95	0.95	0.98	1.01	0.97	0.99	1.00
0.5	0.1	1	0.95	0.95	0.94	0.97	1.00	0.93	0.96	0.98
0.5	0.5	1	0.95	0.95	0.92	0.96	0.99	0.90	0.93	0.96
0.9	0.1	1	0.95	0.95	0.71	0.78	0.85	0.95	0.99	1.02
0.9	0.5	1	0.95	0.95	0.37	0.44	0.51	0.90	0.98	1.04

Note: The table presents the summary of the results of 1000 Monte Carlo simulations. For each replication 600 observations of a higher-frequency variable x_t and 200 observations of a lower-frequency variable y_t are generated according to a bivariate MS-VAR(1) model with two regimes. Then the MS-U-MIDAS-AR, MS-MIDAS-AR and MS-ADL-MIDAS models are estimated and their in-sample fit is measured by Root Mean Squared Error. The table presents the 25th, 50th and 75th percentiles of the ratio of the RMSE of the MS-U-MIDAS-AR to the RMSE of MS-MIDAS-AR and MS-ADL-MIDAS over all 1000 simulations. Values below/above 1 indicate a better/worse in-sample performance of the MS-U-MIDAS-AR model in comparison to the MS-MIDAS-AR or MS-ADL-MIDAS model. The analysis is done for different transition probabilities between the two regimes and for different values of the parameters of the MS-VAR model (see equation (2.9)).

be thought of as using 600 monthly observations. Then we assume that y_t is observed only every third period, which corresponds to observing y_t on a quarterly basis. Thus, we obtain 200 low-frequency observations. Then for each replication we estimate MS-U-MIDAS-AR, MS-MIDAS-AR and MS-ADL-MIDAS, and investigate the in-sample fit of these models by means of Root Mean Squared Error (RMSE) and Quadratic Probability Score (QPS). RMSE is defined as a square root of the average squared differences between the estimated values of the dependent variable $\hat{y}_t$ and the actually observed values of y_t:

$$RMSE = \sqrt{\frac{\sum_{t=\tau}^{T}(\hat{y}_t - y_t)^2}{T - \tau + 1}},$$

where τ denotes the beginning of the evaluation period.

Quadratic Probability Score is a measure of the accuracy of regime prediction and is defined as follows:

$$QPS = \frac{2 \cdot \sum_{t=\tau}^{T}(P(S_t = 1) - S_t)^2}{T - \tau + 1},$$

where S_t is a dummy variable taking the value of 1 for the first regime and 0 for the second regime, and $P(S_t = 1)$ is the predicted probability of being in the first regime in period t. For the in-sample analysis $\tau = 1$.

We replicate the above-described process 1000 times and obtain results that can be found in Tables 2.3.1 and 2.3.2. The tables show the 25th, 50th, 75th percentiles of the ratio of RMSE/QPS of MS-U-MIDAS-AR to the RMSE/QPS of MS-MIDAS-AR or MS-ADL-MIDAS, calculated over 1000 simulations to provide an overview of the distribution of the results for all replications. The ratio values below/above 1 mean that MS-U-MIDAS-

Table 2.3.2: In-sample Quadratic Probability Score of MS-U-MIDAS-AR relative to MS-MIDAS-AR and MS-ADL-MIDAS (DGP is a bivariate MS-VAR(1) with two regimes)

					QPS (25th, 50th and 75th percentiles)					
	δ_l		transition probabilities		MS-U-MIDAS-AR vs. MS-MIDAS-AR			MS-U-MIDAS-AR vs. MS-ADL-MIDAS		
ρ	$S_t = 1$	$S_t = 2$	p_{11}	p_{22}	25^{th}	50^{th}	75^{th}	25^{th}	50^{th}	75^{th}
0.1	0.1	1	0.95	0.85	0.97	1.00	1.08	0.98	1.00	1.03
0.1	0.5	1	0.95	0.85	0.97	1.01	1.06	0.98	1.00	1.03
0.5	0.1	1	0.95	0.85	0.93	1.00	1.09	0.95	1.00	1.06
0.5	0.5	1	0.95	0.85	0.91	0.97	1.06	0.93	0.98	1.05
0.9	0.1	1	0.95	0.85	0.23	0.94	1.02	0.90	0.99	1.04
0.9	0.5	1	0.95	0.85	0.88	1.00	1.00	1.00	1.00	1.03
0.1	0.1	1	0.95	0.95	0.97	1.01	1.04	0.98	1.00	1.02
0.1	0.5	1	0.95	0.95	0.97	1.00	1.03	0.98	1.00	1.03
0.5	0.1	1	0.95	0.95	0.89	0.98	1.04	0.95	0.98	1.03
0.5	0.5	1	0.95	0.95	0.87	0.95	1.00	0.92	0.98	1.02
0.9	0.1	1	0.95	0.95	0.11	0.73	1.00	0.88	1.00	1.00
0.9	0.5	1	0.95	0.95	0.16	0.98	1.06	0.85	1.00	1.08

Note: The table presents the summary of the results of 1000 Monte Carlo simulations. For each replication 600 observations of a higher-frequency variable x_t and 200 observations of a lower-frequency variable y_t are generated according to a bivariate MS-VAR(1) model with two regimes. Then the MS-U-MIDAS-AR, MS-MIDAS-AR and MS-ADL-MIDAS models are estimated and their accuracy in predicting regimes is measured by Quadratic Probability Score. The table presents the 25th, 50th and 75th percentiles of the ratio of the QPS of the MS-U-MIDAS-AR to the QPS of MS-MIDAS-AR and MS-ADL-MIDAS over all 1000 simulations. Values below/above 1 indicate a better/worse in-sample performance of the MS-U-MIDAS-AR model in comparison to the MS-MIDAS-AR or MS-ADL-MIDAS model. The analysis is done for different transition probabilities between the two regimes and for different values of the parameters of the MS-VAR model (see equation (2.9)).

AR performs better/worse than MS-MIDAS-AR or MS-ADL-MIDAS in terms of the in-sample performance.

Simulations carried out for different sets of parameters, according to which the DGP was generated, show that in terms of the median of the RMSE the MS-U-MIDAS-AR outperforms the MS-MIDAS-AR in all considered cases, and in all but one case it performs better than the MS-ADL-MIDAS model as well. However, in most cases the differences between the models are small. The only exception are the cases when $\rho = 0.9$. Then the MS-U-MIDAS-AR model outperforms the MS-MIDAS-AR considerably. However, no big difference is reported between the MS-U-MIDAS-AR and MS-ADL-MIDAS in those cases. This reveals that the MS-U-MIDAS-AR and MS-ADL-MIDAS show better in-sample performance than the MS-MIDAS-AR model when the persistence of the variable y_t is high and the analyzed case is close to the unit root.

In terms of the QPS the in-sample performance of the MS-U-MIDAS-AR is comparable to the MS-ADL-MIDAS, while better than MS-MIDAS-AR in most considered cases.

2.3.2 Out-of-sample analysis

For the study of the out-of-sample performance of the MS-U-MIDAS-AR model versus MS-MIDAS-AR and MS-ADL-MIDAS, we generate additional 30 out-of-sample low-frequency observations from a specific DGP. In other words, we consider 200 low-frequency observations for the in-sample estimation and 30 for forecasting evaluation. Then we compare the forecasting performance of MS-U-MIDAS-AR relative to MS-MIDAS-AR and MS-ADL-MIDAS for one-step ahead forecasts by means of the RMSE

Table 2.3.3: Out-of-sample Root Mean Squared Error of MS-U-MIDAS-AR relative to MS-MIDAS-AR and MS-ADL-MIDAS (DGP is a bivariate MS-VAR(1) with two regimes)

					RMSE (25th, 50th and 75th percentiles)					
	δ_l		transition probabilities		MS-U-MIDAS-AR vs. MS-MIDAS-AR			MS-U-MIDAS-AR vs. MS-ADL-MIDAS		
ρ	$S_t = 1$	$S_t = 2$	p_{11}	p_{22}	25^{th}	50^{th}	75^{th}	25^{th}	50^{th}	75^{th}
0.1	0.1	1	0.95	0.85	0.98	1.03	1.09	0.99	1.01	1.04
0.1	0.5	1	0.95	0.85	0.98	1.03	1.10	0.99	1.01	1.04
0.5	0.1	1	0.95	0.85	0.97	1.03	1.09	0.97	1.03	1.12
0.5	0.5	1	0.95	0.85	0.93	1.00	1.08	0.99	1.06	1.17
0.9	0.1	1	0.95	0.85	0.76	0.90	1.03	0.88	0.99	1.11
0.9	0.5	1	0.95	0.85	0.47	0.56	0.67	0.88	1.01	1.16
0.1	0.1	1	0.95	0.95	0.98	1.03	1.10	0.99	1.00	1.03
0.1	0.5	1	0.95	0.95	0.98	1.04	1.10	0.99	1.00	1.02
0.5	0.1	1	0.95	0.95	0.94	1.01	1.09	0.98	1.04	1.12
0.5	0.5	1	0.95	0.95	0.92	1.00	1.08	0.99	1.06	1.14
0.9	0.1	1	0.95	0.95	0.63	0.79	0.98	0.84	1.01	1.21
0.9	0.5	1	0.95	0.95	0.42	0.51	0.63	0.90	1.06	1.28

Note: The table presents the summary of the results of 1000 Monte Carlo simulations. For each replication 600 observations of a higher-frequency variable x_t and 200 observations of a lower-frequency variable y_t are generated for the in-sample period, whereas 30 lower-frequency (90 higher-frequency) observations are generated for the out-of-sample evaluation according to a bivariate MS-VAR(1) model with two regimes. Then the MS-U-MIDAS-AR, MS-MIDAS-AR and MS-ADL-MIDAS models are estimated and their out-of-sample performance is measured by Root Mean Squared Error. The table presents the 25th, 50th and 75th percentiles of the ratio of the RMSE of the MS-U-MIDAS-AR to the RMSE of MS-MIDAS-AR and MS-ADL-MIDAS over all 1000 simulations. Values below/above 1 indicate a better/worse out-of-sample performance of the MS-U-MIDAS-AR model in comparison to the MS-MIDAS-AR or MS-ADL-MIDAS model. The analysis is done for different transition probabilities between the two regimes and for different values of the parameters of the MS-VAR model (see equation (2.9)).

and QPS. We replicate the procedure 1000 times for two different DGPs that were described in the earlier sections.

2.3.2.1 DGP generated as a two-regime MS-VAR

The first out-of-sample experiment is carried out for the DGP generated as a MS-VAR(1) (see equation (2.9)) according to the procedure described above. The results of the forecasting evaluation of the MS-U-MIDAS-AR model versus MS-MIDAS-AR and MS-ADL-MIDAS can be found in Tables 2.3.3 and 2.3.4. For different combinations of the parameters of the DGP, the tables contain the 25th, 50th and 75th percentiles of the ratio of the RMSE/QPS of MS-U-MIDAS-AR relative to the RMSE/QPS of MS-MIDAS-AR and to the RMSE/QPS of MS-ADL-MIDAS, calculated over all 1000 replications. Values below/above 1 indicate that MS-U-MIDAS-AR performs better/worse than MS-MIDAS-AR or MS-ADL-MIDAS in the out-of-sample analysis.

When the true DGP is MS-VAR(1), there is no clear winner of the out-of-sample comparison. Looking at the median of the results for the RMSE, the MS-U-MIDAS-AR performs clearly better than the MS-MIDAS-AR for the cases when the persistence of the low-frequency variable is high ($\rho = 0.9$), and thus when more information relevant for the future can be exploited from the past data. This confirms the results of the in-sample analysis. However, for other cases, the MS-U-MIDAS performs comparably or slightly worse than the MS-MIDAS-AR and the MS-ADL-MIDAS. On the other hand,

Table 2.3.4: Out-of-sample Quadratic Probability Score of MS-U-MIDAS-AR relative to MS-MIDAS-AR and MS-ADL-MIDAS (DGP is a bivariate MS-VAR(1) with two regimes)

					QPS (25th, 50th and 75th percentiles)					
	δ_l		transition probabilities		MS-U-MIDAS-AR vs. MS-MIDAS-AR			MS-U-MIDAS-AR vs. MS-ADL-MIDAS		
ρ	$S_t = 1$	$S_t = 2$	p_{11}	p_{22}	25^{th}	50^{th}	75^{th}	25^{th}	50^{th}	75^{th}
0.1	0.1	1	0.95	0.85	0.87	1.00	1.14	0.97	1.00	1.07
0.1	0.5	1	0.95	0.85	0.82	0.98	1.12	0.96	1.00	1.06
0.5	0.1	1	0.95	0.85	0.79	1.04	1.78	0.66	0.97	1.30
0.5	0.5	1	0.95	0.85	0.61	0.95	1.36	0.54	0.91	1.34
0.9	0.1	1	0.95	0.85	0.79	0.99	1.25	0.71	1.00	1.32
0.9	0.5	1	0.95	0.85	0.78	0.99	1.17	0.69	1.00	1.37
0.1	0.1	1	0.95	0.95	0.84	0.97	1.10	0.97	1.00	1.03
0.1	0.5	1	0.95	0.95	0.80	0.95	1.07	0.97	1.00	1.03
0.5	0.1	1	0.95	0.95	0.62	0.97	1.06	0.66	0.98	1.06
0.5	0.5	1	0.95	0.95	0.54	0.93	1.03	0.52	0.96	1.05
0.9	0.1	1	0.95	0.95	0.67	0.94	1.20	0.71	1.01	1.39
0.9	0.5	1	0.95	0.95	0.71	0.96	1.20	0.76	1.01	1.41

Note: The table presents the summary of the results of 1000 Monte Carlo simulations. For each replication 600 observations of a higher-frequency variable x_t and 200 observations of a lower-frequency variable y_t are generated for the in-sample period, whereas 30 lower-frequency (90 higher-frequency) observations are generated for the out-of-sample evaluation according to a bivariate MS-VAR(1) model with two regimes. Then the MS-U-MIDAS-AR, MS-MIDAS-AR and MS-ADL-MIDAS models are estimated and their accuracy in predicting regimes is measured by Quadratic Probability Score. The table presents the 25th, 50th and 75th percentiles of the ratio of the QPS of the MS-U-MIDAS-AR to the QPS of MS-MIDAS-AR and MS-ADL-MIDAS over all 1000 simulations. Values below/above 1 indicate a better/worse out-of-sample performance of the MS-U-MIDAS-AR model in comparison to the MS-MIDAS-AR or MS-ADL-MIDAS model. The analysis is done for different transition probabilities between the two regimes and for different values of the parameters of the MS-VAR model (see equation (2.9)).

looking at the QPS, we can observe that MS-U-MIDAS outperforms the MS-MIDAS-AR in predicting the true regime in almost all cases. It also performs at least as well as the MS-ADL-MIDAS model.

As a robustness check, we repeat the out-of-sample comparison for the case when the true DGP is MS-VAR(4), thus allowing for more dynamics. The results of this exercise can be found in Tables 2.A.3 and 2.A.4 in Appendix 2.A. In terms of the RMSE the performance of the MS-U-MIDAS-AR deteriorates slightly relative to the MS-MIDAS-AR and MS-ADL-MIDAS. One possible explanation of this deterioration is that AIC suggests large number of lags, and since the unrestricted model is less parsimonious, its forecasting performance becomes worse. However, in terms of predicting the regime changes, the MS-U-MIDAS-AR still performs on average better than both the MS-MIDAS-AR and MS-ADL-MIDAS.

2.3.2.2 DGP generated as a two-regime MS-MIDAS-AR

In order to investigate the out-of-sample performance of MS-U-MIDAS-AR versus MS-MIDAS-AR and MS-ADL-MIDAS in the case when MS-MIDAS-AR is the true DGP, we generate data according to the MS-MIDAS-AR model with an exponential Almon lag (with 6 lags of the higher-frequency variable[4]) and two regimes (see equation (2.6)). The

[4]We also carried out the exercise for 3 lags of the higher-frequency variable, but the results were similar to the ones presented here, so we refrain from including them in the paper.

Table 2.3.5: Choice of the parameters for the Monte Carlo simulations (DGP is a MS-MIDAS-AR with two regimes)

set	regime	β_0	θ_1	θ_2	β_1	λ	σ^2
1	$S_t = 1$	-1	$2 \cdot 10^{-1}$	$3 \cdot 10^{-2}$	0.6	0.2	1
	$S_t = 2$	1	$2 \cdot 10^{-1}$	$3 \cdot 10^{-2}$	0.2	0.2	0.67
2	$S_t = 1$	-0.5	0.7	-0.5	0.8	0.3	1
	$S_t = 2$	0.5	0.7	-0.5	0.1	0.3	0.67

higher frequency variable x_t is generated from the following AR(1) process:[5]

$$x_t = 0.025 + 0.9 \cdot x_{t-1} + \varepsilon_t, \quad \text{where} \quad \varepsilon_t \sim N(0,1) \tag{2.10}$$

We allow the intercept β_0, the slope parameter β_1 and the variance of the error term σ^2 to switch. We consider two possible sets of parameters for the DGP. The details of this parametrization can be found in Table 2.3.5. The transition probabilities remain the same as for the first DGP.

The evaluation of the out-of-sample performance of the models is done in terms of forecasting accuracy and the ability to predict regimes. Thus, we consider the 25th, 50th and 75th percentiles of the ratio of the RMSE of MS-U-MIDAS-AR relative to the RMSE of MS-MIDAS-AR and the RMSE of MS-ADL-MIDAS, calculated over 1000 replications (Table 2.3.6). We also calculate the Quadratic Probability Score of the MS-U-MIDAS-AR relative to the QPS of the MS-MIDAS-AR and MS-ADL-MIDAS models (Table 2.3.7). For both tables values below/above 1 indicate that MS-U-MIDAS-AR performs better/worse than MS-MIDAS-AR or MS-ADL-MIDAS.

Looking at the median of the results, for most considered combinations of parameters the MS-U-MIDAS-AR model is slightly outperformed both by the MS-MIDAS-AR and MS-ADL-MIDAS in terms of forecasting accuracy. However, in predicting regimes the MS-U-MIDAS-AR model outperforms its both counterparts for all considered parameter combinations. Therefore, it seems that even in the case when MS-MIDAS-AR is favored (as this is the true DGP), MS-U-MIDAS-AR outperforms its restricted counterparts in regime prediction.

[5] We also conducted the exercise for different degree of persistence of variable x_t, namely for $\rho = 0.3$, but the results were similar to the ones presented here, so we refrain from including them in the paper.

Table 2.3.6: Out-of-sample Root Mean Squared Error of MS-U-MIDAS-AR relative to MS-MIDAS-AR and MS-ADL-MIDAS (DGP is a MS-MIDAS-AR with two regimes)

	transition probabilities		MS-U-MIDAS-AR vs. MS-MIDAS-AR			MS-U-MIDAS-AR vs. MS-ADL-MIDAS		
set	p_{11}	p_{22}	25^{th}	50^{th}	75^{th}	25^{th}	50^{th}	75^{th}
1	0.95	0.85	0.97	1.03	1.09	0.96	1.00	1.05
1	0.95	0.95	0.96	1.02	1.08	0.95	1.00	1.05
2	0.95	0.85	0.98	1.04	1.11	0.98	1.03	1.09
2	0.95	0.95	0.98	1.03	1.09	0.98	1.02	1.07

Note: The table presents the summary of the results of 1000 Monte Carlo simulations. For each replication 600 observations of a higher-frequency variable x_t and 200 observations of a lower-frequency variable y_t are generated for the in-sample period, whereas 30 lower-frequency (90 higher-frequency) observations are generated for the out-of-sample evaluation according to a MS-MIDAS-AR model with two regimes. Then the MS-U-MIDAS-AR, MS-MIDAS-AR and MS-ADL-MIDAS models are estimated and their out-of-sample performance is measured by Root Mean Squared Error. The table presents the 25th, 50th and 75th percentiles of the ratio of the RMSE of the MS-U-MIDAS-AR to the RMSE of MS-MIDAS-AR or MS-ADL-MIDAS, calculated over all 1000 simulations. Values below/above 1 indicate a better/worse out-of-sample performance of the MS-U-MIDAS-AR model in comparison with its restricted counterpart. The analysis is done for different transition probabilities between the two regimes and for different values of the parameters of the data generating process (see equation (2.6) and Table 2.3.5).

Table 2.3.7: Out-of-sample Quadratic Probability Score of MS-U-MIDAS-AR relative to MS-MIDAS-AR and MS-ADL-MIDAS (DGP is a MS-MIDAS-AR with two regimes)

	transition probabilities		MS-U-MIDAS-AR vs. MS-MIDAS-AR			MS-U-MIDAS-AR vs. MS-ADL-MIDAS		
set	p_{11}	p_{22}	25^{th}	50^{th}	75^{th}	25^{th}	50^{th}	75^{th}
1	0.95	0.85	0.69	0.96	1.08	0.63	0.95	1.08
1	0.95	0.95	0.63	0.98	1.09	0.71	0.99	1.10
2	0.95	0.85	0.73	0.97	1.14	0.68	0.94	1.12
2	0.95	0.95	0.76	0.98	1.09	0.76	0.98	1.09

Note: The table presents the summary of the results of 1000 Monte Carlo simulations. For each replication 600 observations of a higher-frequency variable x_t and 200 observations of a lower-frequency variable y_t are generated for the in-sample period, whereas 30 lower-frequency (90 higher-frequency) observations are generated for the out-of-sample evaluation according to a MS-MIDAS-AR model with two regimes. Then the MS-U-MIDAS-AR, MS-MIDAS-AR and MS-ADL-MIDAS models are estimated and their out-of-sample performance in predicting regimes is measured by Quadratic Probability Score. The table presents the 25th, 50th and 75th percentiles of the ratio of the QPS of the MS-U-MIDAS-AR to the QPS of MS-MIDAS-AR and MS-ADL-MIDAS, calculated over all 1000 simulations. Values below/above 1 indicate a better/worse out-of-sample performance of the MS-U-MIDAS-AR model in comparison with its restricted counterpart. The analysis is done for different transition probabilities between the two regimes and for different values of the parameters of the data generating process (see equation (2.6) and Table 2.3.5).

2.4 Forecasting GDP growth of the United States

In our empirical study we investigate the in- and out-of-sample performance of the class of MS-U-MIDAS models in forecasting quarterly GDP growth of the United States with the help of monthly macroeconomic and financial variables. For horizons $h = \left\{\frac{1}{3}, \frac{2}{3}, 1, 2, 4\right\}$ (fractions denote the cases of nowcasting) we compare the forecasting performance of the MS-U-MIDAS(-AR) models with the corresponding models of the MS-MIDAS(-AR) and MS-ADL-MIDAS class. In addition, for one-, two- and four-step-ahead forecasts we include further Markov-switching models in the comparison: Markov-Switching Distributed Lag model (MS-DL) and Markov-Switching Autoregressive Distributed Lag model (MS-ADL). The MS-DL and MS-ADL models are equivalent to MS-MIDAS and MS-ADL-MIDAS correspondingly with all lags of the explanatory variable equally weighted. Thus, it is reasonable to compare these models with MS-MIDAS regressions in order to see whether the use of models with estimated lag polynomial weights is nec-

essary. However, a major drawback of the distributed lag class of models is that they do not allow for leads, and thus they cannot use the available data on monthly regressors for the quarter for which the forecast is calculated. That is why, these models cannot be used for nowcasting.

In our comparison we also include benchmark models without Markov-switching, in particular random walk and AR(2) model, U-MIDAS and MIDAS (with and without autoregressive dynamics), Distributed Lag model (DL) and Autoregressive Distributed Lag model (ADL). These constant-parameter models are restricted versions of the models with Markov-switching, so it is reasonable to use them for the sake of comparison of the model performance. An overview of the models we use in the analysis can be found in Table 2.A.1 in Appendix 2.A.

The first part of the empirical study concentrates on the description and the introductory analysis of the dataset, as well as on the extraction of factors from the data. Further parts include the analysis of the in-sample fit of the MS-U-MIDAS-AR model and its forecasting performance (in terms of the RMSE and QPS) in comparison to a wide spectrum of other models mentioned above.

2.4.1 Data

For the empirical exercise on forecasting quarterly GDP growth of the United States, we use a set of 156 monthly macroeconomic and financial variables, yielding information on i.a.: industrial production, employment, inflation, federal debt, bank assets, interest rates, government bonds, stock prices and some macroeconomic leading indicators. This data comes from Datastream. The data on output covers the period from 1959:Q1 to 2011:Q3 (211 quarters). The monthly data covers the period from June 1958 to September 2011. The information on the business cycles in the United States comes from the National Bureau of Economic Research[6] and is used to assess the performance of the model in predicting regime changes in the economy.

The dataset we use in our analysis is qualitatively similar to other forecasting studies on the US GDP growth (e.g. Giannone and Small (2008)), but includes fewer variables (156 compared to 200 variables in the cited paper). This is due to the fact that Markov-switching models involve the estimation of a large number of parameters. Thus, the use of such models requires a long sample, which means that fewer variables are available throughout the analyzed period in comparison with some other studies. Although in our sample we include a wide spectrum of macroeconomic and financial variables, our data selection is limited by the availability of time series.

The data we use is a final vintage, balanced dataset, collected in September 2012. Thus we do not account for data revisions and publication lags of the monthly variables. As

[6]Data available at: http://www.nber.org/cycles/cyclesmain.html

the dataset we use includes more than 150 variables, this would simply complicate the analysis to a great extent. Besides, we do not know the exact publication pattern for all the variables we use in the analysis. We also do not want to create any kind of artificial pattern, especially when we cannot realistically assume that this pattern remains stable over the whole period we consider in our analysis. However, as a robustness check we repeat the forecasting exercise for real-time data on the GDP growth.[7] The results of this real-time analysis can be found in Appendix 2.A (Tables 2.A.10 - 2.A.13).
We carried out Augmented Dickey-Fuller and Philips-Perron unit root tests for all time series included in our data set to investigate their order of integration. Based on the results we transformed the data to ensure stationarity. Depending on the characteristics and behavior of the data we either used first/second differences or first/second differences of logarithms of the time series to stationarize them. The GDP growth was calculated as: $100(\ln(GDP_t) - \ln(GDP_{t-1}))$. The details of the transformation for specific variables and the exact description of all time series used in the analysis can be found in Table 2.A.2 in Appendix 2.A.

2.4.2 Extracting factors from the dataset

MIDAS models are usually applied within a univariate framework, that is, only one explaining variable is included in the model. That ensures parsimony and simplifies the estimation, but does not seem to be an optimal solution, as it is difficult to pick up a single variable that summarizes the overall economic situation accurately and preserves the same level of relevance for the economic activity over a long time period. A reasonable approach should explore the informational content of a wide range of available macroeconomic and financial time series, which only as a whole, not as single variables, can reflect the current state of the economy. However, the inclusion of many regressors in the model results in parameter proliferation and therefore is very problematic. A possible solution to that issue is the use of factor analysis. There is a vast literature available on techniques of factor extraction, e.g. Forni, Hallin, Lippi, and Reichlin (2000, 2005), Bai and Ng (2002), Stock and Watson (2002a) or Bai (2003). It is assumed that an N-dimensional set of explanatory variables $\boldsymbol{X}_t$ can be represented by a few common latent factors $\boldsymbol{F}_t$, which are then used as regressors in the main analysis:

$$\boldsymbol{X}_t = \Delta \boldsymbol{F}_t + \boldsymbol{e}_t,$$

where $\boldsymbol{e}_t$ is a vector of idiosyncratic disturbances, and Δ is the loading matrix.
The main idea behind factor analysis is to transform the available dataset in such a way that a substantial part of the variation of the observed variables can be explained by just

[7] The real-time data on the GDP comes from the website: http://www.philadelphiafed.org/research-and-data/real-time-center/real-time-data/data-files/ROUTPUT/

a few unobserved factors. Thus, using a single factor that explains a large part of the variation, instead of a single observed variable, may capture more information from the available dataset and ensure the parsimony of the model. However, as useful as this method is, one should use it with some caution. Factor analysis is a purely statistical way of summarizing the variation of the dataset in an efficient way in order to reduce the dimension of the system. The factors which explain the biggest part of the overall variation in the dataset, are not always the best predictors of the dependent variable. Consequently, the choice of factors may play a crucial role in the analysis and the forecasting performance of the model might heavily depend on it. To achieve good forecasting results and at the same time maintain parsimony of the model, one may use forecast combinations of single-factor regressions. We follow this approach in further parts of the paper.

Following the above-described way of reducing the dimension of the dataset, we use principal component analysis to extract factors from our set of monthly macroeconomic and financial variables for the United States. For the introductory analysis, we extract factors using the whole available sample of the monthly data, that is, from June 1958 to September 2011. However, for further analysis of the forecasting performance of the models, we first extract factors for the in-sample period only and then for the out-of-sample period factors are extracted recursively, that is, they are updated with each forecast calculation. For the whole sample we find that the first factor explains about 10% of the variation of the dataset, whereas the first five factors together account for about 27% of the variation. These numbers might not sound impressive, but they are not uncommon for large datasets which include a wide spectrum of different variables (see e.g. Stock and Watson (2002b)). Figure 2.A.1 in Appendix 2.A illustrates graphically the percentage of the whole variation of the dataset, explained by the first ten factors.

The choice of the optimal number of factors for further analysis is not a trivial issue. We follow the approach of Bai and Ng (2002), who treat the selection of the number of factors as a problem of optimizing the trade-off between the goodness-of-fit of the model and its parsimony. We apply the first and the second criterion proposed by these authors and find that both criteria consistently point to four and five factors respectively. Thus, considering five factors for further analysis seems to be a reasonable approach. One can make use of the informational content of each of these factors by considering them together as regressors within one model or by combining forecasts obtained through models which use them as single explanatory variables. To avoid parameter proliferation we focus on the latter option and in further parts of the paper we investigate the forecasting accuracy of the single-factor models, as well as their combinations.

It turns out that factor 1 loads mainly on variables such as industrial production, industrial confidence indicator, leading macroeconomic indicators and manufacturers' survey data. Factor 2 loads mainly on interest rates, bond yields and stock market indices. Factor 3 loads mainly on inflation data (CPI, PPI, oil price index), whereas factor 4 on bond yields,

industrial production and number of working hours. Finally, factor 5 loads on stock prices, employment and manufacturers' survey data. Further analysis shows how useful each of these factors is in forecasting GDP growth and to what extent the forecasting performance of the tested models can be enhanced by combining the forecasts obtained from single factors. The graphical representation of the five factors together with the GDP growth can be found in Figure 2.A.2 in Appendix 2.A.

2.4.3 Further issues concerning the MS-MIDAS class of models

An issue of utmost importance for the models of Markov-switching type is the choice of the optimal number of regimes and the determination of the parameters that are allowed to switch in the model. For the model specification we use the Akaike (AIC) and Bayesian (BIC) Information Criteria. We test the cases when the number of regimes equals two (recession and expansion) and three (recession, stable growth and rapid expansion). However, the information criteria do not deliver unanimous results on the optimal number of regimes. AIC points towards three regimes (three regimes were also used in a similar study for the US GDP by Guérin and Marcellino (2013), although that result was obtained through BIC), whereas BIC, which penalizes the growth of the number of parameters in the model more strongly, points towards a model with two regimes. Thus, for the sake of robustness we present results for models with two and three regimes. In addition, we find it important to see how the performance of the MS-U-MIDAS model changes in comparison with its restricted counterpart in the case when the number of parameters grows (two versus three regimes).

Furthermore, with the help of AIC and BIC we investigate models that allow for a switch only in the intercept β_0, in the intercept β_0 and variance of the error term σ^2, as well as in the intercept β_0, variance σ^2 and slope parameter β_1 (the coefficient of the autoregressive term λ and the parameters of the lag polynomial $\boldsymbol{\theta}$ do not switch between regimes). Both criteria favor models with all parameters switching. As the volatility of the analyzed time series of GDP growth changes over time, and increases especially dramatically during the crisis periods, we do not think it is reasonable to consider a model without a switch in the variance of the error term and this case is not examined further in our paper. However, we do consider the other cases, that is, for the sake of completeness we investigate the performance of models with a switch in intercept and variance only, as well as with all the parameters allowed to switch between the regimes.

We also use the above-mentioned information criteria to determine the optimal number of lags of the explanatory variables included in the analyzed models, setting the maximum number of autoregressive lags to 4 (four quarters can be taken into account) and the maximum number of lags of the other explanatory variables to 6 (six for the monthly data, that is the information from the last two quarters can be included) in order to avoid parameter

proliferation. In most cases the information criteria opt for a different number of lags, but we find hardly any differences between the performance of the models estimated according to AIC or BIC. In the paper we only present results for the number of lags chosen according to AIC, as this criterion tends to overestimate the optimal number of lags and thus creates a potentially more difficult test for the unrestricted class of MIDAS models, which are more prone to parameter proliferation than their restricted counterparts.

2.4.4 In-sample fit of the MS-U-MIDAS model

In this paper we consider many different models with a lot of parameters, so it is difficult to present the estimation results for all of them. Generally, for regime-switching models, one can observe that the parameters differ between the states of the world - small intercept β_0 and high variance σ^2 indicate a recession, whereas high intercept β_0 and low variance σ^2 point to expansion. A useful feature of Markov-switching models is that, apart from the estimated parameters and fitted values of the dependent variable, one can also obtain the probabilities of being in a specific regime in a given point in time. Thus, one can calculate the probabilities of being in a period of recession and expansion. As this feature is particularly important for the policy makers and gives the opportunity to show the in-sample performance of the model in a graphical way, we present the smoothed probabilities of being in a specific regime in relation to the actual crisis periods (taken from NBER database).

We consider the performance of the five factors taken for further analysis and present the results for the MS-U-MIDAS model with two and three regimes (with intercept, slope and variance of the error term switching). For the case of two regimes all of the five factors perform quite well in detecting the recent periods of crisis (after 1990). However, most of them (especially factors 1, 4 and 5) face substantial problems in matching the earlier recessions, which is mainly due to the fact that the overall volatility of the series before 1990 is considerably higher than after 1990. Factor 2, on the other hand, seems to match the crisis periods before 1990 especially well, whereas the spike representing the dot-com bubble from 2000-2001 is in its case not so conspicuous (see Figure 2.4.1). This points to the fact that some of the factors (factor 2 and 3) perform better in matching the recessions before 1990, while others excel in detecting the more recent crises. This might be an argument in favor of using multiple factors within the same model or combining results obtained from single-factor regressions.

The unsatisfactory performance of the model in identifying recessionary periods before 1990 could also be a point in favor of a model with three regimes. Due to higher parameter flexibility such a model might be able to deal with the change in volatility of the GDP growth of the United States across the analyzed period better than the model with two regimes.

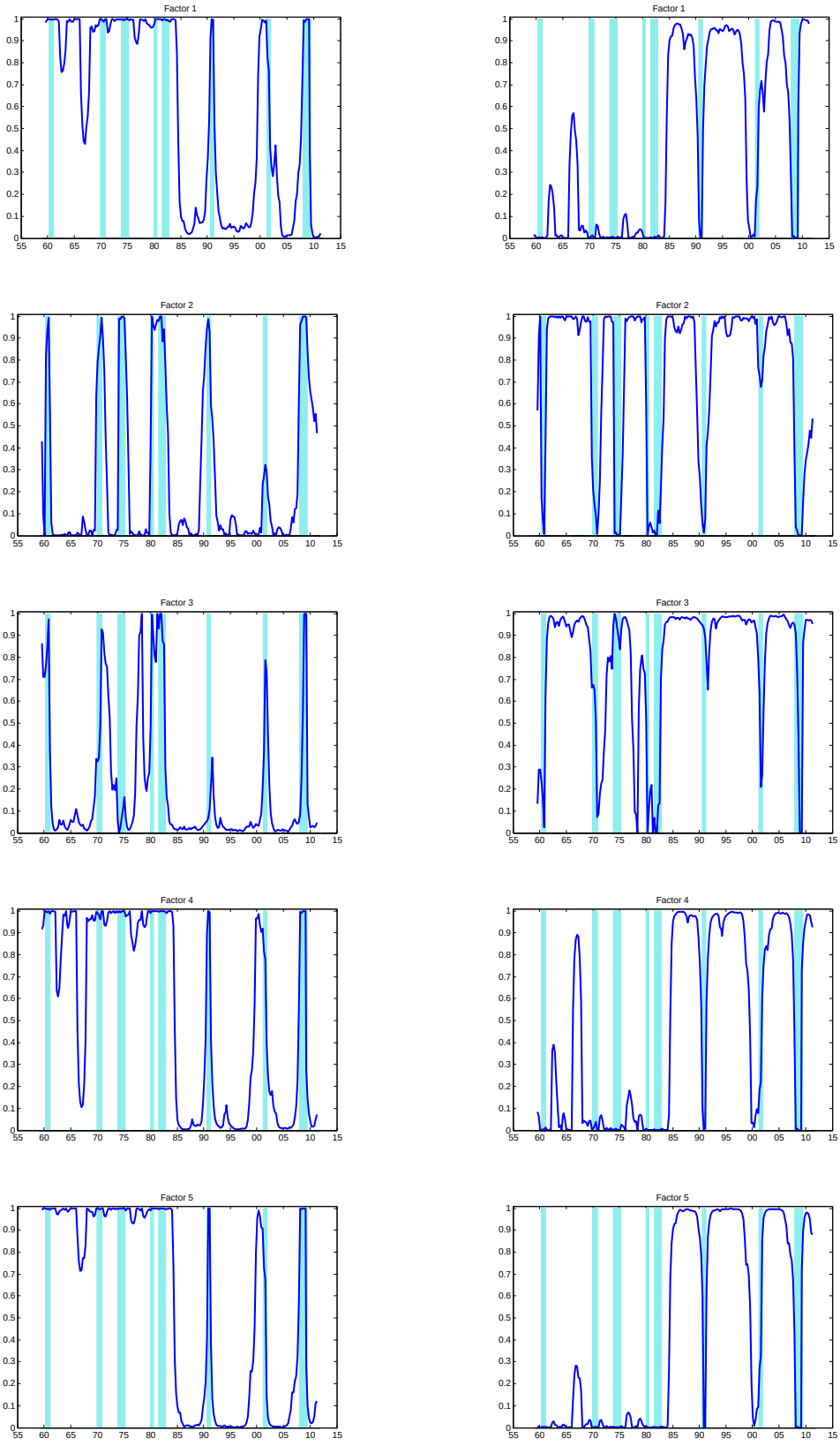


Figure 2.4.1: Smoothed probabilities (dark line) of a crisis (left) and expansion (right), calculated for the period from 1959:Q1 to 2011:Q3 for the MS-U-MIDAS model with two regimes (all parameters allowed to switch). The probabilities are compared with the actual recessionary periods according to NBER (bars).

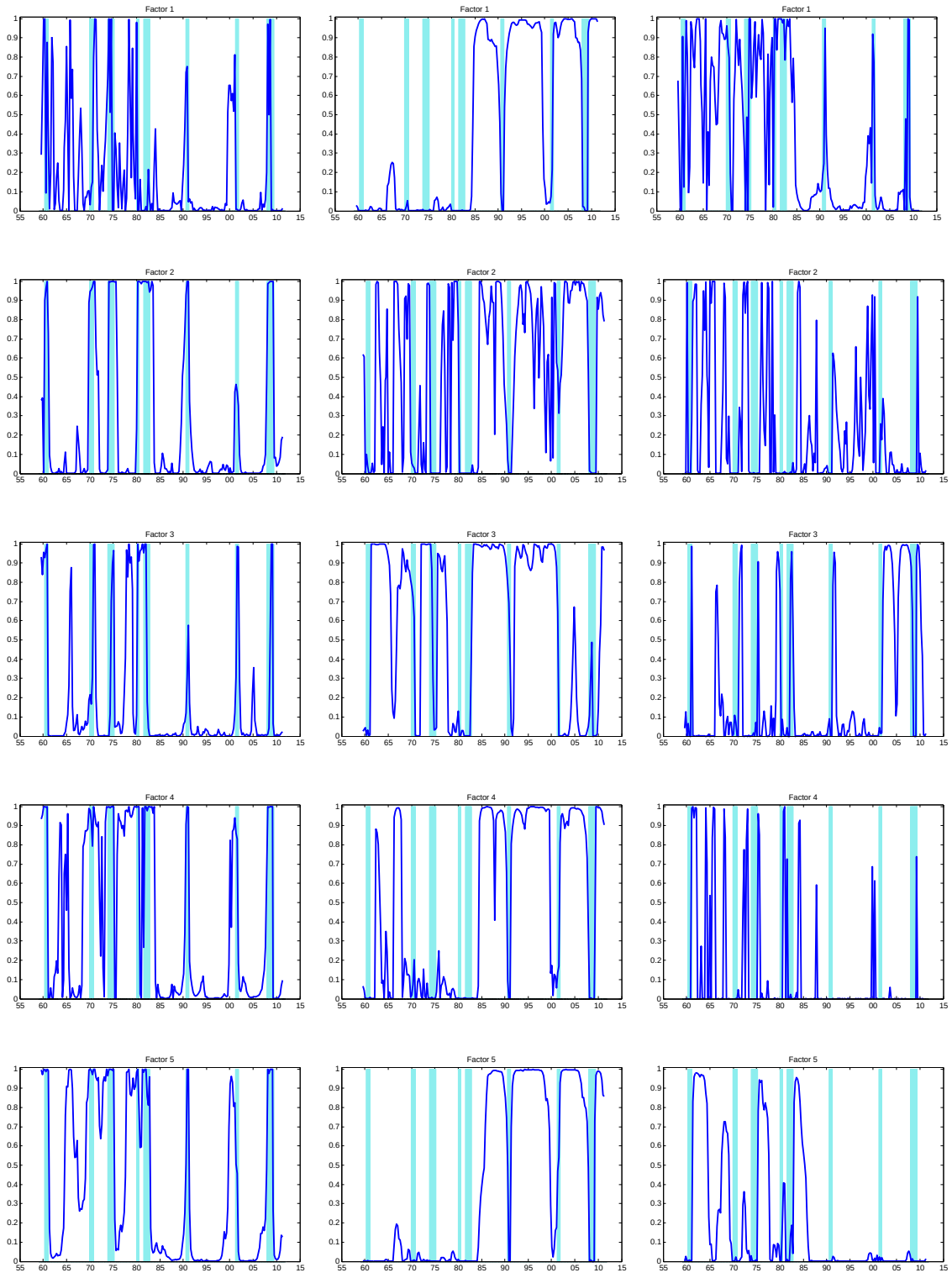


Figure 2.4.2: Smoothed probabilities (dark line) of a crisis (left), stable growth (middle) and expansion (right), calculated for the period from 1959:Q1 to 2011:Q3 for the MS-U-MIDAS model with three regimes (all parameters allowed to switch). The probabilities are compared with the actual recessionary periods according to NBER (bars).

The estimation of the MS-U-MIDAS model with three regimes and all parameters switching yields slightly better in-sample results for the period before 1990 in comparison to the model with two regimes (see Figure 2.4.2), although the results for factors 1,4 and 5 are still not satisfactory for this time period. The recent recessions are again matched more accurately. However, a relative in-sample performance improvement for some factors in the case of three regimes does not guarantee that models with three regimes will perform better than those with two regimes in the out-of-sample analysis, which is the main purpose of this work.

2.4.5 Out-of-sample performance of the MS-U-MIDAS model

In order to investigate the forecasting performance of the MS-U-MIDAS model, we divide our original sample into two parts: the time between 1959:Q1 and 1999:Q4 is considered the in-sample period (160 quarters), whereas the time from 2000:Q1 to 2011:Q3 (47 quarters) is used for the forecasting exercise. The choice of the in- and out-of-sample periods is arbitrary. However, the in-sample period should be long enough to ensure precise parameter estimation, whereas the out-of-sample period, which encompasses both some expansion and recession periods, is chosen to be long enough to help to reliably assess the forecasting performance of the model. For the exercise presented here we use final-vintage data, but we also repeat the analysis for the real-time dataset for the US GDP. The results of this exercise for horizons $\left\{h = \frac{1}{3}, \frac{2}{3}, 1\right\}$ can be found in Appendix 2.A (Tables 2.A.10 - 2.A.13), and overall they are comparable to the results for the final vintage data. We calculate forecasts recursively for horizons $\left\{h = \frac{1}{3}, \frac{2}{3}, 1, 2, 4\right\}$. We also extract factors from the explanatory dataset in a recursive way. For nowcasting the horizon is defined as a fraction and the forecasts are calculated using leads, that is, in the MIDAS class of models we include monthly observations from the quarter for which the forecast is calculated.

The forecasting exercise is carried out not only for the MS-U-MIDAS class of models, but also for a wide range of other models: MS-MIDAS(-AR) models, MS-ADL-MIDAS model, Markov-switching Distributed Lag model (MS-DL), Markov-switching Autoregressive Distributed Lag model (MS-ADL), and some models without Markov-switching: MIDAS and U-MIDAS (with and without autoregressive dynamics), Distributed Lag model (DL), Autoregressive Distributed Lag model (ADL), AR(2) and random walk (RW). In the case of models that do not allow for mixed frequency, it is not possible to use leads. That is why, these models are only included in the comparison for horizons $h = \{1, 2, 4\}$, but not for nowcasting.

The forecasts are first calculated separately for models that use each of the five single factors considered in the analysis. Then those forecasts are combined according to five different schemes in order to enhance the forecasting performance of the single factors. We first consider the mean (Mean) and median (Med.) of the forecasts from all single-factor

models. Further we use a scheme, proposed by Stock and Watson (2004), that assigns weights to single-factor forecasts according to their Squared Discounted Mean Forecast Error (S.D.E.), thus accounting for past forecasting performance of the model and at the same time giving more weight to more recent observations. The forecast weights w_{it} in this method are calculated as follows:

$$w_{it} = \frac{m_{it}^{-1}}{\sum_{j=1}^{n} m_{jt}^{-1}}, \quad \text{where} \quad m_{it} = \sum_{s=\tau}^{t-h} \delta^{t-h-s} (y_{s+h} - \hat{y}_{i,s+h|s})^2.$$

δ denotes the discount factor, which in our analysis is equal to 0.9, h is the forecast horizon, y the actual and $\hat{y}$ the estimated GDP growth, n the number of forecasts combined, t is the time index and i is the index denoting the forecast of i-th model considered for the combination.

Finally, we also consider a forecast combination scheme which trims the recently worst model - we take account for the last quarter (Tr.(1)) and the last four quarters (Tr.(4)).

The forecasts obtained through the above-described combination methods are then compared in terms of RMSE and QPS. We also compare the forecasting performance of the combination schemes with the performance of single-factor models. The results of such exercise for different forecasting horizons can be found in Tables 2.A.5 - 2.A.9 in Appendix 2.A. To save space, in the main part of the paper in Table 2.4.1 we present results for different forecasting horizons, but only for one forecast combination scheme (Mean). The RMSEs are presented relative to the benchmark model, which is an AR(2). Values below/above 1 indicate better/worse performance of the specific model in comparison to AR(2). We also present the out-of-sample results for the QPS in Table 2.4.2. A concise summary of all the results from Tables 2.A.5 - 2.A.9 from Appendix 2.A can be found in Table 2.4.3.

There is no clear pattern which could help us to rank the factors in terms of their forecasting suitability. However, it seems that especially factor 1, and factors 3 and 5 to a less extent, perform decently in forecasting GDP growth for some of the considered cases, whereas factor 2 deals with the task considerably worse. This might seem surprising, as factor 2 performs very well in detecting periods of recession in the in-sample analysis. A reason for such situation might be the fact that factor 2 loads mainly on financial variables, which are helpful in detecting the periods of financial crises, but are no longer particularly useful in forecasting GDP growth during periods of stable growth. That results in an overall unsatisfactory forecasting performance. On the other hand, factor 1 and, to a less extent, factors 3, 4 and 5 load on macroeconomic variables, which prevents them from being very accurate in detecting financial crises, but adds to their relatively good performance in forecasting GDP growth.

In general, our results confirm the findings of many forecasting exercises, which conclude that combining forecasts gives more robust and in many cases also better results than

Table 2.4.1: Root Mean Squared Errors relative to AR(2) model. Final vintage data used. Number of lags in the models chosen according to AIC.

Model	Switch	h=1/3	h=2/3	h=1	h=2	h=4
Benchmarks						
RW	—	X	X	1.11	1.09	1.23
AR(2)	—			1.00	1.00	1.00
2 regimes						
MS-U-MIDAS	I,V	0.93*	0.93	1.04	1.06	1.00
MS-U-MIDAS	I,S,V	0.91*	0.96	1.04	1.04	0.96
MS-U-MIDAS-AR	I,V	0.83***	0.83**	0.90	0.96	0.98
MS-U-MIDAS-AR	I,S,V	0.83***	0.81***	0.93	0.97	0.98
MS-MIDAS	I,V	0.89**	0.91	1.04	1.06	1.00
MS-MIDAS	I,S,V	0.86**	0.90*	1.05	1.05	1.00
MS-MIDAS-AR	I,V	0.87***	0.86*	0.94	0.96	0.97
MS-MIDAS-AR	I,S,V	0.85***	0.85***	0.94	0.97	0.99
MS-ADL-MIDAS	I,V	0.81***	0.84***	0.92	0.97	1.01
MS-ADL-MIDAS	I,S,V	0.79***	0.83***	0.96	1.00	1.02
MS-ADL	I,V	X	X	0.93	0.96	0.97
MS-ADL	I,S,V			0.93	0.96	0.96
MS-DL	I,V	X	X	1.05	1.05	0.99
MS-DL	I,S,V			1.02	1.05	0.96
3 regimes						
MS-U-MIDAS	I,V	0.92*	0.91	0.97	1.01	0.94
MS-U-MIDAS	I,S,V	0.85**	0.92**	0.97	0.99	0.95
MS-U-MIDAS-AR	I,V	0.80***	0.87*	0.94	0.95	0.95
MS-U-MIDAS-AR	I,S,V	0.83***	0.81***	0.95	0.97	0.97
MS-MIDAS	I,V	0.90**	0.90**	0.97	1.01	0.96
MS-MIDAS	I,S,V	0.89**	0.86**	0.96	1.00	0.96
MS-MIDAS-AR	I,V	0.84***	0.87**	0.94	0.98	0.95
MS-MIDAS-AR	I,S,V	0.83***	0.84**	0.92	0.99	0.94
MS-ADL-MIDAS	I,V	0.77***	0.85***	0.91	0.97	0.99
MS-ADL-MIDAS	I,S,V	0.84**	0.85***	0.94	0.98	1.00
MS-ADL	I,V	X	X	0.93	0.98	0.96
MS-ADL	I,S,V			0.93	0.97	0.94
MS-DL	I,V	X	X	1.00	1.00	0.95
MS-DL	I,S,V			0.98	0.96	0.94
Models without Markov-switching						
U-MIDAS	—	0.93*	0.95	1.04	1.05	1.01
U-MIDAS-AR	—	0.82***	0.85***	0.92***	0.97	1.00
MIDAS	—	0.85**	0.91	1.02	1.07	1.01
MIDAS-AR	—	0.82***	0.85***	0.94***	0.98	0.99
ADL-MIDAS	—	0.79***	0.84***	0.92	0.97	1.01
DL	—	X	X	1.00	0.97	1.08
ADL	—			0.94***	0.98	0.98

Note: *** - significant at 1% level, ** - at 5% level, * - at 10% level (significance of the forecasting performance relative to the random walk model was investigated with the help of Diebold-Mariano test).

Column "Switch" gives information on the parameters that are allowed to switch in the model: I-intercept β_0, V-variance of the error term σ^2, S-slope β_1.

The table presents the out-of-sample RMSEs for the models compared in this paper. The original sample is divided into the in-sample period between 1959:Q1 and 1999:Q4 (160 quarters) and the out-of-sample period between 2000:Q1 and 2011:Q3 (47 quarters). For the out-of-sample period the forecasts are calculated recursively. In order to evaluate the forecasting performance of the models we calculate the RMSE for each model for the whole out-of-sample period. The RMSEs are calculated for the forecast combination scheme that involves taking the mean of the forecasts from single factor models.

Table 2.4.2: Quadratic Probability Scores calculated for filtered probabilities of the crisis regime for the out-of-sample period. Final vintage data is used.

Model	Switch	h=1/3	h=2/3	h=1
2 regimes				
MS-U-MIDAS	I,V	0.360^{**}	0.345^{*}	0.392
MS-U-MIDAS	I,S,V	0.314^{**}	0.442	0.505
MS-U-MIDAS-AR	I,V	0.295^{***}	0.381^{**}	0.450
MS-U-MIDAS-AR	I,S,V	0.381^{**}	0.324^{***}	0.383
MS-MIDAS	I,V	0.345^{**}	0.391	0.443
MS-MIDAS	I,S,V	0.372	0.503	0.528
MS-MIDAS-AR	I,V	0.331^{***}	0.388^{**}	0.437
MS-MIDAS-AR	I,S,V	0.332	0.479	0.514
MS-ADL-MIDAS	I,V	0.405^{**}	0.410^{**}	0.452
MS-ADL-MIDAS	I,S,V	0.368^{**}	0.271^{***}	0.490
MS-ADL	I,V	X	X	0.497
MS-ADL	I,S,V			0.473
MS-DL	I,V	X	X	0.441
MS-DL	I,S,V			0.481
3 regimes				
MS-U-MIDAS	I,V	0.261^{***}	0.297^{***}	0.296^{***}
MS-U-MIDAS	I,S,V	0.316^{**}	0.297^{***}	0.276^{***}
MS-U-MIDAS-AR	I,V	0.353^{*}	0.342^{**}	0.308^{***}
MS-U-MIDAS-AR	I,S,V	0.320^{**}	0.344^{*}	0.335^{**}
MS-MIDAS	I,V	0.349^{*}	0.290^{***}	0.305^{**}
MS-MIDAS	I,S,V	0.342^{*}	0.295^{***}	0.279^{***}
MS-MIDAS-AR	I,V	0.327^{**}	0.319^{**}	0.312^{**}
MS-MIDAS-AR	I,S,V	0.301^{***}	0.285^{***}	0.327^{**}
MS-ADL-MIDAS	I,V	0.354^{*}	0.337^{**}	0.341^{*}
MS-ADL-MIDAS	I,S,V	0.300^{**}	0.352^{*}	0.316^{**}
MS-ADL	I,V	X	X	0.355^{*}
MS-ADL	I,S,V			0.349^{*}
MS-DL	I,V	X	X	0.264^{***}
MS-DL	I,S,V			0.306^{**}

Note: *** - significant at 1% level, ** - at 5% level, * - at 10% level (significance of the regime predicting performance relative to the MS-ADL model with 2 regimes was investigated with the help of Diebold-Mariano test).
Column "Switch" gives information on the parameters that are allowed to switch in the model: I-intercept β_0, V-variance of the error term σ^2, S-slope β_1.
The table presents the out-of-sample QPS for the models compared in this paper. The original sample is divided into the in-sample period between 1959:Q1 and 1999:Q4 (160 quarters) and the out-of-sample period between 2000:Q1 and 2011:Q3 (47 quarters). For the out-of-sample period the predicted probabilities of the crisis regime are calculated recursively for each single factor model. These probability forecasts are then combined by taking the mean of the single forecasts. The combined probability forecasts are then compared with the actual recessionary periods according to NBER.

using forecasts of single-variable models (Timmermann (2006)). Forecast combinations do not only usually display more forecasting accuracy, but also show more reliability than the individual forecasts. For most analyzed models the out-of-sample performance of individual forecasts depends heavily on the single factor used for forecasting. Thus, the same model may display very good or very poor performance depending on which of the five factors is used for forecasting. Moreover, the differences in the average performance of the five combination schemes (Mean, Med., S.D.E., Tr.(1) and Tr.(4)) are small for

Table 2.4.3: Summary of the results

Model	h=1/3	h=2/3	h=1	h=2	h=4
in terms of RMSE					
MS-U-MIDAS	0.0	0.0	0.0	0.0	47.2
MS-U-MIDAS-AR	25.0	66.6	66.7	41.7	5.6
MS-MIDAS	0.0	0.0	0.0	0.0	0.0
MS-MIDAS-AR	0.0	16.7	0.0	25.0	47.2
MS-ADL-MIDAS	75.0	16.7	33.3	33.3	0.0
in terms of QPS					
MS-U-MIDAS	66.7	16.7	50.0		
MS-U-MIDAS-AR	33.3	16.7	8.3		
MS-MIDAS	0.0	33.3	25.0		
MS-MIDAS-AR	0.0	0.0	16.7		
MS-ADL-MIDAS	0.0	33.3	0.0		

Note: The table contains the summary of the results from Tables 2.A.5 - 2.A.9 in Appendix 2.A. It shows the proportion of times (in %) when a specific type of model is better then the other models. The comparison is done in terms of the RMSE and QPS, and includes the specifications for single factor models, as well as for forecast combination made by taking the mean of the single forecasts. The models considered in the comparison are the models that are the main scope of this paper: MS-U-MIDAS(-AR), MS-MIDAS(-AR) and MS-ADL-MIDAS. The models with all parameters switching (I,V,S) and the models without the slope parameters switching (I,V) are considered as one type of model and classified together.

each of the considered regressions.

It is worth noting that in some cases models without Markov-switching perform surprisingly well after combining the forecasts from different factors. However, if we take a closer look at their performance in forecasting using single factors, we can observe that they perform worse compared to their Markov-switching counterparts. So in many cases models without Markov-switching parameters gain slightly more from forecast combination than the class of Markov-switching models that we consider in this paper. In several cases, the performance of the Markov-switching models after combining the forecasts for different factors is worse than for the best performing factor. On the other hand, in most of the cases, the forecasting performance of the models without Markov-switching parameters after forecast combination is better than the best performing factor. Therefore, when comparing the forecasting performance of the models, one should not only focus on the combined forecasts, but also consider the forecasting accuracy of the single factors.

The overall results show that the MS-U-MIDAS-AR models perform especially good in terms of the RMSE for horizons $h = 2/3$ and $h = 1$ (they are better than other models in more than 60% of the considered cases). Only for $h = 1/3$ the MS-ADL-MIDAS model shows better performance than the MS-U-MIDAS-AR, and for $h = 4$ the MS-U-MIDAS model beats its counterpart with autoregressive dynamics. The MS-MIDAS(-AR) types of models are clearly beaten by both the MS-U-MIDAS(-AR) and MS-ADL-MIDAS. However, one has to admit that in most cases the differences are rather small and statistically insignificant. In fact, the results of equal predictive accuracy test (Diebold-Mariano test), conducted against the benchmark model, show that both in terms

of forecasting performance, as well as in the case of regime predicting performance, most results are insignificant for horizons $h = 2$ and $h = 4$. For shorter horizons $h = \left\{\frac{1}{3}, \frac{2}{3}, 1\right\}$ most of the results are highly significant. That points to the fact that the MIDAS type of models are especially useful for nowcasting.
In terms of the QPS the MS-U-MIDAS model performs well, especially for horizons $h = 1/3$ and $h = 1$. For horizon $h = 2/3$ the performance of MS-U-MIDAS(-AR), MS-MIDAS and MS-ADL-MIDAS is comparable. Although adding autoregressive dynamics is very important in improving the forecasting accuracy in terms of RMSE for all considered models and all forecasting horizons, this is not the case when the interest is in forecasting the true regime. The forecasting results for QPS show that in most of the cases adding autoregressive dynamics leads to deterioration of the regime predicting ability of the models. It is also worth noting that in most of the cases models with 3 regimes outperform their equivalents with 2 regimes in predicting the true regime, whereas the forecasting accuracy in terms of RMSE is robust to the choice of the number of regimes.

2.5 Conclusion

The class of MIDAS models opens new possibilities for researchers to use the available data of different frequencies in forecasting and deal with the problem of different publication lags of many macroeconomic variables. The Markov-switching MIDAS additionally offers the possibility of modeling the business cycle pattern present in many macroeconomic time series. However, one of the issues still open for research on MIDAS is the optimal choice of the shape of weights in the lag polynomial used in this class of models. In most applications this choice is restricted by a specific function shaping the lag polynomial and thus might not fully reflect the true data generating process.
In this paper we investigate the usefulness of factor MIDAS models with unrestricted lag polynomial and Markov-switching component for modeling large datasets. We show that it can be implemented with good results for forecasting tasks, when the difference between the frequencies of the analyzed variables is small (e.g. quarterly - monthly data). We compare the MS-U-MIDAS(-AR), MS-MIDAS(-AR) and MS-ADL-MIDAS through Monte Carlo simulations for different DGPs and through an empirical forecasting exercise for the GDP growth of the United States. In both cases, the MS-U-MIDAS class of models performs comparably or better than its restricted counterparts. This makes the unrestricted Markov-switching MIDAS a useful alternative to the restricted MS-MIDAS model for many macroeconomic applications, especially when the difference in frequencies is small. Furthermore, we show that using forecast combinations of models with different factors often provides better results than using forecasts from single factor models. To sum up, the methods presented and applied in this paper help to make better use of the informational content of the available datasets and thus, in many cases, obtain better forecasts for the

variables of interest.

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2.A Appendix

Table 2.A.1: Regression models used in the analysis

Models without Markov-switching	
RW	$y_t^Q = \beta_0 + y_{t-1}^Q + \varepsilon_t$
AR(p)	$y_t^Q = \beta_0 + \sum_{i=1}^{p} \lambda_i y_{t-i}^Q + \varepsilon_t$
ADL(p,q)	$y_t^Q = \beta_0 + \sum_{i=1}^{p} \lambda_i y_{t-i}^Q + \sum_{j=1}^{q} \beta_j x_{t-j}^Q + \varepsilon_t$
ADL-MIDAS	$y_t^Q = \beta_0 + \sum_{i=0}^{p-1} \lambda_{i+1} y_{t-1-i}^Q + \beta_1 B(L^{1/m}; \boldsymbol{\theta}) x_{t-1}^M + \varepsilon_t$
MIDAS	$y_t^Q = \beta_0 + \beta_1 B(L^{1/m}; \boldsymbol{\theta}) x_{t-h}^M + \varepsilon_t$
MIDAS-AR	$y_t^Q = \beta_0 + \lambda y_{t-d}^Q + \beta_1 B(L^{1/m}; \boldsymbol{\theta})(1 - \lambda L^d) x_{t-h}^M + \varepsilon_t$
U-MIDAS	$y_t^Q = \beta_0 + \sum_{j=0}^{J-1} \beta_{j+1} x_{t-h-j/m}^M + \varepsilon_t$
U-MIDAS-AR	$y_t^Q = \beta_0 + \sum_{i=0}^{p-1} \lambda_{i+1} y_{t-d-i}^Q + \sum_{j=0}^{J-1} \beta_{j+1} x_{t-h-j/m}^M + \varepsilon_t$
Markov-switching Models	
MS-U-MIDAS (I,V)	$y_t^Q = \beta_0(S_t) + \sum_{j=0}^{J-1} \beta_{j+1} x_{t-h-j/m}^M + \varepsilon_t(S_t)$
MS-U-MIDAS (I,V,S)	$y_t^Q = \beta_0(S_t) + \sum_{j=0}^{J-1} \beta_{j+1}(S_t) x_{t-h-j/m}^M + \varepsilon_t(S_t)$
MS-U-MIDAS-AR (I,V)	$y_t^Q = \beta_0(S_t) + \sum_{i=0}^{p-1} \lambda_{i+1} y_{t-d-i}^Q + \sum_{j=0}^{J-1} \beta_{j+1} x_{t-h-j/m}^M + \varepsilon_t(S_t)$
MS-U-MIDAS-AR (I,V,S)	$y_t^Q = \beta_0(S_t) + \sum_{i=0}^{p-1} \lambda_{i+1} y_{t-d-i}^Q + \sum_{j=0}^{J-1} \beta_{j+1}(S_t) x_{t-h-j/m}^M + \varepsilon_t(S_t)$
MS-MIDAS (I,V)	$y_t^Q = \beta_0(S_t) + \beta_1 B(L^{1/m}; \boldsymbol{\theta}) x_{t-h}^M + \varepsilon_t(S_t)$
MS-MIDAS (I,V,S)	$y_t^Q = \beta_0(S_t) + \beta_1(S_t) B(L^{1/m}; \boldsymbol{\theta}) x_{t-h}^M + \varepsilon_t(S_t)$
MS-MIDAS-AR (I,V)	$y_t^Q = \beta_0(S_t) + \lambda y_{t-d}^Q + \beta_1 B(L^{1/m}; \boldsymbol{\theta})(1 - \lambda L^d) x_{t-h}^M + \varepsilon_t(S_t)$
MS-MIDAS-AR (I,V,S)	$y_t^Q = \beta_0(S_t) + \lambda y_{t-d}^Q + \beta_1(S_t) B(L^{1/m}; \boldsymbol{\theta})(1 - \lambda L^d) x_{t-h}^M + \varepsilon_t(S_t)$
MS-ADL-MIDAS (I,V)	$y_t^Q = \beta_0(S_t) + \sum_{i=0}^{p-1} \lambda_{i+1} y_{t-d-i}^Q + \beta_1 B(L^{1/m}; \boldsymbol{\theta}) x_{t-h}^M + \varepsilon_t(S_t)$
MS-ADL-MIDAS (I,V,S)	$y_t^Q = \beta_0(S_t) + \sum_{i=0}^{p-1} \lambda_{i+1} y_{t-d-i}^Q + \beta_1(S_t) B(L^{1/m}; \boldsymbol{\theta}) x_{t-h}^M + \varepsilon_t(S_t)$
MS-DL(q) (I,V)	$y_t^Q = \beta_0(S_t) + \sum_{j=1}^{q} \beta_j x_{t-j}^Q + \varepsilon_t(S_t)$
MS-DL(q) (I,V,S)	$y_t^Q = \beta_0(S_t) + \sum_{j=1}^{q} \beta_j(S_t) x_{t-j}^Q + \varepsilon_t(S_t)$
MS-ADL(p,q) (I,V)	$y_t^Q = \beta_0(S_t) + \sum_{i=1}^{p} \lambda_i y_{t-i}^Q + \sum_{j=1}^{q} \beta_j x_{t-j}^Q + \varepsilon_t(S_t)$
MS-ADL(p,q) (I,V,S)	$y_t^Q = \beta_0(S_t) + \sum_{i=1}^{p} \lambda_i y_{t-i}^Q + \sum_{j=1}^{q} \beta_j(S_t) x_{t-j}^Q + \varepsilon_t(S_t)$

Note: Q-quarterly data; M-monthly data; $S_t = \{1, ..., R\}$ and S_t-regime in period t; I-switch in the intercept; V-switch in the variance of the error term; S-switch in the slope.

Table 2.A.2: Data used in the empirical exercise for the United States

No.	Data description	Transf. code
	REAL GROSS DOMESTIC PRODUCT	5
1	AVERAGE DURATION OF UNEMPLOYMENT (WEEKS)	5
2	AVERAGE PRIME RATE CHARGED BY BANKS	2
3	AVERAGE WEEKLY INITIAL CLAIMS - UNEMPLOYMENT INSURANCE	5
4	AVG HOURLY REAL EARNINGS - CONSTRUCTION	6
5	AVG HOURLY REAL EARNINGS - GOODS-PRODUCING	5
6	AVG HOURLY REAL EARNINGS - MANUFACTURING	5
7	AVG HOURLY REAL EARNINGS - NATURAL RESOURCES & MINING	5
8	AVG OVERTIME HOURS - DURABLE GOODS	5
9	AVG OVERTIME HOURS - MANUFACTURING	5
10	AVG OVERTIME HOURS - NONDURABLE GOODS	5
11	AVG WKLY HOURS - CONSTRUCTION	5
12	AVG WKLY HOURS - DURABLE GOODS	5
13	AVG WKLY HOURS - GOODS-PRODUCING	5
14	AVG WKLY HOURS - MANUFACTURING	5
15	AVG WKLY HOURS - NATURAL RESOURCES & MINING	5
16	AVG WKLY HOURS - NONDURABLE GOODS	5
17	AVG WKLY HOURS - NONMETALLIC MINERAL PRODUCTS	5
18	CHANGE IN EMPLMT. - NONFARM INDUSTRIES	1
19	CHANGE IN PRIVATE EMPLOYMENT - NONFARM INDUSTRIES	1
20	CHICAGO PRCHSG MNGR DIFFUSION INDEX: ORDERS BACKLOG - SMALLER	5
21	CHICAGO PRCHSG MNGR DIFFUSION INDEX: SUPPLIER DELIVERIES - SAME	5
22	CHICAGO PRCHSG MNGR DIFFUSION INDEX: SUPPLIER DELIVERIES, FASTER	2
23	CHICAGO PRCHSG MNGR DIFFUSION INDEX: SUPPLIER DELIVERIES, SLOWER	2
24	CHICAGO PURCHASING MANAGER DIFFUSION INDEX - BACKLOG	5
25	CHICAGO PURCHASING MANAGER DIFFUSION INDEX - DELIVERIES	5
26	CHICAGO PURCHASING MANAGER DIFFUSION INDEX - EMPLOYMENT	5
27	CHICAGO PURCHASING MANAGER DIFFUSION INDEX - INVENTORIES	5
28	CHICAGO PURCHASING MANAGER DIFFUSION INDEX - PRICES PAID	5
29	CHICAGO PURCHASING MANAGER DIFFUSION INDEX - PRODUCTION	5
30	CHICAGO PURCHASING MANAGER DIFFUSION INDEX: EMPLOYMENT - FEWER	5
31	CHICAGO PURCHASING MANAGER DIFFUSION INDEX: EMPLOYMENT - MORE	2
32	CHICAGO PURCHASING MANAGER DIFFUSION INDEX: EMPLOYMENT - SAME	5
33	CHICAGO PURCHASING MANAGER DIFFUSION INDEX: INVENTORIES - LARGER	5
34	CHICAGO PURCHASING MANAGER DIFFUSION INDEX: INVENTORIES - SAME	5
35	CHICAGO PURCHASING MANAGER DIFFUSION INDEX: PRICES PAID - HIGHER	5
36	CHICAGO PURCHASING MANAGER DIFFUSION INDEX: PRICES PAID - LOWER	2
37	CHICAGO PURCHASING MANAGER DIFFUSION INDEX: PRICES PAID - SAME	2
38	CHICAGO PURCHASING MANAGER DIFFUSION INDEX: PRODUCTION - HIGHER	5
39	CHICAGO PURCHASING MANAGER DIFFUSION INDEX: PRODUCTION - LOWER	5
40	CHICAGO PURCHASING MANAGER DIFFUSION INDEX: PRODUCTION - SAME	5
41	CHICAGO PURCHASING MANAGER: BUYING POLICY - 16-30 DAYS	5
42	CHICAGO PURCHASING MANAGER: BUYING POLICY - 31-60 DAYS	5
43	CHICAGO PURCHASING MANAGER: BUYING POLICY - AVERAGE DAYS	5
44	CHICAGO PURCHASING MANAGER: BUYING POLICY - MORE THAN 60 DAYS	5
45	CHICAGO PURCHASING MNGR DIFFUSION INDEX: INVENTORIES - SMALLER	5
46	CHICAGO PURCHASING MNGR DIFFUSION INDEX: ORDERS BACKLOG - LARGER	5
47	CHICAGO PURCHASING MNGR DIFFUSION INDEX: ORDERS BACKLOG - SAME	5
48	CIVILIAN UNEMPLOYMENT RATE	2
49	COML BANK ASSETS - COMMERCIAL & INDL LOANS	1
50	COMMERCIAL BANK ASSETS - BANK CREDIT	2
51	COMMERCIAL BANK ASSETS - CONSUMER LOANS	2
52	COMMERCIAL BANK ASSETS - LOANS & LEASES IN BANK CREDIT	6
53	COMMERCIAL BANK ASSETS - OTHER LOANS & LEASES	1
54	COMMERCIAL BANK ASSETS - OTHER SECURITIES	2

Continued on Next Page . . .

Table 2.A.2: Data used in the empirical exercise for the US. – Continued

No.	Data description	Transf. code
55	COMMERCIAL BANK ASSETS - REAL ESTATE LOANS	2
56	COMMERCIAL BANK ASSETS - SECURITIES IN BANK CREDIT	5
57	COMMERCIAL BANK ASSETS - US GOVERNMENT SECURITIES	5
58	COMMERCIAL BANK LIABILITIES - OTHER	2
59	COMMERCIAL BANK RESIDUAL (ASSETS LESS LIABILITIES)	3
60	CONSUMER CONFIDENCE - EXPECTATIONS	5
61	CONSUMER CREDIT OUTSTANDING	6
62	CONSUMER CREDIT: TOTAL PERCENT CHANGE	2
63	CONSUMER INSTALLMENT CREDIT NET CHANGE	3
64	CORPORATE BOND YIELD - MOODY'S AAA SEASONED ISSUES	2
65	CORPORATE BOND YIELD - MOODY'S BAA SEASONED ISSUES	2
66	CPI - ALL ITEMS LESS FOOD & ENERGY (CORE)	6
67	CPI - ALL URBAN: ALL ITEMS	6
68	CPI ENERGY	5
69	CPI: PURCHASING POWER OF THE CONSUMER DOLLAR	6
70	CRB SPOT INDEX (1967=100)	5
71	CRB SPOT INDEX FATS & OILS	5
72	CRB SPOT INDEX FOODSTUFFS	5
73	CRB SPOT INDEX LIVESTOCK	5
74	CRB SPOT INDEX METALS	5
75	CRB SPOT INDEX RAW INDUSTRIALS	5
76	CRB SPOT INDEX TEXTILES	5
77	DOW JONES INDUSTRIALS	5
78	ECONOMIC CYCLE RESEARCH INSTITUTE LEADING INDEX	5
79	EURO TO US $	5
80	EXPORTS	5
81	FEDERAL DEBT - MARKETABLE SEC. TREASURY BILLS	5
82	FEDERAL DEBT - MARKETABLE SEC. TREASURY BONDS	6
83	FEDERAL DEBT - MARKETABLE SEC. TREASURY NOTES	6
84	GOLD HOLDINGS	5
85	GOODS AND SERVICES BALANCE ON A BALANCE OF PAYMENTS BASIS	2
86	GOVERNMENT BENCHMARK BOND - REAL - 10Y YIELD	2
87	HOURLY WAGES	6
88	IMPORTS - PETROLEUM PRODUCTS - CRUDE OIL	6
89	IMPORTS	5
90	INDUSTRIAL PRODUCTION	5
91	INDUSTRIAL PRODUCTION - TOTAL INDEX	5
92	INTERNATIONAL RESERVES	5
93	ISM MANUFACTURERS SURVEY RESULTS: EMPLOYMENT - HIGHER	5
94	ISM MANUFACTURERS SURVEY RESULTS: EMPLOYMENT - LOWER	5
95	ISM MANUFACTURERS SURVEY RESULTS: EMPLOYMENT - SAME	5
96	ISM MANUFACTURERS SURVEY RESULTS: INVENTORIES - HIGHER	5
97	ISM MANUFACTURERS SURVEY RESULTS: INVENTORIES - LOWER	5
98	ISM MANUFACTURERS SURVEY RESULTS: INVENTORIES - SAME	5
99	ISM MANUFACTURERS SURVEY RESULTS: NEW ORDERS - BETTER	5
100	ISM MANUFACTURERS SURVEY RESULTS: NEW ORDERS - SAME	5
101	ISM MANUFACTURERS SURVEY RESULTS: NEW ORDERS - WORSE	5
102	ISM MANUFACTURERS SURVEY RESULTS: PRICES PAID - HIGHER	5
103	ISM MANUFACTURERS SURVEY RESULTS: PRICES PAID - LOWER	2
104	ISM MANUFACTURERS SURVEY RESULTS: PRICES PAID - SAME	5
105	ISM MANUFACTURERS SURVEY RESULTS: PRODUCTION - BETTER	5
106	ISM MANUFACTURERS SURVEY RESULTS: PRODUCTION - SAME	5
107	ISM MANUFACTURERS SURVEY RESULTS: PRODUCTION - WORSE	5
108	ISM MANUFACTURERS SURVEY: EMPLOYMENT INDEX	5
109	ISM MANUFACTURERS SURVEY: INVENTORIES INDEX	5
110	ISM MANUFACTURERS SURVEY: NEW ORDERS INDEX	5
111	ISM MANUFACTURERS SURVEY: PRICES PAID INDEX	5

Continued on Next Page . . .

Table 2.A.2: Data used in the empirical exercise for the US. – Continued

No.	Data description	Transf. code
112	ISM MANUFACTURERS SURVEY: PRODUCTION INDEX	5
113	ISM MANUFACTURERS SURVEY: SUPPLIER DELIVERY INDEX	5
114	ISM MANUFACTURERS SVY RESULTS: EMPLOYMENT - NET	1
115	ISM MANUFACTURERS SVY RESULTS: NEW ORDERS - NET	1
116	ISM MANUFACTURERS SVY RESULTS: PRICES - NET	2
117	ISM MANUFACTURERS SVY RESULTS: PRODUCTION - NET	1
118	ISM PURCHASING MANAGERS INDEX	5
119	LEADING INDEX - COPPER INDUSTRY	5
120	LEADING INDEX - METAL PRICES	5
121	LEADING INDEX - PRIMARY METALS	5
122	LEADING INDEX - STEEL INDUSTRY	5
123	LEADING INDEX - VENDOR PERFORMANCE, SLOWER DELIVERIES	5
124	MFG - INDUSTRIAL CONFIDENCE INDICATOR	5
125	MONEY MARKET RATE (FEDERAL FUNDS)	2
126	NEW PRIVATE HOUSING UNITS STARTED	5
127	NIKKEI 225 STOCK AVERAGE	5
128	PPI - FINISHED GOODS	6
129	PRODUCER PRICE INDEX - CAPITAL EQUIPMENT	6
130	PRODUCER PRICE INDEX - CRUDE MATERIALS	5
131	PRODUCER PRICE INDEX - FINISHED CONSUMER GOODS	6
132	PRODUCER PRICE INDEX - INTERMEDIATE MATERIALS	6
133	S&P/TSX COMPOSITE INDEX	5
134	SDR TO US $	5
135	STANDARD & POOR'S INDEX OF 500 COMMON STOCKS	5
136	STOCK PRICES - US	5
137	STOCK PRICES - CANADA	5
138	STOCK PRICES - FEDERAL REPUBLIC OF GERMANY	5
139	STOCK PRICES - FRANCE	5
140	STOCK PRICES - ITALY	5
141	STOCK PRICES - JAPAN	5
142	STOCK PRICES - UNITED KINGDOM	5
143	TOPIX	5
144	TOTAL RETAIL TRADE	5
145	TOTAL TREASURY SECURITIES OUTSTANDING (PUBLIC DEBT)	6
146	TREASURY YIELD ADJUSTED TO CONSTANT MATURITY - 1 YEAR	2
147	TREASURY YIELD ADJUSTED TO CONSTANT MATURITY - 10 YEAR	2
148	TREASURY YIELD ADJUSTED TO CONSTANT MATURITY - 3 YEAR	2
149	TREASURY YIELD ADJUSTED TO CONSTANT MATURITY - 5 YEAR	2
150	UK TO US $	5
151	UNITED STATES GOLD RESERVES	5
152	US FED FUNDS EFF RATE	2
153	US STATE & LOCAL BOND MIDDLE RATE	2
154	US T-BILL SEC MARKET 3 MONTH	2
155	WORKERS ON INVOLUNTARY PARTTIME - ALL INDUSTRIES	5
156	WTI CRUDE OIL SPOT PRICE	5

Note: The above-described data are taken from Datastream.
Transformation codes used for stationarizing the data:
1 - stationary data, no transformation needed
2 - data stationarized by taking first differences
3 - data stationarized by taking second differences
5 - data stationarized by taking first differences of logarithms
6 - data stationarized by taking second differences of logarithms

MS-VAR(4) model with two regimes, used as data generating process in Monte Carlo simulations (see Tables 2.A.3 and 2.A.4 for results):

$$\begin{pmatrix} y_t \\ x_t \end{pmatrix} = \begin{pmatrix} \boldsymbol{\rho}_i & \boldsymbol{\delta}_i(S_t) \\ \mathbf{0}_{(1\times 4)} & \boldsymbol{\rho}_i \end{pmatrix} \boldsymbol{Z} + \begin{pmatrix} e_{y,t}(S_t) \\ e_{x,t}(S_t) \end{pmatrix}, \tag{2.11}$$

where $\boldsymbol{Z} = \begin{pmatrix} y_{t-1} \\ y_{t-2} \\ y_{t-3} \\ y_{t-4} \\ x_{t-1} \\ x_{t-2} \\ x_{t-3} \\ x_{t-4} \end{pmatrix}$, whereas $\boldsymbol{\rho}_i$ and $\boldsymbol{\delta}_i(S_t)$ for $i = \{1, 2, 3\}$ are defined as follows:

$$\boldsymbol{\rho}_1 = \begin{pmatrix} 0.1 \\ 0.1 \\ 0.1 \\ 0.05 \end{pmatrix}^T, \boldsymbol{\rho}_2 = \begin{pmatrix} 0.3 \\ 0.15 \\ 0.1 \\ 0.05 \end{pmatrix}^T, \boldsymbol{\rho}_3 = \begin{pmatrix} 0.5 \\ 0.15 \\ 0.1 \\ 0.05 \end{pmatrix}^T, \boldsymbol{\delta}_1 = \begin{pmatrix} 0.1 \\ 0.1 \\ 0.1 \\ 0.05 \end{pmatrix}^T,$$

$$\boldsymbol{\delta}_2 = \begin{pmatrix} 0.3 \\ 0.15 \\ 0.1 \\ 0.05 \end{pmatrix}^T, \boldsymbol{\delta}_3 = \begin{pmatrix} 0.5 \\ 0.15 \\ 0.1 \\ 0.05 \end{pmatrix}^T.$$

Table 2.A.3: Out-of-sample Root Mean Squared Error of MS-U-MIDAS-AR relative to MS-MIDAS-AR and MS-ADL-MIDAS (DGP is a bivariate MS-VAR(4) with two regimes)

					RMSE (25th, 50th and 75th percentiles)					
	δ_i		transition probabilities		MS-U-MIDAS-AR vs. MS-MIDAS-AR			MS-U-MIDAS-AR vs. MS-ADL-MIDAS		
ρ_i	$S_t = 1$	$S_t = 2$	p_{11}	p_{22}	25^{th}	50^{th}	75^{th}	25^{th}	50^{th}	75^{th}
ρ_1	δ_1	δ_3	0.95	0.85	1.00	1.08	1.17	0.98	1.05	1.13
ρ_1	δ_2	δ_3	0.95	0.85	1.01	1.09	1.20	0.99	1.06	1.15
ρ_2	δ_1	δ_3	0.95	0.85	1.00	1.09	1.20	0.98	1.07	1.18
ρ_2	δ_2	δ_3	0.95	0.85	1.01	1.10	1.23	0.99	1.08	1.19
ρ_3	δ_1	δ_3	0.95	0.85	0.92	1.03	1.16	0.92	1.01	1.11
ρ_3	δ_2	δ_3	0.95	0.85	0.90	1.04	1.19	0.92	1.02	1.13
ρ_1	δ_1	δ_3	0.95	0.95	1.00	1.07	1.15	0.98	1.04	1.11
ρ_1	δ_2	δ_3	0.95	0.95	1.01	1.08	1.16	0.99	1.04	1.12
ρ_2	δ_1	δ_3	0.95	0.95	0.97	1.08	1.18	0.96	1.05	1.14
ρ_2	δ_2	δ_3	0.95	0.95	0.99	1.10	1.22	0.96	1.06	1.17
ρ_3	δ_1	δ_3	0.95	0.95	0.90	1.04	1.21	0.91	1.02	1.13
ρ_3	δ_2	δ_3	0.95	0.95	0.90	1.06	1.27	0.92	1.03	1.16

Table 2.A.4: Out-of-sample Quadratic Probability Score of MS-U-MIDAS-AR relative to MS-MIDAS-AR and MS-ADL-MIDAS (DGP is a bivariate MS-VAR(4) with two regimes)

					QPS (25th, 50th and 75th percentiles)					
	δ_i		transition probabilities		MS-U-MIDAS-AR vs. MS-MIDAS-AR			MS-U-MIDAS-AR vs. MS-ADL-MIDAS		
ρ_i	$S_t = 1$	$S_t = 2$	p_{11}	p_{22}	25^{th}	50^{th}	75^{th}	25^{th}	50^{th}	75^{th}
ρ_1	δ_1	δ_3	0.95	0.85	0.80	1.09	1.87	0.62	0.98	1.43
ρ_1	δ_2	δ_3	0.95	0.85	0.74	1.04	1.69	0.56	0.95	1.38
ρ_2	δ_1	δ_3	0.95	0.85	0.55	0.92	1.30	0.55	0.92	1.34
ρ_2	δ_2	δ_3	0.95	0.85	0.52	0.89	1.28	0.58	0.97	1.54
ρ_3	δ_1	δ_3	0.95	0.85	0.74	1.00	1.27	0.72	1.02	1.60
ρ_3	δ_2	δ_3	0.95	0.85	0.72	1.00	1.24	0.68	1.02	1.63
ρ_1	δ_1	δ_3	0.95	0.95	0.82	1.00	1.25	0.73	0.98	1.12
ρ_1	δ_2	δ_3	0.95	0.95	0.80	1.00	1.27	0.64	0.97	1.12
ρ_2	δ_1	δ_3	0.95	0.95	0.52	0.90	1.26	0.51	0.89	1.33
ρ_2	δ_2	δ_3	0.95	0.95	0.58	0.93	1.33	0.48	0.84	1.34
ρ_3	δ_1	δ_3	0.95	0.95	0.79	1.00	1.33	0.80	1.04	1.41
ρ_3	δ_2	δ_3	0.95	0.95	0.77	1.00	1.33	0.83	1.04	1.41

Note: The above tables (2.A.3 and 2.A.4) present the summary of results for 1000 Monte Carlo simulations. For each replication 600 observations of a higher-frequency variable x_t and 200 observations of a lower-frequency variable y_t are generated for the in-sample period, whereas 30 lower-frequency (90 higher-frequency) observations are generated for the out-of-sample evaluation according to a bivariate MS-VAR(4) model with two regimes. Then the MS-U-MIDAS-AR, MS-MIDAS-AR and MS-ADL-MIDAS models are estimated and their out-of-sample performance is measured by Root Mean Squared Error (Table 2.A.3) and Quadratic Probability Score (Table 2.A.4). The tables present the 25th, 50th and 75th percentiles of the ratio of the RMSE and QPS of the MS-U-MIDAS-AR to the RMSE and QPS of MS-MIDAS-AR and MS-ADL-MIDAS, calculated over all 1000 simulations. Values below/above 1 indicate a better/worse out-of-sample performance of the MS-U-MIDAS-AR model in comparison to the MS-MIDAS-AR or MS-ADL-MIDAS model. The analysis is done for different transition probabilities between the two regimes and for different values of the parameters of the MS-VAR model (see equation (2.11)).

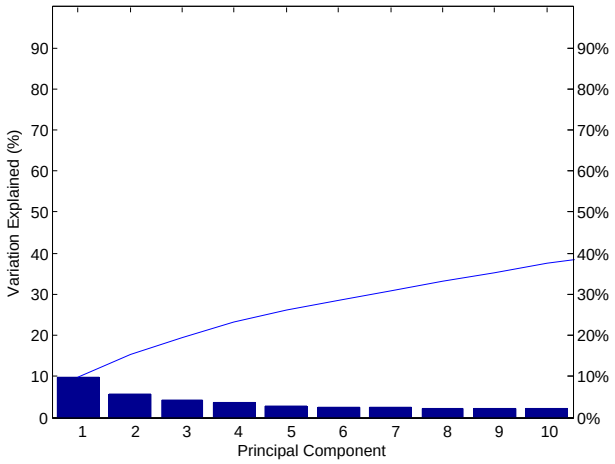

Figure 2.A.1: Variation of the monthly dataset explained by the first ten factors

Note: The bars show the percentage of overall variation of the dataset explained by each of the first ten factors obtained by principal component analysis. The line shows the cumulated percentage of explained variation for the first ten factors. The maximum number of factors is equal to the dimension of the dataset, which is 156.

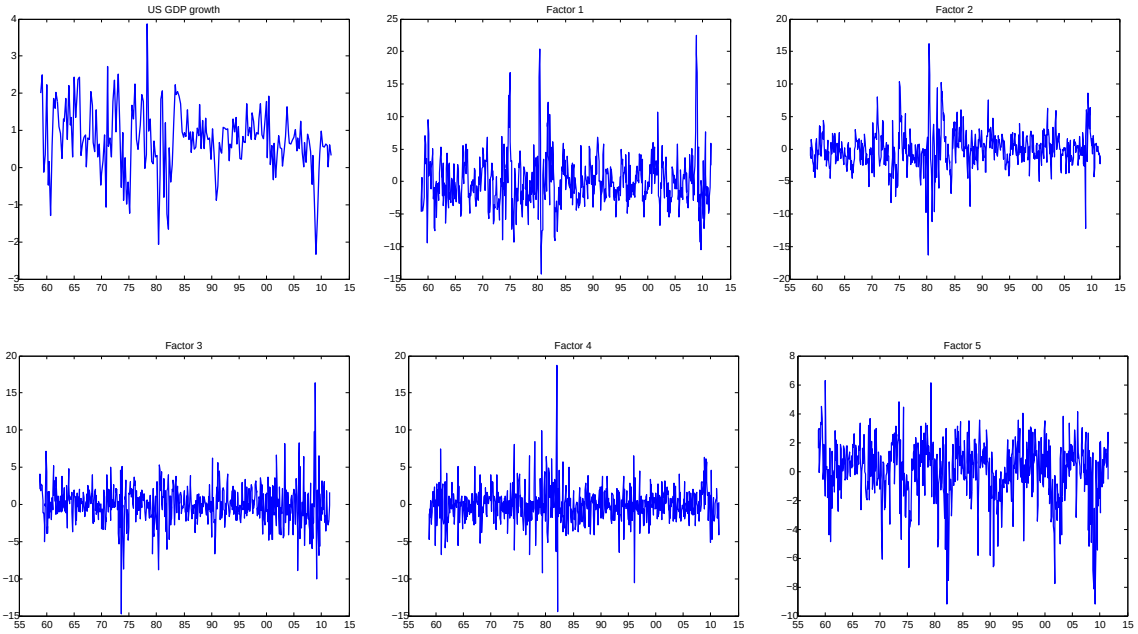

Figure 2.A.2: GDP growth of the United States and the first five factors extracted from the monthly database by principal component analysis

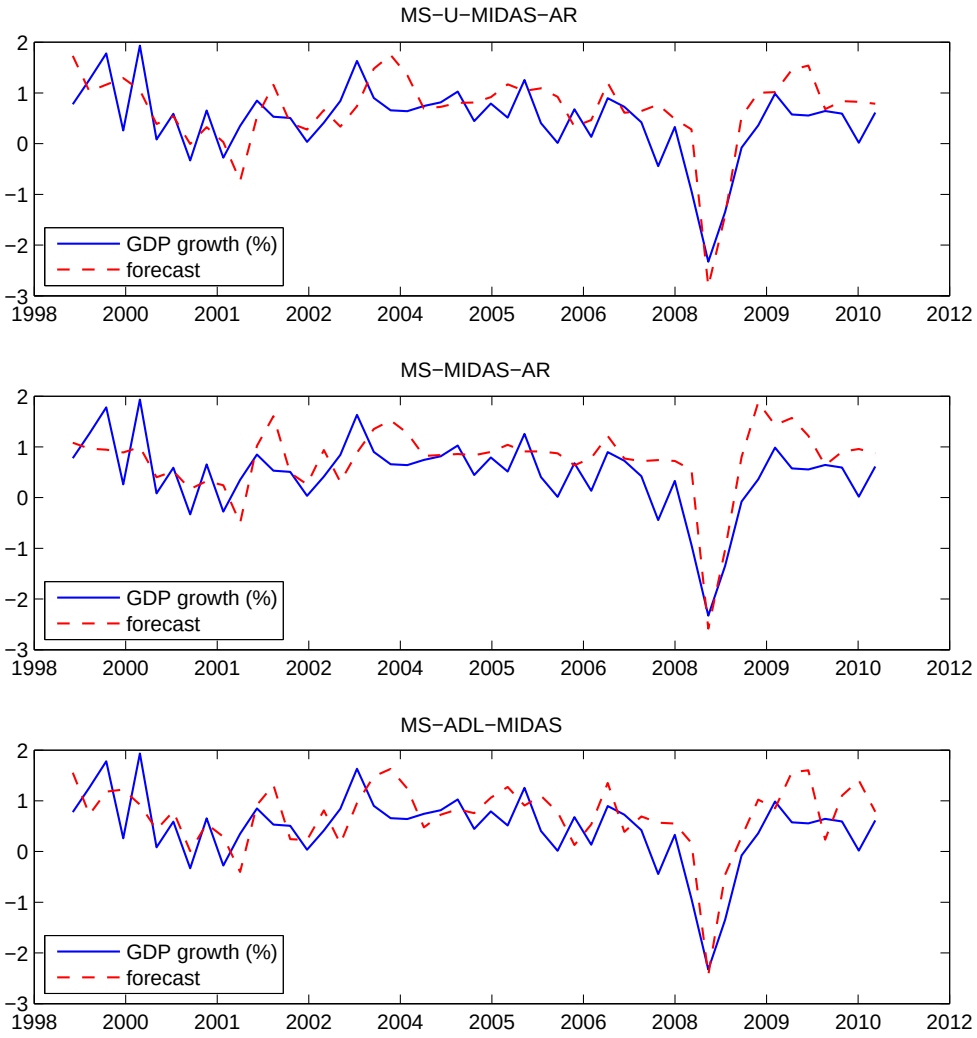

Figure 2.A.3: MS-U-MIDAS-AR, MS-MIDAS-AR and MS-ADL-MIDAS forecasts for factor 1 and horizon $\frac{2}{3}$, plotted against the actual GDP growth (in %). All models allow for 3 regimes and switching of the intercept, slope parameters and variance of the error term.

Table 2.A.5: Root Mean Squared Errors relative to AR(2) model. Forecast horizon $h = \frac{1}{3}$. Final vintage data is used. Number of lags in the models chosen according to AIC.

Benchmarks	**RMSE**										
RW	1.11										
AR(2)	1.00										
Model	**Switch**	**Fac.1**	**Fac.2**	**Fac.3**	**Fac.4**	**Fac.5**	**Mean**	**Med.**	**S.D.E.**	**Tr.(1)**	**Tr.(4)**
2 regimes											
MS-U-MIDAS	I,V	0.95	1.35	0.94	1.18	0.93	0.93	0.93	0.91	0.88	0.89
MS-U-MIDAS	I,S,V	1.03	1.62	1.14	1.19	0.95	0.91	0.87	0.89	0.89	0.86
MS-U-MIDAS-AR	I,V	0.82	1.14	***0.79***	1.07	0.89	0.83	0.87	0.81	***0.79***	0.81
MS-U-MIDAS-AR	I,S,V	***0.79***	1.22	0.92	1.07	0.91	0.83	0.81	0.83	***0.79***	0.83
MS-MIDAS	I,V	0.88	1.21	0.91	1.17	0.92	0.89	0.88	0.87	0.85	0.85
MS-MIDAS	I,S,V	0.96	1.23	1.09	1.13	0.89	0.86	0.88	0.84	0.83	0.81
MS-MIDAS-AR	I,V	0.87	1.06	0.84	1.08	0.93	0.87	0.90	0.86	0.85	0.84
MS-MIDAS-AR	I,S,V	0.89	1.17	0.91	1.07	0.89	0.85	0.83	0.83	0.83	0.82
MS-ADL-MIDAS	I,V	***0.79***	0.99	0.81	***1.00***	0.91	0.81	0.86	0.81	***0.79***	***0.80***
MS-ADL-MIDAS	I,V,S	0.89	***0.98***	0.84	1.01	***0.87***	***0.79***	***0.79***	***0.80***	***0.79***	***0.80***
3 regimes											
MS-U-MIDAS	I,V	0.91	1.39	0.87	1.09	0.95	0.92	0.92	0.89	0.89	0.88
MS-U-MIDAS	I,S,V	0.94	1.50	0.96	1.21	0.98	0.85	0.86	0.81	0.84	0.80
MS-U-MIDAS-AR	I,V	0.85	1.00	***0.77***	1.13	1.02	0.80	0.88	***0.77***	0.82	0.80
MS-U-MIDAS-AR	I,S,V	***0.81***	1.21	0.98	1.16	0.88	0.83	0.80	0.82	0.80	0.81
MS-MIDAS	I,V	0.85	1.15	1.13	1.12	0.94	0.90	0.96	0.87	0.87	0.87
MS-MIDAS	I,S,V	0.90	1.11	1.17	1.12	0.94	0.89	0.96	0.90	0.89	0.87
MS-MIDAS-AR	I,V	0.84	1.06	0.83	1.05	0.90	0.84	0.88	0.84	0.82	0.79
MS-MIDAS-AR	I,S,V	0.93	1.02	0.88	1.06	0.98	0.83	0.86	0.82	0.85	0.82
MS-ADL-MIDAS	I,V	0.84	***0.95***	0.78	1.00	***0.86***	***0.77***	***0.74***	0.78	***0.77***	***0.78***
MS-ADL-MIDAS	I,S,V	***0.81***	1.00	0.92	***0.92***	0.95	0.84	0.90	0.84	0.82	0.82
Models without Markov-switching											
U-MIDAS	—	0.95	1.49	1.10	1.17	0.91	0.93	0.92	0.89	0.87	0.85
U-MIDAS-AR	—	0.90	1.24	***0.89***	1.06	0.90	0.82	0.83	0.81	0.79	0.79
MIDAS	—	0.93	1.23	1.12	1.09	0.91	0.85	0.85	0.85	0.87	0.81
MIDAS-AR	—	0.93	1.10	0.90	1.06	***0.89***	0.82	0.84	0.81	0.80	0.78
ADL-MIDAS	—	***0.87***	***1.04***	0.91	***1.01***	***0.89***	***0.79***	***0.82***	***0.79***	***0.77***	***0.76***

Note: Column "Switch" gives information on the parameters that are allowed to switch in the model: I-intercept β_0, V-variance of the error term σ^2, S-slope β_1.
The table presents the out-of-sample RMSEs for different models compared in this paper. Final vintage data are used for all variables. The original sample is divided into the in-sample period between 1959:Q1 and 1999:Q4 (160 quarters) and the out-of-sample period between 2000:Q1 and 2011:Q3 (47 quarters). For the out-of-sample period forecasts are calculated recursively for forecast horizon $h = \frac{1}{3}$. In order to evaluate the forecasting performance of the models we calculate the RMSE for each model for the whole out-of-sample period. The RMSEs are calculated for the cases when only a forecast from a single factor is taken into account (columns 3-8), as well as for different forecast combination schemes (in this case the forecasts from single-factor-models are combined). The forecast combination schemes include: simple averaging (Mean), median (Med.), forecasts weighted according to Squared Discounted Mean Forecast Error (S.D.E.) and forecast combinations which trim the recently worst model - when last period is considered (Tr.(1)) and when the last four quarters are considered (Tr.(4)). Numbers in italics indicate the best performing model within a class of models without Markov-switching, with two regimes or with three regimes.

Table 2.A.6: Root Mean Squared Errors relative to AR(2) model. Forecast horizon $h = \frac{2}{3}$. Final vintage data is used. Number of lags in the models chosen according to AIC.

Benchmarks	**RMSE**										
RW	1.11										
AR(2)	1.00										
Model	**Switch**	**Fac.1**	**Fac.2**	**Fac.3**	**Fac.4**	**Fac.5**	**Mean**	**Med.**	**S.D.E.**	**Tr.(1)**	**Tr.(4)**
2 regimes											
MS-U-MIDAS	I,V	0.95	1.24	0.95	1.16	0.87	0.93	0.92	0.92	0.91	0.89
MS-U-MIDAS	I,S,V	0.92	1.35	1.14	1.24	0.88	0.96	0.90	0.94	0.92	0.91
MS-U-MIDAS-AR	I,V	0.89	1.05	0.80	***0.97***	0.88	0.83	0.86	0.83	***0.80***	0.82
MS-U-MIDAS-AR	I,S,V	***0.80***	1.12	0.94	1.00	***0.86***	***0.81***	***0.78***	***0.81***	0.81	0.81
MS-MIDAS	I,V	0.94	1.21	0.95	1.14	0.87	0.91	0.92	0.90	0.89	0.88
MS-MIDAS	I,S,V	0.91	1.27	0.90	1.20	0.87	0.90	0.90	0.87	0.85	0.85
MS-MIDAS-AR	I,V	0.95	1.07	0.80	1.03	0.90	0.86	0.89	0.84	0.84	0.83
MS-MIDAS-AR	I,S,V	0.92	1.11	***0.79***	1.11	0.87	0.85	0.84	0.82	0.82	0.81
MS-ADL-MIDAS	I,V	0.88	1.00	0.80	1.01	0.91	0.84	0.88	0.84	0.81	0.82
MS-ADL-MIDAS	I,S,V	0.94	***0.99***	0.81	1.07	0.91	0.83	0.82	0.82	***0.80***	***0.80***
3 regimes											
MS-U-MIDAS	I,V	0.94	1.12	0.91	1.12	0.89	0.91	0.89	0.90	0.88	0.88
MS-U-MIDAS	I,S,V	1.07	1.21	1.01	1.21	0.98	0.92	0.91	0.92	0.92	0.90
MS-U-MIDAS-AR	I,V	0.91	1.21	0.81	1.07	0.90	0.87	0.88	0.85	0.83	0.86
MS-U-MIDAS-AR	I,S,V	***0.88***	1.07	1.01	1.10	***0.84***	***0.81***	***0.82***	***0.81***	***0.78***	***0.78***
MS-MIDAS	I,V	0.93	1.08	0.91	1.06	0.93	0.90	0.90	0.89	0.88	0.88
MS-MIDAS	I,S,V	0.93	1.09	0.88	1.12	0.94	0.86	0.89	0.85	0.85	0.85
MS-MIDAS-AR	I,V	0.92	1.02	0.91	1.03	0.91	0.87	0.91	0.87	0.86	0.85
MS-MIDAS-AR	I,S,V	0.98	1.10	***0.80***	1.09	0.86	0.84	0.84	***0.81***	0.81	0.82
MS-ADL-MIDAS	I,V	0.89	1.00	0.85	***1.01***	0.98	0.85	0.90	0.85	0.83	0.83
MS-ADL-MIDAS	I,S,V	0.94	***0.99***	0.87	1.09	0.93	0.85	0.86	0.85	0.85	0.85
Models without Markov-switching											
U-MIDAS	—	0.99	1.32	1.07	1.17	0.86	0.95	0.95	0.94	0.90	0.90
U-MIDAS-AR	—	***0.94***	1.13	0.91	1.03	***0.85***	0.85	***0.84***	0.84	0.82	0.82
MIDAS	—	1.00	1.23	1.06	1.16	0.87	0.91	0.90	0.91	0.87	0.86
MIDAS-AR	—	1.00	1.09	***0.84***	1.06	***0.85***	0.85	0.85	***0.83***	0.81	0.81
ADL-MIDAS	—	0.95	***1.06***	0.85	***1.00***	0.89	***0.84***	0.86	***0.83***	***0.80***	***0.79***

Note: Column "Switch" gives information on the parameters that are allowed to switch in the model: I-intercept β_0, V-variance of the error term σ^2, S-slope β_1.
The table presents the out-of-sample RMSEs for different models compared in this paper. Final vintage data are used for all variables. The original sample is divided into the in-sample period between 1959:Q1 and 1999:Q4 (160 quarters) and the out-of-sample period between 2000:Q1 and 2011:Q3 (47 quarters). For the out-of-sample period forecasts are calculated recursively for forecast horizon $h = \frac{2}{3}$. In order to evaluate the forecasting performance of the models we calculate the RMSE for each model for the whole out-of-sample period. The RMSEs are calculated for the cases when only a forecast from a single factor is taken into account (columns 3-8), as well as for different forecast combination schemes (in this case the forecasts from single-factor-models are combined). The forecast combination schemes include: simple averaging (Mean), median (Med.), forecasts weighted according to Squared Discounted Mean Forecast Error (S.D.E.) and forecast combinations which trim the recently worst model - when last period is considered (Tr.(1)) and when the last four quarters are considered (Tr.(4)). Numbers in italics indicate the best performing model within a class of models without Markov-switching, with two regimes or with three regimes.

Table 2.A.7: Root Mean Squared Errors relative to AR(2) model. Forecast horizon $h = 1$. Final vintage data is used. Number of lags in the models chosen according to AIC.

Benchmarks	**RMSE**										
RW	1.11										
AR(2)	1.00										
Model	**Switch**	**Fac.1**	**Fac.2**	**Fac.3**	**Fac.4**	**Fac.5**	**Mean**	**Med.**	**S.D.E.**	**Tr.(1)**	**Tr.(4)**
2 regimes											
MS-U-MIDAS	I,V	0.97	1.24	1.09	1.17	1.07	1.04	1.02	1.03	1.03	1.03
MS-U-MIDAS	I,S,V	0.97	1.32	1.24	1.22	1.01	1.04	1.02	1.02	1.02	1.01
MS-U-MIDAS-AR	I,V	***0.88***	1.01	0.89	0.99	***0.95***	***0.90***	***0.90***	***0.90***	***0.88***	***0.91***
MS-U-MIDAS-AR	I,S,V	0.95	1.02	1.01	1.03	1.02	0.93	0.95	0.93	0.93	0.92
MS-MIDAS	I,V	0.98	1.19	1.10	1.18	1.05	1.04	1.05	1.03	1.04	1.03
MS-MIDAS	I,S,V	0.99	1.24	1.44	1.21	1.01	1.05	1.06	1.04	1.03	1.03
MS-MIDAS-AR	I,V	0.93	1.06	0.91	1.03	0.99	0.94	0.97	0.93	0.93	0.93
MS-MIDAS-AR	I,S,V	0.97	1.11	0.97	1.11	0.99	0.94	0.91	0.94	0.94	0.93
MS-ADL-MIDAS	I,V	0.90	0.98	***0.86***	1.03	0.98	0.92	0.95	0.91	0.91	***0.91***
MS-ADL-MIDAS	I,S,V	1.01	0.99	1.04	1.09	1.04	0.96	0.96	0.96	0.97	0.95
MS-DL	I,V	1.03	1.19	1.34	1.14	1.04	1.05	1.08	1.06	1.03	1.03
MS-DL	I,S,V	1.03	1.18	1.65	1.15	1.01	1.02	1.01	1.07	1.02	1.02
MS-ADL	I,V	0.92	***0.94***	1.07	***0.97***	0.97	0.93	0.94	0.93	0.94	0.92
MS-ADL	I,S,V	0.92	***0.94***	1.30	0.98	0.96	0.93	0.93	0.93	0.94	0.94
3 regimes											
MS-U-MIDAS	I,V	0.94	1.06	1.01	1.12	1.01	0.97	1.00	0.97	0.98	0.97
MS-U-MIDAS	I,S,V	1.10	1.17	1.35	1.16	1.05	0.97	1.06	0.95	0.94	0.94
MS-U-MIDAS-AR	I,V	***0.89***	1.08	1.04	1.04	0.96	0.94	***0.90***	0.94	0.97	0.95
MS-U-MIDAS-AR	I,S,V	1.10	1.10	1.56	1.31	1.02	0.95	1.00	0.95	0.98	0.98
MS-MIDAS	I,V	0.94	1.06	0.99	1.09	1.07	0.97	1.02	0.96	0.96	0.97
MS-MIDAS	I,S,V	0.96	1.12	0.94	1.18	1.00	0.96	0.97	0.95	0.94	0.94
MS-MIDAS-AR	I,V	0.95	1.02	0.94	1.04	1.00	0.94	0.98	0.94	0.94	0.94
MS-MIDAS-AR	I,S,V	0.96	1.06	0.93	1.06	0.96	0.92	0.91	0.92	***0.93***	0.90
MS-ADL-MIDAS	I,V	0.92	0.97	***0.91***	1.07	1.00	***0.91***	0.96	***0.90***	0.94	***0.89***
MS-ADL-MIDAS	I,S,V	0.98	1.18	1.07	1.04	0.97	0.94	0.94	0.94	0.96	0.96
MS-DL	I,V	0.95	1.03	1.11	1.08	1.04	1.00	1.02	0.99	0.99	0.98
MS-DL	I,S,V	1.00	1.10	1.63	1.02	0.99	0.98	0.98	1.01	0.98	0.98
MS-ADL	I,V	0.93	***0.93***	1.16	***0.97***	0.97	0.93	0.92	0.93	0.94	0.92
MS-ADL	I,S,V	0.96	0.98	1.22	1.05	***0.94***	0.93	0.95	0.93	0.95	0.94
Models without Markov-switching											
U-MIDAS	—	1.02	1.30	1.19	1.18	1.03	1.04	1.05	1.02	1.02	1.02
U-MIDAS-AR	—	***0.96***	1.07	0.95	1.02	***0.97***	***0.92***	***0.90***	***0.91***	0.90	0.92
MIDAS	—	1.02	1.23	1.21	1.15	1.04	1.02	1.00	1.01	1.00	1.00
MIDAS-AR	—	1.01	1.09	0.95	1.05	0.98	0.94	0.93	0.93	0.93	0.93
ADL-MIDAS	—	***0.96***	1.02	***0.92***	1.03	1.00	***0.92***	0.91	***0.91***	***0.89***	***0.91***
DL	—	1.12	1.55	1.01	1.11	1.00	1.00	0.96	0.96	0.93	0.97
ADL	—	0.97	***1.01***	1.09	***1.00***	1.00	0.94	0.96	0.94	0.93	0.93

Note: Column "Switch" gives information on the parameters that are allowed to switch in the model: I-intercept β_0, V-variance of the error term σ^2, S-slope β_1.
The table presents the out-of-sample RMSEs for different models compared in this paper. Final vintage data are used for all variables. The original sample is divided into the in-sample period between 1959:Q1 and 1999:Q4 (160 quarters) and the out-of-sample period between 2000:Q1 and 2011:Q3 (47 quarters). For the out-of-sample period forecasts are calculated recursively for forecast horizon $h = 1$. In order to evaluate the forecasting performance of the models we calculate the RMSE for each model for the whole out-of-sample period. The RMSEs are calculated for the cases when only a forecast from a single factor is taken into account (columns 3-8), as well as for different forecast combination schemes (in this case the forecasts from single-factor-models are combined). The forecast combination schemes include: simple averaging (Mean), median (Med.), forecasts weighted according to Squared Discounted Mean Forecast Error (S.D.E.) and forecast combinations which trim the recently worst model - when last period is considered (Tr.(1)) and when the last four quarters are considered (Tr.(4)). Numbers in italics indicate the best performing model within a class of models without Markov-switching, with two regimes or with three regimes.

Table 2.A.8: Root Mean Squared Errors relative to AR(2) model. Forecast horizon $h = 2$. Final vintage data is used. Number of lags in the models chosen according to AIC.

Benchmarks	**RMSE**										
RW	1.09										
AR(2)	1.00										
Model	**Switch**	**Fac.1**	**Fac.2**	**Fac.3**	**Fac.4**	**Fac.5**	**Mean**	**Med.**	**S.D.E.**	**Tr.(1)**	**Tr.(4)**
2 regimes											
MS-U-MIDAS	I,V	1.07	1.10	1.08	1.11	1.06	1.06	1.07	1.06	1.06	1.05
MS-U-MIDAS	I,S,V	1.04	1.16	1.12	1.11	1.02	1.04	1.05	1.05	1.05	1.03
MS-U-MIDAS-AR	I,V	1.00	***0.98***	0.97	1.00	***0.96***	***0.96***	***0.97***	***0.96***	0.98	0.97
MS-U-MIDAS-AR	I,S,V	1.00	1.02	1.01	1.01	***0.96***	0.97	0.98	***0.96***	0.97	0.97
MS-MIDAS	I,V	1.05	1.10	1.08	1.11	1.06	1.06	1.08	1.07	1.06	1.05
MS-MIDAS	I,S,V	1.03	1.18	1.13	1.12	1.03	1.05	1.07	1.06	1.06	1.04
MS-MIDAS-AR	I,V	***0.98***	***0.98***	0.97	1.01	***0.96***	***0.96***	***0.97***	***0.96***	0.97	0.97
MS-MIDAS-AR	I,S,V	0.99	1.00	0.99	1.01	***0.96***	0.97	0.98	0.97	0.97	0.98
MS-ADL-MIDAS	I,V	0.99	1.00	***0.96***	1.00	0.98	0.97	***0.97***	0.97	0.98	0.98
MS-ADL-MIDAS	I,S,V	1.00	1.06	0.99	1.07	1.03	1.00	0.99	1.00	1.02	1.00
MS-DL	I,V	1.04	1.09	1.09	1.13	1.03	1.05	1.06	1.05	1.04	1.03
MS-DL	I,S,V	1.05	1.17	1.25	1.15	1.02	1.05	1.05	1.06	1.05	1.03
MS-ADL	I,V	***0.98***	***0.98***	0.97	***0.99***	0.98	***0.96***	***0.97***	***0.96***	***0.96***	***0.96***
MS-ADL	I,S,V	***0.98***	1.02	1.11	1.03	0.97	***0.96***	0.98	0.97	***0.96***	0.97
3 regimes											
MS-U-MIDAS	I,V	1.04	1.02	1.00	1.02	1.03	1.01	1.02	1.01	1.02	1.01
MS-U-MIDAS	I,S,V	1.02	1.03	1.04	1.05	1.00	0.99	1.00	0.98	0.98	0.98
MS-U-MIDAS-AR	I,V	1.00	0.98	0.98	0.97	0.96	***0.95***	***0.96***	***0.96***	0.96	0.97
MS-U-MIDAS-AR	I,S,V	0.98	1.00	1.01	1.18	***0.95***	0.97	0.98	***0.96***	***0.95***	***0.94***
MS-MIDAS	I,V	1.00	1.06	1.01	1.00	1.06	1.01	1.02	1.01	1.02	1.00
MS-MIDAS	I,S,V	0.99	1.04	1.06	1.06	1.02	1.00	1.01	1.00	1.00	1.00
MS-MIDAS-AR	I,V	0.98	***0.97***	1.03	1.02	1.01	0.98	0.99	0.98	0.98	0.98
MS-MIDAS-AR	I,S,V	0.99	1.08	0.98	1.03	0.97	0.99	0.99	0.99	1.00	0.99
MS-ADL-MIDAS	I,V	0.99	0.98	1.01	***0.95***	1.02	0.97	0.99	0.97	0.97	0.98
MS-ADL-MIDAS	I,S,V	1.02	1.04	***0.97***	1.04	1.04	0.98	1.00	0.98	0.98	0.97
MS-DL	I,V	0.98	1.01	1.02	1.05	1.02	1.00	1.00	1.00	0.99	1.00
MS-DL	I,S,V	***0.96***	1.05	1.10	1.08	0.96	0.96	0.97	0.98	***0.95***	0.95
MS-ADL	I,V	1.00	***0.97***	0.99	1.06	***0.95***	0.98	0.98	0.97	0.98	0.97
MS-ADL	I,S,V	1.00	1.04	1.07	1.03	0.98	0.97	0.98	0.98	0.98	0.98
Models without Markov-switching											
U-MIDAS	—	1.09	1.14	1.12	1.10	1.03	1.05	1.06	1.06	1.06	1.06
U-MIDAS-AR	—	1.03	***0.99***	1.01	0.99	***0.97***	***0.97***	***0.98***	***0.97***	0.98	0.97
MIDAS	—	1.06	1.15	1.12	1.15	1.07	1.07	1.07	1.07	1.07	1.06
MIDAS-AR	—	1.01	1.03	1.01	1.02	1.00	0.98	1.00	0.99	0.99	0.99
ADL-MIDAS	—	1.02	1.02	1.01	***0.98***	1.00	***0.97***	***0.98***	***0.97***	0.98	0.98
DL	—	1.16	1.32	1.04	1.13	1.09	***0.97***	***0.98***	***0.97***	***0.95***	1.00
ADL	—	***0.99***	1.00	***0.98***	1.03	0.98	0.98	0.99	***0.97***	0.98	***0.96***

Note: Column "Switch" gives information on the parameters that are allowed to switch in the model: I-intercept β_0, V-variance of the error term σ^2, S-slope β_1.
The table presents the out-of-sample RMSEs for different models compared in this paper. Final vintage data are used for all variables. The original sample is divided into the in-sample period between 1959:Q1 and 1999:Q4 (160 quarters) and the out-of-sample period between 2000:Q1 and 2011:Q3 (47 quarters). For the out-of-sample period forecasts are calculated recursively for forecast horizon $h = 2$. In order to evaluate the forecasting performance of the models we calculate the RMSE for each model for the whole out-of-sample period. The RMSEs are calculated for the cases when only a forecast from a single factor is taken into account (columns 3-8), as well as for different forecast combination schemes (in this case the forecasts from single-factor-models are combined). The forecast combination schemes include: simple averaging (Mean), median (Med.), forecasts weighted according to Squared Discounted Mean Forecast Error (S.D.E.) and forecast combinations which trim the recently worst model - when last period is considered (Tr.(1)) and when the last four quarters are considered (Tr.(4)). Numbers in italics indicate the best performing model within a class of models without Markov-switching, with two regimes or with three regimes.

Table 2.A.9: Root Mean Squared Errors relative to AR(2) model. Forecast horizon $h = 4$. Final vintage data is used. Number of lags in the models chosen according to AIC.

Benchmarks	**RMSE**										
RW	1.23										
AR(2)	1.00										
Model	**Switch**	**Fac.1**	**Fac.2**	**Fac.3**	**Fac.4**	**Fac.5**	**Mean**	**Med.**	**S.D.E.**	**Tr.(1)**	**Tr.(4)**
2 regimes											
MS-U-MIDAS	I,V	1.04	1.05	0.99	0.99	1.02	1.00	1.02	1.00	1.01	1.00
MS-U-MIDAS	I,S,V	1.00	***0.99***	1.03	0.98	1.01	***0.96***	0.99	0.96	0.97	0.97
MS-U-MIDAS-AR	I,V	***0.98***	1.02	0.97	0.98	1.00	0.98	***0.98***	0.98	0.98	0.98
MS-U-MIDAS-AR	I,S,V	1.00	1.04	1.03	1.00	1.01	0.98	1.00	0.98	0.99	0.97
MS-MIDAS	I,V	1.06	1.03	0.97	0.99	1.02	1.00	1.01	1.00	1.00	1.00
MS-MIDAS	I,S,V	1.03	1.04	1.06	1.00	1.02	1.00	1.00	1.00	1.00	1.01
MS-MIDAS-AR	I,V	1.01	***0.99***	0.97	0.97	***0.99***	0.97	***0.98***	0.97	0.97	0.98
MS-MIDAS-AR	I,S,V	1.04	1.03	1.00	0.97	***0.99***	0.99	0.99	0.99	0.99	0.99
MS-ADL-MIDAS	I,V	1.04	1.04	***0.96***	1.04	1.02	1.01	1.01	1.01	1.00	1.01
MS-ADL-MIDAS	I,S,V	1.03	1.04	1.03	1.09	1.04	1.02	1.01	1.02	1.02	1.03
MS-DL	I,V	1.03	1.01	0.99	1.01	1.00	0.99	1.00	0.99	1.00	1.00
MS-DL	I,S,V	1.00	1.01	1.04	***0.95***	1.01	***0.96***	0.99	0.96	0.97	0.97
MS-ADL	I,V	1.01	***0.99***	0.97	0.96	1.00	0.97	***0.98***	0.97	0.98	0.98
MS-ADL	I,S,V	1.01	1.00	1.02	***0.95***	1.00	***0.96***	***0.98***	***0.95***	***0.96***	***0.96***
3 regimes											
MS-U-MIDAS	I,V	0.96	***0.95***	0.94	0.94	0.97	***0.94***	***0.95***	0.94	0.95	0.95
MS-U-MIDAS	I,S,V	1.00	1.02	0.97	0.98	***0.95***	0.95	0.97	0.96	0.97	0.96
MS-U-MIDAS-AR	I,V	0.96	0.97	0.96	0.95	0.98	0.95	0.97	0.95	0.96	0.95
MS-U-MIDAS-AR	I,S,V	1.07	1.02	0.95	1.03	0.99	0.97	0.99	0.98	0.99	0.98
MS-MIDAS	I,V	0.99	0.98	0.96	0.95	0.98	0.96	0.96	0.96	0.96	0.97
MS-MIDAS	I,S,V	0.98	1.00	0.97	0.99	1.02	0.96	0.97	0.96	0.97	0.98
MS-MIDAS-AR	I,V	0.97	0.97	0.95	***0.92***	0.97	0.95	***0.95***	0.95	0.95	0.95
MS-MIDAS-AR	I,S,V	0.96	0.99	0.93	0.96	1.00	***0.94***	0.96	0.94	0.95	***0.94***
MS-ADL-MIDAS	I,V	1.00	1.00	1.00	1.03	1.03	0.99	0.99	0.99	1.00	0.99
MS-ADL-MIDAS	I,S,V	1.00	1.01	1.02	1.07	1.03	1.00	0.99	1.00	1.02	1.01
MS-DL	I,V	***0.95***	***0.95***	0.93	0.97	0.96	0.95	***0.95***	0.95	***0.94***	***0.94***
MS-DL	I,S,V	0.98	1.00	0.92	0.93	0.96	***0.94***	0.97	***0.93***	***0.94***	***0.94***
MS-ADL	I,V	0.98	***0.95***	0.95	0.98	0.98	0.96	***0.95***	0.96	0.96	0.96
MS-ADL	I,S,V	0.99	0.97	***0.91***	***0.92***	1.01	***0.94***	***0.95***	***0.93***	***0.94***	***0.94***
Models without Markov-switching											
U-MIDAS	—	1.06	1.09	1.04	0.99	1.02	1.01	1.02	1.00	1.01	1.00
U-MIDAS-AR	—	1.07	1.08	***1.01***	0.98	1.00	1.00	1.02	1.00	1.01	1.00
MIDAS	—	1.07	1.07	1.03	1.00	1.03	1.01	1.03	1.01	1.00	1.01
MIDAS-AR	—	1.04	1.06	***1.01***	0.98	***0.97***	0.99	1.00	0.99	0.99	***0.98***
ADL-MIDAS	—	1.03	1.03	1.04	1.08	1.00	1.01	1.02	1.01	1.00	1.01
DL	—	1.22	***1.02***	1.08	1.14	1.10	1.08	1.06	1.08	1.07	1.07
ADL	—	***1.00***	***1.02***	***1.01***	***0.97***	1.00	***0.98***	***0.99***	***0.98***	***0.98***	***0.98***

Note: Column "Switch" gives information on the parameters that are allowed to switch in the model: I-intercept β_0, V-variance of the error term σ^2, S-slope β_1.
The table presents the out-of-sample RMSEs for different models compared in this paper. Final vintage data are used for all variables. The original sample is divided into the in-sample period between 1959:Q1 and 1999:Q4 (160 quarters) and the out-of-sample period between 2000:Q1 and 2011:Q3 (47 quarters). For the out-of-sample period forecasts are calculated recursively for forecast horizon $h = 4$. In order to evaluate the forecasting performance of the models we calculate the RMSE for each model for the whole out-of-sample period. The RMSEs are calculated for the cases when only a forecast from a single factor is taken into account (columns 3-8), as well as for different forecast combination schemes (in this case the forecasts from single-factor-models are combined). The forecast combination schemes include: simple averaging (Mean), median (Med.), forecasts weighted according to Squared Discounted Mean Forecast Error (S.D.E.) and forecast combinations which trim the recently worst model - when last period is considered (Tr.(1)) and when the last four quarters are considered (Tr.(4)). Numbers in italics indicate the best performing model within a class of models without Markov-switching, with two regimes or with three regimes.

Table 2.A.10: Quadratic Probability Scores calculated for filtered probabilities of the crisis regime for the out-of-sample period. Real-time data on the GDP growth is used.

Model	Switch	h=$\frac{1}{3}$	h=$\frac{2}{3}$	h=1
2 regimes				
MS-U-MIDAS	I,V	0.367	0.419	0.466
MS-U-MIDAS	I,S,V	0.356	0.346	0.537
MS-U-MIDAS-AR	I,V	0.356	0.379	0.441
MS-U-MIDAS-AR	I,S,V	0.315	0.333	0.412
MS-MIDAS	I,V	0.381	0.380	0.452
MS-MIDAS	I,S,V	0.453	0.467	0.622
MS-MIDAS-AR	I,V	0.398	0.338	0.441
MS-MIDAS-AR	I,S,V	0.415	0.393	0.432
MS-ADL-MIDAS	I,V	0.380	0.384	0.437
MS-ADL-MIDAS	I,S,V	0.347	0.376	0.434
MS-ADL	I,V	X	X	0.454
MS-ADL	I,S,V			0.414
MS-DL	I,V	X	X	0.466
MS-DL	I,S,V			0.585
3 regimes				
MS-U-MIDAS	I,V	0.345	0.335	0.344
MS-U-MIDAS	I,S,V	0.289	0.270	0.338
MS-U-MIDAS-AR	I,V	0.336	0.352	0.327
MS-U-MIDAS-AR	I,S,V	0.327	0.339	0.349
MS-MIDAS	I,V	0.344	0.346	0.341
MS-MIDAS	I,S,V	0.358	0.326	0.342
MS-MIDAS-AR	I,V	0.345	0.346	0.358
MS-MIDAS-AR	I,S,V	0.346	0.331	0.349
MS-ADL-MIDAS	I,V	0.359	0.351	0.353
MS-ADL-MIDAS	I,S,V	0.350	0.351	0.355
MS-ADL	I,V	X	X	0.361
MS-ADL	I,S,V			0.360
MS-DL	I,V	X	X	0.362
MS-DL	I,S,V			0.351

Note: Column "Switch" gives information on the parameters that are allowed to switch in the model: I-intercept β_0, V-variance of the error term σ^2, S-slope β_1.
The table presents the out-of-sample QPS for chosen models compared in this paper. The original sample is divided into the in-sample period between 1959:Q1 and 1999:Q4 (160 quarters) and the out-of-sample period between 2000:Q1 and 2011:Q3 (47 quarters). For the out-of-sample period the predicted probabilities of the crisis regime are calculated recursively for each single factor model. These probability forecasts are then combined by taking the mean of the single forecasts. The combined probability forecasts are then compared with the actual recessionary periods according to NBER.

Table 2.A.11: Root Mean Squared Errors relative to AR(2) model. Forecast horizon $h = \frac{1}{3}$. Real-time dataset is used for the US GDP. Number of lags in the models chosen according to AIC.

Benchmarks	**RMSE**										
RW	1.04										
AR(2)	1.00										
Model	**Switch**	**Fac.1**	**Fac.2**	**Fac.3**	**Fac.4**	**Fac.5**	**Mean**	**Med.**	**S.D.E.**	**Tr.(1)**	**Tr.(4)**
2 regimes											
MS-U-MIDAS	I,V	0.87	1.33	1.15	1.09	0.89	0.84	0.86	0.80	0.82	0.83
MS-U-MIDAS	I,S,V	0.85	1.21	1.21	1.07	0.95	0.87	0.88	0.85	0.84	0.85
MS-U-MIDAS-AR	I,V	0.86	1.17	0.98	***1.00***	0.86	0.79	0.83	0.79	0.78	0.78
MS-U-MIDAS-AR	I,S,V	***0.79***	***0.99***	0.95	1.05	0.96	0.80	0.82	0.80	0.79	0.81
MS-MIDAS	I,V	0.83	1.08	0.93	1.09	0.87	***0.76***	***0.75***	***0.74***	***0.75***	***0.75***
MS-MIDAS	I,S,V	0.81	1.22	1.03	1.01	0.91	0.86	0.82	0.85	***0.75***	***0.75***
MS-MIDAS-AR	I,V	0.82	***0.99***	0.92	***1.00***	***0.85***	0.77	0.84	0.76	0.78	***0.75***
MS-MIDAS-AR	I,S,V	***0.79***	***0.99***	0.90	1.02	0.97	0.83	0.87	0.83	0.82	0.84
MS-ADL-MIDAS	I,V	0.81	***0.99***	0.97	1.01	***0.85***	0.77	0.84	0.77	0.78	0.76
MS-ADL-MIDAS	I,S,V	0.92	***0.99***	***0.88***	1.05	0.98	0.78	0.83	0.80	0.76	0.77
3 regimes											
MS-U-MIDAS	I,V	0.98	1.26	1.02	1.06	0.91	0.90	0.89	0.88	0.86	0.85
MS-U-MIDAS	I,S,V	0.96	1.42	1.00	1.08	1.07	0.90	0.92	0.88	0.87	0.87
MS-U-MIDAS-AR	I,V	1.11	1.22	1.01	1.00	0.83	0.81	0.81	0.83	0.81	0.79
MS-U-MIDAS-AR	I,S,V	***0.79***	1.36	1.38	1.15	0.90	0.84	***0.79***	0.80	0.82	0.82
MS-MIDAS	I,V	0.85	1.02	1.35	1.08	0.92	0.85	0.86	0.83	0.84	0.84
MS-MIDAS	I,S,V	***0.79***	1.00	1.03	1.06	0.91	0.82	0.88	0.84	0.79	0.80
MS-MIDAS-AR	I,V	0.92	1.06	***0.92***	***0.98***	0.90	***0.77***	0.81	***0.77***	***0.78***	***0.73***
MS-MIDAS-AR	I,S,V	0.95	1.04	0.94	1.00	***0.82***	0.82	0.87	0.83	0.82	0.81
MS-ADL-MIDAS	I,V	0.92	1.01	1.04	1.04	0.84	0.82	0.86	0.83	0.80	0.77
MS-ADL-MIDAS	I,S,V	0.84	***0.99***	0.95	1.08	0.98	0.84	0.82	0.84	0.82	0.83
Models without Markov-switching											
U-MIDAS	—	0.96	1.44	1.36	1.08	0.91	0.87	0.88	0.80	0.84	0.83
U-MIDAS-AR	—	0.96	1.28	1.11	1.02	0.90	0.80	0.86	0.79	0.81	0.79
MIDAS	—	0.94	1.14	1.37	0.97	0.90	0.78	0.77	0.76	0.75	0.72
MIDAS-AR	—	0.94	1.04	***1.10***	***0.95***	***0.89***	***0.72***	***0.76***	***0.73***	***0.72***	***0.71***
ADL-MIDAS	—	***0.90***	***1.01***	1.12	1.01	***0.89***	0.75	0.80	0.75	0.75	0.73

Note: Column "Switch" gives information on the parameters that are allowed to switch in the model: I-intercept β_0, V-variance of the error term σ^2, S-slope β_1.
The table presents the out-of-sample RMSEs for different models compared in this paper. The original sample is divided into the in-sample period between 1959:Q1 and 1999:Q4 (160 quarters) and the out-of-sample period between 2000:Q1 and 2011:Q3 (47 quarters). For the out-of-sample period forecasts are calculated recursively for forecast horizon $h = \frac{1}{3}$. In order to evaluate the forecasting performance of the models we calculate the RMSE for each model for the whole out-of-sample period. The RMSEs are calculated for the cases when only a forecast from a single factor is taken into account (columns 3-8), as well as for different forecast combination schemes (in this case the forecasts from single-factor-models are combined). The forecast combination schemes include: simple averaging (Mean), median (Med.), forecasts weighted according to Squared Discounted Mean Forecast Error (S.D.E.) and forecast combinations which trim the recently worst model - when last period is considered (Tr.(1)) and when the last four quarters are considered (Tr.(4)). Numbers in italics indicate the best performing model within a class of models without Markov-switching, with two regimes or with three regimes.

Table 2.A.12: Root Mean Squared Errors relative to AR(2) model. Forecast horizon $h = \frac{2}{3}$. Real-time dataset is used for the US GDP. Number of lags in the models chosen according to AIC.

Benchmarks	**RMSE**										
RW	1.04										
AR(2)	1.00										
Model	**Switch**	**Fac.1**	**Fac.2**	**Fac.3**	**Fac.4**	**Fac.5**	**Mean**	**Med.**	**S.D.E.**	**Tr.(1)**	**Tr.(4)**
2 regimes											
MS-U-MIDAS	I,V	0.97	1.09	1.08	1.10	0.93	0.87	0.88	0.88	0.83	0.84
MS-U-MIDAS	I,S,V	0.92	1.17	1.16	1.14	0.99	0.96	0.96	0.97	0.94	0.94
MS-U-MIDAS-AR	I,V	0.95	1.09	0.89	0.99	0.87	0.84	0.86	0.84	0.82	0.82
MS-U-MIDAS-AR	I,S,V	0.97	***0.92***	0.89	1.07	0.97	0.78	0.84	0.80	0.83	0.77
MS-MIDAS	I,V	0.92	1.17	1.05	1.00	0.88	0.83	***0.82***	0.85	0.79	0.80
MS-MIDAS	I,S,V	***0.87***	1.14	1.01	1.04	1.02	0.90	0.93	0.89	0.89	0.92
MS-MIDAS-AR	I,V	1.02	0.99	***0.86***	***0.93***	0.87	***0.77***	***0.82***	***0.79***	***0.74***	***0.74***
MS-MIDAS-AR	I,S,V	0.89	1.01	0.88	0.98	0.96	0.86	0.85	0.86	0.86	0.86
MS-ADL-MIDAS	I,V	0.92	1.00	0.89	1.00	***0.86***	0.81	0.86	0.82	0.81	0.78
MS-ADL-MIDAS	I,S,V	1.03	0.99	0.91	1.07	1.01	0.85	0.89	0.86	0.85	0.85
3 regimes											
MS-U-MIDAS	I,V	1.03	1.07	0.92	1.06	0.95	0.87	0.92	0.87	0.86	0.85
MS-U-MIDAS	I,S,V	***0.82***	1.36	1.31	1.08	0.90	0.91	0.88	0.86	0.87	0.84
MS-U-MIDAS-AR	I,V	1.12	1.11	0.98	1.05	0.92	0.83	0.89	0.85	0.81	0.79
MS-U-MIDAS-AR	I,S,V	0.97	***0.98***	1.01	1.01	0.94	***0.82***	0.86	0.84	0.81	0.84
MS-MIDAS	I,V	0.88	1.16	0.94	1.10	0.90	0.89	0.95	0.87	0.85	0.86
MS-MIDAS	I,S,V	0.87	1.00	1.04	1.09	0.93	0.88	0.93	0.87	0.86	0.86
MS-MIDAS-AR	I,V	1.04	1.12	0.90	1.04	0.91	0.83	0.90	0.84	***0.80***	0.79
MS-MIDAS-AR	I,S,V	0.98	1.14	***0.83***	***0.98***	1.06	***0.82***	0.88	***0.82***	0.81	***0.76***
MS-ADL-MIDAS	I,V	1.04	1.00	1.13	1.07	***0.78***	0.84	***0.84***	0.88	0.85	0.83
MS-ADL-MIDAS	I,S,V	0.86	1.04	0.92	1.08	0.90	0.88	***0.84***	0.88	0.85	0.84
Models without Markov-switching											
U-MIDAS	—	***1.00***	1.26	1.15	1.09	0.93	0.89	0.91	0.90	0.85	0.85
U-MIDAS-AR	—	1.01	1.18	0.90	1.01	***0.90***	0.82	0.86	0.83	0.81	0.80
MIDAS	—	1.03	1.14	1.18	1.00	0.91	0.82	***0.81***	0.86	0.82	0.82
MIDAS-AR	—	1.04	1.06	***0.88***	***0.90***	0.91	***0.76***	0.82	***0.78***	***0.75***	***0.75***
ADL-MIDAS	—	1.01	***1.02***	0.91	1.01	***0.90***	0.79	0.83	0.81	0.79	0.78

Note: Column "Switch" gives information on the parameters that are allowed to switch in the model: I-intercept β_0, V-variance of the error term σ^2, S-slope β_1.
The table presents the out-of-sample RMSEs for different models compared in this paper. The original sample is divided into the in-sample period between 1959:Q1 and 1999:Q4 (160 quarters) and the out-of-sample period between 2000:Q1 and 2011:Q3 (47 quarters). For the out-of-sample period forecasts are calculated recursively for forecast horizon $h = \frac{2}{3}$. In order to evaluate the forecasting performance of the models we calculate the RMSE for each model for the whole out-of-sample period. The RMSEs are calculated for the cases when only a forecast from a single factor is taken into account (columns 3-8), as well as for different forecast combination schemes (in this case the forecasts from single-factor-models are combined). The forecast combination schemes include: simple averaging (Mean), median (Med.), forecasts weighted according to Squared Discounted Mean Forecast Error (S.D.E.) and forecast combinations which trim the recently worst model - when last period is considered (Tr.(1)) and when the last four quarters are considered (Tr.(4)). Numbers in italics indicate the best performing model within a class of models without Markov-switching, with two regimes or with three regimes.

Table 2.A.13: Root Mean Squared Errors relative to AR(2) model. Forecast horizon $h = 1$. Real-time dataset is used for the US GDP. Number of lags in the models chosen according to AIC.

Benchmarks	**RMSE**										
RW	1.04										
AR(2)	1.00										
Model	**Switch**	**Fac.1**	**Fac.2**	**Fac.3**	**Fac.4**	**Fac.5**	**Mean**	**Med.**	**S.D.E.**	**Tr.(1)**	**Tr.(4)**
2 regimes											
MS-U-MIDAS	I,V	0.82	1.14	1.11	1.08	0.97	0.92	0.94	0.90	0.93	0.91
MS-U-MIDAS	I,S,V	0.86	1.39	1.27	1.13	1.14	1.05	1.04	1.05	1.02	1.02
MS-U-MIDAS-AR	I,V	***0.80***	1.05	0.92	1.02	0.95	0.90	0.93	0.88	0.87	0.89
MS-U-MIDAS-AR	I,S,V	0.92	***0.90***	***0.87***	1.09	1.06	0.92	0.95	0.91	0.88	0.91
MS-MIDAS	I,V	0.84	1.08	1.08	1.03	0.92	0.90	0.91	0.89	0.88	0.87
MS-MIDAS	I,S,V	0.88	1.22	1.11	1.08	1.12	1.01	1.04	0.99	1.01	1.01
MS-MIDAS-AR	I,V	0.83	0.95	***0.87***	0.99	0.89	***0.83***	***0.88***	***0.82***	***0.84***	***0.82***
MS-MIDAS-AR	I,S,V	0.89	0.98	0.92	0.99	1.03	0.91	0.95	0.91	0.92	0.92
MS-ADL-MIDAS	I,V	0.81	0.98	0.92	1.03	0.92	0.87	0.92	0.86	0.86	0.86
MS-ADL-MIDAS	I,S,V	0.89	0.99	0.95	1.05	1.08	0.94	0.95	0.93	0.94	0.93
MS-ADL	I,V	0.84	1.00	1.05	***0.97***	***0.87***	0.88	0.89	0.88	0.86	0.87
MS-ADL	I,S,V	0.89	0.98	0.99	1.03	0.88	0.90	0.92	0.89	0.89	0.90
MS-DL	I,V	0.83	1.10	1.17	1.04	0.90	0.92	0.96	0.90	0.90	0.90
MS-DL	I,S,V	0.91	1.17	1.45	1.07	0.94	1.00	1.02	0.98	0.97	0.96
3 regimes											
MS-U-MIDAS	I,V	0.86	1.06	0.92	1.06	1.06	0.88	0.97	***0.86***	0.88	0.88
MS-U-MIDAS	I,S,V	***0.81***	1.28	1.32	1.09	2.45	1.06	0.96	1.06	1.11	1.13
MS-U-MIDAS-AR	I,V	0.91	1.15	***0.90***	1.05	0.98	0.88	***0.86***	0.88	0.89	0.88
MS-U-MIDAS-AR	I,S,V	***0.81***	1.11	0.95	1.15	1.17	0.96	0.97	0.93	0.96	0.96
MS-MIDAS	I,V	0.84	1.04	0.91	1.09	0.99	0.90	0.96	0.87	***0.86***	0.87
MS-MIDAS	I,S,V	0.86	1.00	1.08	1.13	1.11	0.94	0.95	0.94	0.95	0.96
MS-MIDAS-AR	I,V	0.85	***0.95***	0.99	1.04	0.99	0.89	0.93	0.87	0.90	0.88
MS-MIDAS-AR	I,S,V	0.96	0.99	0.96	1.04	1.03	0.94	0.96	0.94	0.95	0.93
MS-ADL-MIDAS	I,V	0.84	0.99	0.91	1.06	0.92	***0.87***	0.89	***0.86***	0.87	***0.85***
MS-ADL-MIDAS	I,S,V	0.85	0.99	1.00	1.05	1.02	0.91	0.90	0.91	0.93	0.93
MS-ADL	I,V	0.85	***0.95***	1.03	1.01	***0.91***	0.88	0.91	0.88	0.87	0.86
MS-ADL	I,S,V	0.91	0.97	1.04	***1.00***	0.95	0.92	0.94	0.91	0.91	0.91
MS-DL	I,V	0.86	1.05	1.15	1.08	0.96	0.96	0.99	0.95	0.94	0.95
MS-DL	I,S,V	0.89	1.01	1.50	1.07	0.97	0.98	0.95	0.98	0.98	0.98
Models without Markov-switching											
U-MIDAS	—	0.89	1.25	1.21	1.13	1.05	0.95	0.98	0.93	0.91	0.92
U-MIDAS-AR	—	***0.88***	1.13	0.95	1.03	0.92	0.86	0.91	0.86	0.84	0.83
MIDAS	—	0.90	1.14	1.41	1.04	0.99	0.92	0.95	0.93	0.92	0.89
MIDAS-AR	—	0.90	1.01	***0.91***	***0.94***	0.93	***0.81***	***0.81***	***0.81***	***0.79***	***0.80***
ADL-MIDAS	—	***0.88***	***0.98***	0.92	1.03	0.93	0.82	0.86	0.82	0.81	***0.80***
ADL	—	***0.88***	1.03	1.06	0.97	***0.89***	0.86	0.90	0.86	0.84	0.85
DL	—	0.90	1.19	1.38	1.03	0.93	0.95	0.97	0.93	0.90	0.90

Note: Column "Switch" gives information on the parameters that are allowed to switch in the model: I-intercept β_0, V-variance of the error term σ^2, S-slope β_1.
The table presents the out-of-sample RMSEs for different models compared in this paper. The original sample is divided into the in-sample period between 1959:Q1 and 1999:Q4 (160 quarters) and the out-of-sample period between 2000:Q1 and 2011:Q3 (47 quarters). For the out-of-sample period forecasts are calculated recursively for forecast horizon $h = 1$. In order to evaluate the forecasting performance of the models we calculate the RMSE for each model for the whole out-of-sample period. The RMSEs are calculated for the cases when only a forecast from a single factor is taken into account (columns 3-8), as well as for different forecast combination schemes (in this case the forecasts from single-factor-models are combined). The forecast combination schemes include: simple averaging (Mean), median (Med.), forecasts weighted according to Squared Discounted Mean Forecast Error (S.D.E.) and forecast combinations which trim the recently worst model - when last period is considered (Tr.(1)) and when the last four quarters are considered (Tr.(4)). Numbers in italics indicate the best performing model within a class of models without Markov-switching, with two regimes or with three regimes.

CHAPTER 3

Point and Density Forecasts Using an Unrestricted Mixed-Frequency VAR Model

3.1 Introduction

Obtaining accurate forecasts for economic variables is a vital task; it is not merely an interesting research topic for academics but rather an issue of crucial importance to policy makers as well as financial market participants. In general, time series observations are available at different frequencies. For some variables, data is available and can be easily collected, and hence time series can be sampled at high frequencies. While for other variables, collecting data and constructing time series can be a costly and time-consuming process and as a result such variables can only be sampled at low frequencies. When there is an interest in forecasting low-frequency variables, using predictors observed at a higher frequency can be very useful in enhancing the accuracy of the forecasts. A main reason is that high-frequency predictors may include more recent information that can be used to update the forecasts of the low-frequency variables. Therefore, there is a need for time series models that can make accurate forecasts for low-frequency variables using information available at higher frequency variables.

Most of the literature compare competing forecasting models by evaluating their out-of-sample point forecasts. By construction, a point forecast ignores the uncertainties that are associated with the predictions. As opposed to a point forecast, a density forecast provides a predictive probability distribution for the outcome of interest; this allows density forecasting to account for predictions' uncertainties[1]. The ability of density forecasts to acknowledge future uncertainty makes them very attractive for decision making. As a result, recently, many central banks such as Bank of England, Norges Bank, and Sveriges Riksbank publish density forecasts for macroeconomic aggregates. Thus, when the focus is in obtaining accurate forecasts from forecasting models, one should not only consider point forecasts, but also density forecasts as they provide very useful information for policy makers.

Although nowadays there is a vast number of economic and financial variables, many would still argue that the gross domestic product (GDP) is the single most important economic indicator. As a result, a large literature in forecasting focuses on forecasting the GDP growth rate. The GDP is available at a quarterly frequency; however, most of its predictors are available at a monthly frequency. In this paper we contribute to the literature by proposing a Bayesian framework as well as a parametric bootstrap framework that allows the use of data-driven multivariate mixed-frequency models to obtain point and density forecasts for low-frequency variables such as GDP growth rate using high-frequency variables. We also describe how the nowcasts can be obtained using both direct and iterative forecasting methods. In addition, we evaluate the forecasting and nowcasting performance of these models by means of Monte Carlo simulations and an empirical

[1] Garratt et al. (2003) list five possible sources of uncertainties for model-based forecasts: future, parameter, model, policy and measurement uncertainties. In this paper we only consider future and parameter uncertainties as we will discuss in the next section.

study.

When variables observed at mixed-frequencies are available in regression models, a common solution is to aggregate the high-frequency variables to match the frequency of the low-frequency variable, and run the regression at the common low-frequency. Although such an approach is quite attractive due to its simplicity, in forecasting it has two main disadvantages. First, one does not know beforehand the exact aggregation weights that should be given to the high-frequency variables and has to make simplifying assumptions such as an equal weighting scheme which most often does not match the data. Second, this approach ignores the possible availability of high-frequency information within the low-frequency time period (i.e. it does not allow for nowcasting). For instance, if we want to nowcast the first quarter of the GDP using monthly industrial production and we are already in February, the simple aggregation method can not make use of the available useful information in January to nowcast the GDP. In the literature, however, two approaches have been proposed that can utilize the availability of mixed-frequency data in a more useful way[2]. The first approach, based on state space models and the Kalman filter, interpolates the low-frequency variable to match that of the high-frequency one. This parameter-driven approach has been used in several forecasting/nowcasting studies (see e.g. Mariano and Murasawa (2010), Schorfheide and Song (2013), Kuzin et al. (2013), among others). Alternatively, instead of either aggregating the high-frequency variables or interpolating the low-frequency variables, MIxed DAta Sampling (MIDAS) regressions allow the use of mixed-frequency data directly in a data-driven fashion.

MIDAS regression models have been recently introduced to the literature by Ghysels et al. (2004). The MIDAS regressions simply use lag polynomial functions to estimate the weights used to aggregate the high-frequency variables in a regression context. In forecasting, the univariate MIDAS model and its extensions have shown good success that is usually attributed to their ability to nowcast. Clements and Galvão (2008) use monthly indicators to forecast the US GDP growth rate. Andreou et al. (2013) and Barsoum (2011) combine MIDAS with factor models and use large daily datasets to forecast the GDP of the US and the UK, respectively. Guérin and Marcellino (2013), Barsoum and Stankiewicz (2015), and Bessec and Bouabdallah (2015) use Markov-switching MIDAS models in different forecasting applications. The current paper builds on three recent papers in the MIDAS literature. Foroni et al. (2015) show that when the difference between the low-frequency and the high-frequency variables is small (i.e. quarterly and monthly frequency), one can include the high-frequency lags directly in the regression model without the need to use lag polynomials. This so called unrestricted MIDAS (U-MIDAS) shows promising forecasting results in both Monte Carlo simulations and empirical applications in comparison to MIDAS regressions with lag polynomials. Moreover, U-MIDAS regressions are estimated using OLS; this is an attractive feature given that MIDAS re-

[2]Foroni and Marcellino (2013) survey the mixed-frequency literature.

gressions are estimated by means of non-linear least squares. Despite the growing interest in using MIDAS regressions in forecasting, most of the work, so far, focused solely on obtaining point forecasts from these univariate regressions; one notable exception is Aastveit et al. (2014). They used a parametric bootstrap method to obtain density forecasts from univariate MIDAS regressions. Their methodology, which accounts for both parameters and future uncertainty, shows consistency between results obtained from both point forecasts and density forecasts. Another very relevant work is the mixed-frequency vector autoregressive model (MF-VAR) of Ghysels (2015). In this important contribution, Ghysels (2015) stacks both the high- and low-frequency variables together in a VAR framework by decomposing each high-frequency variable into a number of low-frequency variables. Similar to the U-MIDAS of Foroni et al. (2015), all the variables are modeled together at the common low-frequency in a linear fashion. Although the model can be easily estimated using OLS, it is prone to parameters proliferation. Consequently, the model is more useful when the difference between the low- and high-frequency variables is small. This approach may be useful when the interest is in forecasting quarterly GDP since most of the predictors used in the literature are observed at a monthly frequency.

In this paper we are interested in using Ghysels (2015) MF-VAR model and extending the existing methodology to obtain point and density forecasts. The aim is to evaluate the possible gains obtained from using the MF-VAR model in point and density forecasting as opposed to a VAR model sampled at a common low frequency (LF-VAR). Thus, our main focus is to investigate the differences between two models that are similar in every aspect, except for the way they deal with the high-frequency (HF) data. This way, if there are forecasting gains from using the MF-VAR, we can directly relate them to the ability of the MF-VAR[3] to use mixed-frequency data. In addition, exploiting the mixed-frequency structure of the model allows one to obtain nowcasts using the available high-frequency information; this feature can not be obtained from the LF-VAR model. In general, VAR models can provide both direct and iterative forecasts (see e.g. Marcellino et al. (2006) for a comparison between the two forecasting methods). Interestingly, although in standard VAR models iterative forecasting is mainly used for multi-step ahead predictions, due to the structure of the stacked vector in the MF-VAR, iterative forecasting can be used to obtain nowcasts. We compare the forecasting performance of the MF-VAR model using two estimation methods. In the first method OLS is used to estimate the parameters of the model which are then used to obtain point forecasts. To get density forecasts, we extend the work of Fresoli et al. (2015) and use a parametric bootstrap method. In their paper

[3]Other papers in the literature that used MF-VAR models include Mariano and Murasawa (2010), Schorfheide and Song (2013), and Chiu et al. (2011). However, unlike the MF-VAR of Ghysels (2015), other approaches are parameter-driven and are estimated by either the Kalman filter or Bayesian estimation. Therefore, when one compares the forecasting performance of these models with LS-VAR it is not clear whether the gains are due to the the use of mixed-frequency data or due to the parametric structure (Bayesian priors in case of Bayesian estimation) imposed on these models.

they showed the asymptotic validity of their simple method, which, unlike Thombs and Schucany (1990) and Kim (1999), does not use a backward representation. In the second method we use Bayesian estimation to obtain point and density forecasts. We use the priors suggested by Ghysels (2015), while we follow Banbura et al. (2010) and De Mol et al. (2008) and use more shrinkage as the dimension of the model gets larger. Here, however, the large dimension is not only due to the inclusion of more variables but also due to the stacking of the high-frequency variables at the low-frequency.

We assess the forecasting performance of the MF-VAR using both Monte Carlo simulations and an empirical study. In the Monte Carlo simulations we follow Foroni et al. (2015) and generate an HF bivariate VAR model as a data generating process (DGP). We compare the forecasting performance of the MF-VAR to LF-VAR using 9 different sets of parameters. In addition, unlike the previous literature, we also evaluate the nowcasting performance of the MF-VAR. This is important to document the gains that can be achieved by the MF-VAR in nowcasting horizons and understand how the performance of the model depends on the DGP's parameters. The results show that the MF-VAR can provide more accurate forecasts compared to its LF-VAR counterpart. These gains are more pronounced at nowcasting horizons and when the parameters of the DGP show high persistence. The results of density forecasts are in line with the point forecasts' results. Moreover, iterative forecasting slightly outperforms direct forecasting in some cases. In the empirical study we forecast the GDP growth of the US using 6 different commonly used predictors. In forecasting we use different numbers of predictors in both the MF-VAR and the LF-VAR to evaluate the forecasting performance of the MF-VAR in large dimensions, since the model is prone to parameters proliferation. For smaller dimensions, OLS provides comparable or better forecasts, while, as expected, Bayesian estimation with shrinkage performs better for larger dimensions. In general, the results from the empirical study are consistent with those from the Monte Carlo simulations; however, both direct and iterative forecasting show very comparable results.

The paper is organized as follows. In Section 3.2 we describe the models that we use in forecasting and how to obtain point and density forecasts using both parametric bootstrap and Bayesian estimation from these models. The Monte Carlo simulations are discussed in Section 3.3. Section 3.4 presents the empirical study. Section 3.5 concludes.

3.2 Mixed-frequency VAR

3.2.1 Model description

VARs have become one of the standard tools to model the co-movements of different economic time series since their introduction in Sims (1980). They have been used in a large number of papers in both forecasting and structural analysis. Although standard VARs are

quite useful, one of their drawbacks is their inability to deal with mixed-frequency variables. This is restrictive given the availability of macroeconomic and financial variables at different frequencies. For instance, although GDP is observed quarterly, most of its predictors such as industrial production or employment are monthly variables. To model the co-movements of mixed-frequency time series, Ghysels (2015) proposes the use of MF-VAR. Following a similar notation[4], a MF-VAR model with P lags and $K_L = K_H = 1$ can be written as:

$$\begin{bmatrix} x_H(\tau_L, 1) \\ \vdots \\ x_H(\tau_L, m) \\ x_L(\tau_L) \end{bmatrix} = A_0 + \sum_{j=1}^{P} A_j \begin{bmatrix} x_H(\tau_L - j, 1) \\ \vdots \\ x_H(\tau_L - j, m) \\ x_L(\tau_L - j) \end{bmatrix} + \epsilon(\tau_L). \tag{3.1}$$

The MF-VAR is a $K-$dimensional process where $K = K_L + m \times K_H$. K_L is the number of low frequency variables that are observed every fixed m period, while K_H is the number of high frequency variables included in the model. So if we want to include monthly industrial production, monthly employment, and quarterly GDP in the model, then $K_L = 1$, $K_H = 2$, and $m = 3$. The LF variables can be described using the single-indexed vector process $x_L(\tau_L)$ where τ_L is the low frequency time period; for example, for quarterly GDP, it can be 2014Q4. On the other hand, the HF variables can be collected in the double-indexed vector process $x_H(\tau_L, k_H)$ where $k_H = 1, \cdots, m$ is the high frequency period within the low frequency; for instance, τ_L=2014Q4 and k_H=1, correspond to monthly industrial production in October 2014 (i.e. the first month during 2014Q4). A_0 is a $K \times 1$ vector of intercepts and A_j are $K \times K$ coefficient matrices:

$$A_0 = \begin{bmatrix} A_0^1 \\ \vdots \\ A_0^m \\ A_0^{m+1} \end{bmatrix} \quad \text{and} \quad A_j = \begin{bmatrix} A_j^{1,1} & \cdots & A_j^{1,m} & A_j^{1,m+1} \\ \vdots & \cdots & \vdots & \vdots \\ A_j^{m,1} & \cdots & A_j^{m,m} & A_j^{m,m+1} \\ A_j^{m+1,1} & \cdots & A_j^{m+1,m} & A_j^{m+1,m+1} \end{bmatrix}.$$

By defining $x(\tau_L) = [x_H(\tau_L, 1), \cdots, x_H(\tau_L, m), x_L(\tau_L)]'$, a more compact notation for equation (3.1) is simply:

$$x(\tau_L) = A_0 + \sum_{j=1}^{P} A_j x(\tau_L - j) + \epsilon(\tau_L). \tag{3.2}$$

[4]For notation simplicity we are just using one high frequency variable and one low frequency variable. One can for instance assume that $x_H(\tau_L, k_H)$ is a vector $[x_{H1}(\tau_L, k_H), x_{H2}(\tau_L, k_H)]'$ if two high frequency variables are included.

To use equation (3.2) in forecasting h-steps ahead and h is an integer (i.e. no nowcasting is allowed) we can use:

$$x(\tau_L) = A_0 + \sum_{j=0}^{P-1} A_{j+1} x(\tau_L - j - h) + \epsilon(\tau_L). \tag{3.3}$$

Most of the time we are interested in using the high frequency variables to forecast a low frequency variable, i.e. we are interested in using the last equation in (3.1) in forecasting. The univariate last equation in the MF-VAR can be rewritten as:

$$x_L(\tau_L) = A_0^{m+1} + \sum_{j=0}^{P-1} A_{j+1}^{m+1,m+1} x_L(\tau_L - j - h) + \sum_{j=0}^{P-1} \sum_{k=1}^{m} A_{j+1}^{m+1,k} x_H(\tau_L - j - h, k) + \epsilon(\tau_L)^{m+1}. \tag{3.4}$$

The above equation is equivalent to the UMIDAS of Foroni et al. (2015). The term $\sum_{j=0}^{P-1} A_{j+1}^{m+1,m+1} x_L(\tau_L - j - h)$ simply includes the AR(P) lags of the LF variable. In addition, the term $\sum_{j=0}^{P-1} \sum_{k=1}^{m} A_{j+1}^{m+1,k} x_H(\tau_L - j - h, k)$ accounts for the effects of the high frequency variables included in the regression equation. Thus, the number of estimated regression coefficients in equation (3.4) is $1 + P + mP$. In both the UMIDAS and the MF-VAR the dimension of the model is a function of m; therefore, the dimension of the model gets larger when the difference between the low and high frequency variables becomes large. Foroni et al. (2015) document the suitability of using the UMIDAS when the interest is in using monthly predictors to forecast quarterly variables. Moreover, Barsoum and Stankiewicz (2015) show that even in a Markov-switching framework where the number of estimated parameters increases proportionally to the number of regimes, the UMIDAS still provides better forecasting performance compared to its restricted counterpart. Therefore, for small differences in frequencies, parameters proliferation is not very restrictive for forecasting applications.

3.2.2 Nowcasting

In standard VAR models using a reduced-form is sufficient when the interest is in forecasting. Similarly, for the MF-VAR model, when the interest is in forecasting h-steps ahead and h is an integer, one can directly use the reduced form forecasting model in equation (3.3). In this case, as shown in equation (3.4), the forecasts obtained from the univariate UMIDAS model are similar to those obtained from the MF-VAR, and thus it would not be meaningful to use a more complicated model in forecasting when a simpler model can provide similar forecasts. However, for nowcasting, the structure of the stacked vector used in the MF-VAR can allow for different methodologies to obtain nowcasts. In univariate MIDAS models direct nowcasting is obtained by including a more recent lag (observed at the nowcasting horizon) of the HF variable in the regression model. Alter-

natively, in the MF-VAR model, either direct or iterative nowcasts can be obtained by making use of the Cholesky decomposition of the variance-covariance matrix.
The variance-covariance matrix of the MF-VAR model in equation (3.1) is:

$$\mathbb{E}[\epsilon(\tau_L)\epsilon(\tau_L)'] = \Sigma = CC' = M_{[m]}\Omega M'_{[m]}, \tag{3.5}$$

where C is the Cholesky decomposition of Σ, Ω is a diagonal matrix, $M_{[m]}$ is a lower triangular matrix. The use of the subscript in M will be useful in what follows. Using $N_{[m]} = M^{-1}_{[m]}$, we can view $N_{[m]}$ as an equivalent to the contemporaneous matrix in structural VARs:

$$N_{[m]} = \begin{bmatrix} I & 0 & \cdots & \cdots & 0 \\ N^{2,1}_{[m]} & I & 0 & \cdots & 0 \\ \vdots & & & & \vdots \\ \vdots & \cdots & \cdots & \ddots & \vdots \\ N^{m+1,1}_{[m]} & \cdots & N^{m+1,m-1}_{[m]} & N^{m+1,m}_{[m]} & I \end{bmatrix},$$

moreover, for $i = 1, \cdots, m-1$, we define:

$$N_{[i]} = \begin{bmatrix} I & 0 & \cdots & \cdots & 0 & 0 \\ N^{2,1}_{[i]} & I & 0 & \cdots & 0 & 0 \\ \vdots & & & & \vdots & \vdots \\ N^{i+1,1}_{[i]} & \cdots & N^{i+1,i}_{[i]} & I & \vdots & 0 \\ \vdots & & \vdots & 0 & \ddots & \vdots \\ N^{m+1,1}_{[i]} & \cdots & N^{m+1,i}_{[i]} & 0 & \cdots & I \end{bmatrix}.$$

Thus, after we estimate the variance-covariance matrix of the MF-VAR model, we can obtain $N_{[m]}$ from the inverse of the Cholesky decomposition of the variance-covariance matrix and $N_{[i]}$ as a partial truncation of the first i shocks from $N_{[m]}$. Premultiplying equation (3.2) by $N_{[i]}$, for $i = 1, \cdots, m$, we can obtain a structural MF-VAR model:

$$N_{[i]}x(\tau_L) = B_{[i]0} + \sum_{j=1}^{P} B_{[i]j}x(\tau_L - j) + e_{[i]}(\tau_L), \tag{3.6}$$

with $B_{[i]0} = N_{[i]}A_0$, $B_{[i]j} = N_{[i]}A_j$, and $e_{[i]}(\tau_L) = N_{[i]}\epsilon(\tau_L)$. As highlighted earlier, the above structural MF-VAR can be used in nowcasting using either direct or iterative methods. For nowcasting h-steps ahead using direct forecasting we may use:

$$N_{[i]}x(\tau_L) = B_{[i]0} + \sum_{j=0}^{P-1} B_{[i]j+1}x(\tau_L - j - d) + e_{[i]}(\tau_L), \tag{3.7}$$

where h can be a fraction, d is a rounded up integer value for h, and $i = (d-h) \times m$. For instance, if we are interested in forecasting GDP 2015Q1 using industrial production in 2015M2, then $h = 1/3$, $d = 1$, and $i = 2$, and accordingly we would use $N_{[2]}$. For clarity, we can write equation (3.7) as:

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ N^{2,1}_{[2]} & 1 & 0 & 0 \\ N^{3,1}_{[2]} & N^{3,2}_{[2]} & 1 & 0 \\ N^{4,1}_{[2]} & N^{4,2}_{[2]} & 0 & 1 \end{bmatrix} \begin{bmatrix} x_H(\tau_L, 1) \\ x_H(\tau_L, 2) \\ x_H(\tau_L, 3) \\ x_L(\tau_L) \end{bmatrix} = \sum_{j=0}^{P-1} \begin{bmatrix} B^{1,1}_{[2]j+1} & B^{1,2}_{[2]j+1} & B^{1,3}_{[2]j+1} & B^{1,4}_{[2]j+1} \\ B^{2,1}_{[2]j+1} & B^{2,2}_{[2]j+1} & B^{2,3}_{[2]j+1} & B^{2,4}_{[2]j+1} \\ B^{3,1}_{[2]j+1} & B^{3,2}_{[2]j+1} & B^{3,3}_{[2]j+1} & B^{3,4}_{[2]j+1} \\ B^{4,1}_{[2]j+1} & B^{4,2}_{[2]j+1} & B^{4,3}_{[2]j+1} & B^{4,4}_{[2]j+1} \end{bmatrix} \times \begin{bmatrix} x_H(\tau_L - j - 1, 1) \\ x_H(\tau_L - j - 1, 2) \\ x_H(\tau_L - j - 1, 3) \\ x_L(\tau_L - j - 1) \end{bmatrix} + \begin{bmatrix} B^1_{[2]0} \\ B^2_{[2]0} \\ B^3_{[2]0} \\ B^4_{[2]0} \end{bmatrix} + \begin{bmatrix} e^1_{[2]}(\tau_L) \\ e^2_{[2]}(\tau_L) \\ e^3_{[2]}(\tau_L) \\ e^4_{[2]}(\tau_L) \end{bmatrix}. \tag{3.8}$$

The optimal direct nowcast for the last equation in (3.8) reads as:

$$\begin{aligned} x_L(\tau_L) &= B^4_{[2]0} - N^{4,1}_{[2]} x_H(\tau_L, 1) - N^{4,2}_{[2]} x_H(\tau_L, 2) \\ &\quad + \sum_{j=0}^{P-1} (B^{4,1}_{[2]j+1} x_H(\tau_L - j - 1, 1) + B^{4,2}_{[2]j+1} x_H(\tau_L - j - 1, 2) \\ &\quad + B^{4,3}_{[2]j+1} x_H(\tau_L - j - 1, 3) + B^{4,4}_{[2]j+1} x_L(\tau_L - j - 1)) \\ &\quad + E[e^4_{[2]}(\tau_L)], \end{aligned} \tag{3.9}$$

where $E[e^4_{[2]}(\tau_L)] = 0$. Thus, using direct nowcasting, the within quarter information is captured using the $N_{[i]}$ matrix. The available information in the first two months updates the forecasts, while information in the third month is ignored since it is not observed at $h = 1/3$. Due to the lower triangular structure of the $N_{[i]}$ matrix, the order of the variables becomes a crucial issue. The first i columns are non zero as they correspond to the available information for nowcasting in the stacked vectors. Therefore, the variables in the stacked vector should be arranged in an ascending order from the oldest to the most recent.

Alternatively, nowcasts can also be obtained using iterative nowcasting:

$$N_{[m]}x(\tau_L) = B_{[m]0} + \sum_{j=0}^{P-1} B_{[m]j+1}x(\tau_L - j - d) + e_{[m]}(\tau_L). \tag{3.10}$$

Both equation (3.7) and equation (3.10) look quite similar; however, they differ in the subindex of the lower triangular matrix. In direct forecasting we use $N_{[i]}$ while in iterative forecasting we use $N_{[m]}$ regardless to the nowcast horizon. To elaborate, following the same above example used in equation (3.8), we can rewrite equation (3.10) as:

$$\begin{aligned}
\begin{bmatrix} 1 & 0 & 0 & 0 \\ N^{2,1}_{[3]} & 1 & 0 & 0 \\ N^{3,1}_{[3]} & N^{3,2}_{[3]} & 1 & 0 \\ N^{4,1}_{[3]} & N^{4,2}_{[3]} & N^{4,2}_{[3]} & 1 \end{bmatrix} \begin{bmatrix} x_H(\tau_L, 1) \\ x_H(\tau_L, 2) \\ x_H(\tau_L, 3) \\ x_L(\tau_L) \end{bmatrix} &= + \sum_{j=0}^{P-1} \begin{bmatrix} B^{1,1}_{[3]j+1} & B^{1,2}_{[3]j+1} & B^{1,3}_{[3]j+1} & B^{1,4}_{[3]j+1} \\ B^{2,1}_{[3]j+1} & B^{2,2}_{[3]j+1} & B^{2,3}_{[3]j+1} & B^{2,4}_{[3]j+1} \\ B^{3,1}_{[3]j+1} & B^{3,2}_{[3]j+1} & B^{3,3}_{[3]j+1} & B^{3,4}_{[3]j+1} \\ B^{4,1}_{[3]j+1} & B^{4,2}_{[3]j+1} & B^{4,3}_{[3]j+1} & B^{4,4}_{[3]j+1} \end{bmatrix} \\
&\quad \times \begin{bmatrix} x_H(\tau_L - j - 1, 1) \\ x_H(\tau_L - j - 1, 2) \\ x_H(\tau_L - j - 1, 3) \\ x_L(\tau_L - j - 1) \end{bmatrix} + \begin{bmatrix} B^1_{[3]0} \\ B^2_{[3]0} \\ B^3_{[3]0} \\ B^4_{[3]0} \end{bmatrix} \\
&\quad + \begin{bmatrix} e^1_{[3]}(\tau_L) \\ e^2_{[3]}(\tau_L) \\ e^3_{[3]}(\tau_L) \\ e^4_{[3]}(\tau_L) \end{bmatrix},
\end{aligned} \tag{3.11}$$

and the optimal iterative nowcast for the low frequency variable in the last equation in (3.11) reads as:

$$\begin{aligned}
x_L(\tau_L) &= B^4_{[3]0} - N^{4,1}_{[3]}x_H(\tau_L, 1) - N^{4,2}_{[3]}x_H(\tau_L, 2) - N^{4,3}_{[3]}E[x_H(\tau_L, 3)|x_H(\tau_L, 2)] \\
&\quad + \sum_{j=0}^{P-1}(B^{4,1}_{[3]j+1}x_H(\tau_L - j - 1, 1) + B^{4,2}_{[3]j+1}x_H(\tau_L - j - 1, 2) \\
&\quad + B^{4,3}_{[3]j+1}x_H(\tau_L - j - 1, 3) + B^{4,4}_{[3]j+1}x_L(\tau_L - j - 1)) \\
&\quad + E[e^4_{[3]}(\tau_L)],
\end{aligned} \tag{3.12}$$

where $E[x_H(\tau_L, 3)|x_H(\tau_L, 2)]$ is the forecast of the high-frequency variable in the third month of the quarter using the available information up to the second month in the quarter.

The optimal nowcast for $E[x_H(\tau_L,3)|x_H(\tau_L,2)]$:

$$\begin{aligned} E[x_H(\tau_L,3)|x_H(\tau_L,2)] &= B^3_{[3]0} - N^{3,1}_{[3]}x_H(\tau_L,1) - N^{3,2}_{[3]}x_H(\tau_L,2) \\ &\quad + \sum_{j=0}^{P-1}(B^{3,1}_{[3]j+1}x_H(\tau_L-j-1,1) + B^{3,2}_{[3]j+1}x_H(\tau_L-j-1,2) \\ &\quad + B^{3,3}_{[3]j+1}x_H(\tau_L-j-1,3) + B^{3,4}_{[3]j+1}x_L(\tau_L-j-1)) \\ &\quad + E[e^3_{[3]}(\tau_L)]. \end{aligned} \tag{3.13}$$

To summarize, in iterative nowcasting the unavailable high-frequency observations within the quarter are replaced by their optimal forecasts to nowcast the low-frequency variable. Alternatively, direct nowcasting only makes use of the available high-frequency information inside the quarter while ignores the unavailable data. The idea is quite similar to the direct and iterative forecasting used in standard VARs; however, the structure of the stacked vector in the MF-VAR model allows both methods to be extended to nowcasting and not just forecasting.

3.2.3 Frequentist estimation

In the previous two subsections we showed how to use the MF-VAR to obtain forecasts and nowcasts by means of either direct or iterative methods. In this subsection we present a methodology that allows for obtaining density forecasts and nowcasts using a parametric bootstrap method. We follow the bootstrap method of Fresoli et al. (2015) for standard VARs and extend it to the MF-VAR model for both forecasting and nowcasting; other papers that used similar bootstrap methods for VARs inlcude Staszewska-Bystrova and Winker (2013) and Wolf and Wunderli (2015). In order to avoid repetition, instead of presenting the bootstrap algorithm for all the variants of the MF-VAR model discussed earlier, we focus here on the most general representation of the MF-VAR which can be used for both forecasting and nowcasting. For $i = 0, \cdots, m$, the h-steps ahead forecasting equation for the MF-VAR is:

$$N_{[i]}x(\tau_L) = B_{[i]0} + \sum_{j=0}^{P-1} B_{[i]j+1}x(\tau_L - j - d) + e_{[i]}(\tau_L). \tag{3.14}$$

When $i = 0$, $N_{[0]}$ is an identity matrix and the MF-VAR is in reduced form and can be used in forecasting. In such case both direct and iterative forecasting methods are equivalent. Alternatively, for nowcasting, when h is not an integer, i can take any value between 1 and m. Values of i between 1 and $m-1$ are used in direct nowcasting while $i = m$ is used in iterative nowcasting. Since in practice we do not know the actual parameters, we replace the actual parameters by their estimates in order to obtain the optimal h-steps ahead point forecast/nowcast:

$$\hat{N}_{[i]}\hat{x}(T+d) = \hat{B}_{[i]0} + \sum_{j=0}^{P-1} \hat{B}_{[i]j+1} x(T-j), \tag{3.15}$$

where T is the last low-frequency time period used in the in-sample estimation. Thus, we replace the generic low-frequency time period τ_L with T so that the left hand side of equation 3.15 becomes the forecasts obtained from the MF-VAR. Given the available information, we first estimate $\hat{A}_0$ and $\hat{A}_j$ using OLS and then we obtain $\hat{N}_{[i]}$ from the Cholesky decomposition of the estimated variance covariance matrix. $\hat{B}_{[i]0}$ and $\hat{B}_{[i]j}$ can be calculated as $\hat{N}_{[i]}\hat{A}_0$ and $\hat{N}_{[i]}\hat{A}_j$ respectively.
Alternatively, to obtain a density of forecasts, we use the following algorithm:

- *Step 1*. First estimate the parameters $\hat{A}_0$ and $\hat{A}_j$ using OLS from the reduced form equation (3.2). Following Stine (1987), the corresponding matrix of residuals is centered and scaled using the factor $[(T-P)/(T-2P)]^{\frac{1}{2}}$.The scaling is used so that the variance of the residuals is not smaller than the variance of the innovations. Let $\hat{F}_{\hat{e}}$ be the empirical distribution of the centered and rescaled residuals.

- *Step 2*. Use the estimated parameters from *Step 1* and construct bootstrap series $(x(1)^*, \cdots, x(T)^*)$:

$$x^*(\tau_L) = \hat{A}_0 + \sum_{j=1}^{P} \hat{A}_j x^*(\tau_L - j) + \hat{e}^*(\tau_L). \tag{3.16}$$

  For the initial values at time $\tau_L = -p+1, \cdots, 0$ we use $x^*(\tau_L) = x(\tau_L)$. $\hat{e}^*(\tau_L)$ is randomly drawn with replacement from $\hat{F}_{\hat{e}}$.

- *Step 3*. Estimate the parameters of the constructed bootstrapped series from *Step 2* using OLS and denote them by $\hat{A}_0^*$ and $\hat{A}_j^*$. Similarly, for $i = 1, \cdots, m$, calculate $N_{[i]}^*$ from the Cholesky decomposition of the variance-covariance matrix using $\hat{e}^*(\tau_L)$.

- *Step 4*. For forecasting h-steps ahead, we use:

$$N_{[i]}^*\hat{x}^*(T+d) = \hat{B}_{[i]0}^* + \sum_{j=0}^{P-1} \hat{B}_{[i]j+1}^* x^*(T-j) + \hat{e}^*(T+d). \tag{3.17}$$

  The bootstrapped forecasts are conditioned on the actual observations, i.e. for the available information we use $x^*(\tau_L, i) = x(\tau_L, i)$. $\hat{e}^*(T+d)$ are random draws with replacement from $\hat{F}_{\hat{e}}$.

- *Step 5*. Repeat steps $2-4$ R times.

The above algorithm allows us to obtain R different replications of the forecasts/nowcasts $\hat{x}(T+d)$. Consequently, the empirical density that we use is constructed from $\{\hat{x}^{*(r)}(T+d)\}_{r=1}^{R}$, where $\hat{x}^{*(r)}(T+d)$ is the forecast/nowcast for the r^{th} bootstrap. Such an algorithm accounts for both parameter and shock uncertainty. Parameter uncertainty is dealt with by estimating the parameters of the model R times using the different bootstrapped series, while shock uncertainties are accounted for in *Step 4* by adding random draws with replacement to the forecast equation. Fresoli et al. (2015) show the asymptotic validity of this bootstrap method and its suitability for both Gaussian and non-Gaussian forecast errors. In contrast, to Fresoli et al. (2015) and other related literature, we also obtain R replications of the matrix $N_{[i]}$ in order to obtain nowcasts.

3.2.4 Bayesian estimation

Since the number of parameters to be estimated in this MF-VAR is obviously large, Bayesian estimation provides a very useful tool for estimation when the number of the variables in the model increases given the small sample size of most of the macroeconomic data. In the literature different variants of the Minnesota prior have been used with success in forecasting large dimensional Bayesian VARs. The basic idea is to shrink the parameters, other than the first own lag, closer to zero as they tend to go further away in the past since they become less relevant. For the first autoregressive lag, the researcher can shrink the AR(1) parameter to a chosen value depending on her belief about the persistence of the variables. As suggested by Banbura et al. (2010) and De Mol et al. (2008), the overall shrinkage of the model should increase as the dimension of the model increases to avoid overfitting. Following the essence of the Minnesota prior Ghysels (2015) proposed a set of priors for the reduced form MF-VAR:

$\mathbb{E}[A_j^{a,b}] = \mathbf{0}_{K_H^2}, \qquad \mathbb{V}[A_j^{a,b}] = \frac{\lambda^2}{[(j-1)m+(m-b+a)]^2}\mathbb{S}_{HH}, \qquad a = 1, \cdots, m,$
$b = 1, \cdots, m-1.$
$\mathbb{E}[A_1^{a,m}] = \mathrm{diag}(\rho^a)_{K_H^2}, \qquad \mathbb{V}[A_j^{a,b}] = \frac{\lambda^2}{[a]^2}\mathbb{S}_{HH}, \qquad a = 1, \cdots, m.$
$\mathbb{E}[A_j^{a,m}] = \mathbf{0}_{K_H^2}, \qquad \mathbb{V}[A_j^{a,b}] = \frac{\lambda^2}{((j-1)m+a)^2}\mathbb{S}_{HH}, \qquad j > 1, \quad a = 1, \cdots, m.$
$\mathbb{E}[A_j^{a,m+1}] = \mathbf{0}_{K_H, K_L}, \qquad \mathbb{V}[A_j^{a,m+1}] = \frac{\lambda^2}{((j-1)m+a)^2}\mathbb{S}_{HL}, \qquad a = 1, \cdots, m.$
$\mathbb{E}[A_1^{m+1,m+1}] = \mathrm{diag}(\rho^m)_{K_L^m}, \qquad \mathbb{V}[A_j^{a,b}] = \frac{\lambda^2}{[m]^2}\mathbb{S}_{LL}.$

Where $\mathbb{E}$ and $\mathbb{V}$ are matrices of expectations and variances, $\mathbf{0}$ is a matrix of zeros where the subscript refers to the dimension and $\mathrm{diag}(\rho^a)$ is a diagonal matrix with elements ρ^a. The difference in scaling between the different low and high frequency variables is captured by the term $\mathbb{S}$; for example, the difference in scaling between the high and low frequency variables is captured by $\mathbb{S}_{HL} \equiv [\sigma_{i,H}^2/\sigma_{j,L}^2; i = 1, \cdots, K_H; j = 1, \cdots, K_L]$. The overall tightness of the prior distributions is governed by the hyperparameter λ, finally the parameter ρ reflects the researcher's belief about the persistence of the variables in the system.

Following Kadiyala and Karlsson (1997) the reduced form MF-VAR in equation (3.2) can be written in matrix form as:

$$Y = ZA + E, \tag{3.18}$$

where $Y = (x(1), \cdots, x(T))'$ is a $T \times K$ matrix of endogenous variables, $Z = (z(1), \cdots, z(T))'$ is a matrix of ones and lagged endogenous variables and $z(\tau_L) = (1, z(\tau_L - 1)', \cdots, z(\tau_L - P)')'$. The coefficient matrix $A = (A_0, A_1, \cdots, A_P)'$ and $E = (\epsilon(1), \cdots, \epsilon(T))'$ is a matrix of innovations. Using the above set of priors for the parameters' means and their variances for the MF-VAR, the normally distributed priors for the coefficients can be given as:

$$A \sim N(\underline{a}, \underline{V}). \tag{3.19}$$

We define $\underline{a}$ as a vector of the prior mean for the MF-VAR parameters and $\underline{V}$ as the variance of the prior. Consequently the conditional posterior of A has the form:

$$A|\Sigma, Z \sim N(\overline{a}, \overline{V}), \tag{3.20}$$

where

$$\overline{a} = (\underline{V}^{-1} + \Sigma^{-1} \otimes Z'Z)^{-1}(\underline{V}^{-1}\underline{a} + \Sigma^{-1} \otimes Z'Z\hat{a})$$

$$\overline{a} = (\underline{V}^{-1} + \Sigma^{-1} \otimes Z'Z)^{-1},$$

and $\hat{a}$ is the OLS estimate of A. The posterior of Σ conditional on A is inverse Wishart:

$$\Sigma \sim IW(\overline{\Sigma}, T + c), \tag{3.21}$$

where c is the degrees of freedom, and the posterior of the variance covariance matrix:

$$\overline{\Sigma} = (Y - ZA)'(Y - ZA).$$

In the Bayesian estimation of the MF-VAR model, we use Gibbs sampling to obtain point and density forecasts. After discarding initial draws, we draw the reduced form coefficients and the variance-covariance matrix from their conditional posteriors. We draw G different sets of coefficients and variance covariance matrices. Then, in a similar fashion as equation (3.17) in the bootstrap algorithm, we use these sets of parameters for forecasting/nowcasting allowing for both parameters and forecast uncertainties. We obtain $\{\hat{x}^{(g)}(T + d)\}_{g=1}^{G}$ which can be used to construct the density, where $\hat{x}^{(g)}(T + d)$ is the forecast/nowcast for the g^{th} post-burn draw from the posterior. The point forecast $\hat{x}(T + d)$ is obtained as the mean value of the G different forecasts $\{\hat{x}^{(g)}(T + d)\}_{g=1}^{G}$.

3.2.5 Forecast evaluation

Although we are using multivariate models in forecasting, we are only interested in evaluating the forecasts of the low frequency variable, i.e. the point forecast of $\hat{x}_L(T+d)$ and its density. One reason is that, in practice, low-frequency variables such as the GDP are usually observed with delay; therefore, the available information in the low-frequency might not enhance the forecasts of the high-frequency variables that are more readily and accurately available with less delay. To evaluate the point forecasts of the low-frequency variable, we use the Root Mean Squared Predictive Error (RMSPE):

$$\text{RMSPE} = \sqrt{\frac{1}{n}\sum_{\tau_L=T+1}^{T+n}(\hat{x}_L(\tau_L) - x_L(\tau_L))^2}, \tag{3.22}$$

where n is the size of the out-of-sample evaluation period. When we compare forecasting models, the lower the RMSPE, the better the forecasting performance according to this criteria. To evaluate the density forecasts we use the Log Predictive Density Score (LPDS):

$$\text{LPDS} = \frac{1}{n}\sum_{\tau_L=T+1}^{T+n}\log p(x(\tau_L)), \tag{3.23}$$

where $p(x(\tau_L))$ is the predictive density of $x(\tau_L)$ conditional on information up to $\tau_L - h$. For simplicity, we follow Adolfson et al. (2007) and construct the predictive distribution using normal approximation of the forecasts/nowcasts replications obtained from either the parametric bootstrap approach or the Bayesian approach discussed earlier. This is commonly used in the literature. An attractive feature of the LPDS is that it only depends on the realization $x(\tau_L)$. This is useful given that the true density is unknown. However, this also means that it rewards predictive densities that include values equal to the actual realizations. The LPDS can be viewed as an out-of-sample log likelihood function and hence a larger score is better.

3.3 Monte Carlo experiments

To evaluate the forecasting performance of the MF-VAR, we use Monte Carlo simulations to compare its out-of-sample point and density forecasts to a VAR observed at the common low-frequency (LF-VAR). In the LF-VAR model the HF variable is aggregated to the low frequency using the mean[5] of the HF-periods within the low frequency. We compare the forecasting performance of the MF-VAR using both direct and iterative forecasting methods relative to the LF-VAR model. Moreover, we evaluate the relative nowcasting

[5]We also checked the performance of a LF-VAR model when using the last month in the quarter as a measure of the aggregate information in the quarter instead of the mean; however, the results did not differ a lot.

gains that can be obtained from using the MF-VAR model for different nowcasting horizons.

3.3.1 DGP

Following Foroni, Marcellino, and Schumacher (2013), we use a bivariate HF-VAR data generating process (DGP):

$$\begin{bmatrix} x_L(\tau_H) \\ x_H(\tau_H) \end{bmatrix} = \begin{bmatrix} \rho & \delta_L \\ \delta_H & \rho \end{bmatrix} \begin{bmatrix} x_L(\tau_H - 1) \\ x_H(\tau_H - 1) \end{bmatrix} + \begin{bmatrix} e_L(\tau_H) \\ e_H(\tau_H) \end{bmatrix}, \tag{3.24}$$

where $x_L(\tau_H)$ and $x_H(\tau_H)$ are the LF and HF variables generated at the high frequency, ρ specifies the persistence of the variables, and δ_L determines how the HF variable influences the LF variable. Similar to the previous literature, we assume that the LF variable has no effect on the HF one and consequently we set $\delta_H = 0$. In the simulations, we use different sets of values for the parameters ρ and δ_L. For the persistence parameter, we use $\rho = \{0.1; 0.5; 0.9\}$ to account for different degrees of persistence for both variables, while we set $\delta_L = \{0.1; 0.5; 1.0\}$. The error terms are normally distributed with zero mean and the variance is chosen so that the unconditional variance of the low frequency variable is equal to one.

In this DGP both the LF and HF variables are generated at the high frequency, i.e. every month. For each set of parameters' values we use the above DGP to generate a time series for each variable. Each time series consists of 690 monthly observations. To imitate the data pattern that is observed in the quarterly-monthly data, we assume that the low frequency variable is only observed every third month. Thus, for every simulation, we obtain 230 observations for the LF variable observed every quarter, and 690 observations of the HF variable observed each month. The first 200 quarterly observations are used for in-sample estimation, while the last 30 observations are used to evaluate the out-of-sample forecasting performance of the competing models. A rolling-window is used to obtain the forecasts where the size of the rolling-window is 200 quarterly observations and 600 monthly observations. Thus, we keep the window size fixed instead of increasing the size of the sample by expanding the window. Since the MF-VAR model has more parameters to be estimated compared to the LF-VAR model, it would be useful to compare the relative forecasting performance of the two forecasting models using a fixed estimation window.

3.3.2 Out-of-sample comparison

By means of relative RMSPE and relative LPDS, the forecasting performance of the MF-VAR is compared to the LF-VAR model using 1000 simulations. For each simulation we calculate the RMSPE and LPDS for each model using the last 30 observations. Table 3.3.1

Table 3.3.1: Relative RMSPE of MF-VAR compared to LF-VAR

Direct Forecasting										
Parameters		$h=1$			$h=2/3$			$h=1/3$		
ρ	δ_l	25^{th}	50^{th}	75^{th}	25^{th}	50^{th}	75^{th}	25^{th}	50^{th}	75^{th}
0.1	0.1	1.00	1.01	1.01	1.00	1.01	1.02	1.00	1.01	1.02
0.1	0.5	1.00	1.01	1.01	1.00	1.01	1.02	0.87	0.90	0.94
0.1	1.0	1.00	1.01	1.01	0.99	1.00	1.01	0.67	0.71	0.75
0.5	0.1	1.00	1.00	1.01	1.00	1.01	1.02	0.99	1.01	1.02
0.5	0.5	0.97	0.99	1.00	0.91	0.94	0.96	0.80	0.84	0.86
0.5	1.0	0.95	0.97	0.99	0.82	0.85	0.88	0.57	0.61	0.66
0.9	0.1	0.99	1.00	1.01	0.99	1.00	1.02	0.99	1.00	1.02
0.9	0.5	0.88	0.91	0.95	0.80	0.84	0.88	0.73	0.77	0.82
0.9	1.0	0.80	0.84	0.88	0.63	0.67	0.71	0.47	0.51	0.55
Iterative Forecasting										
0.1	0.1				1.00	1.01	1.02	1.00	1.01	1.02
0.1	0.5				0.99	1.01	1.02	0.87	0.90	0.94
0.1	1.0				0.98	1.00	1.01	0.67	0.71	0.76
0.5	0.1				0.99	1.00	1.02	0.99	1.00	1.02
0.5	0.5				0.88	0.92	0.95	0.80	0.84	0.89
0.5	1.0				0.77	0.81	0.86	0.57	0.61	0.66
0.9	0.1				0.98	1.00	1.01	0.98	1.00	1.02
0.9	0.5				0.76	0.80	0.85	0.72	0.77	0.82
0.9	1.0				0.56	0.60	0.65	0.47	0.51	0.55

The table shows the Monte Carlo experiment results using 1000 simulations based on a bivariate HF-VAR model in equation (3.24). It contains the 25^{th}, 50^{th}, and 75^{th} percentiles of the relative RMSPE of MF-VAR compared to LF-VAR at different forecast horizons for different sets of parameters. Values below/above 1 indicate better/worse performance of the MF-VAR model as compared to the LF-VAR model. In the first tab forecasts for the MF-VAR are obtained using direct forecasting while in the second tab iterative forecasting is used. For $h = 1$ we only report results using direct forecasting since both forecasting methods are equivalent.

summarizes the out-of-sample point forecasts performance of both models in the Monte Carlo simulations. Relative RMSPE is computed as the ratio of the MF-VAR's RMSPE to the LF-VAR's RMSPE; thus, values below 1 indicate better forecasting performance of the MF-VAR model while values above 1 are favoring the LS-VAR model.

All models used in Table 3.3.1 are estimated using the frequentist estimation method. The table is divided into two blocks; in the first block we compare the forecasting performance of the MF-VAR using direct forecasting to the performance of the LF-VAR model, while in the second block we evaluate the forecasting performance of the MF-VAR using iterative forecasting. For different forecasting/nowcasting horizons $\{h = 1; 2/3; 1/3\}$, the table shows the relative forecasting performance of the MF-VAR using the two forecasting methods for each set of parameters. For $h = 1$ we only present the results using direct forecasting because in this case both the direct and iterative forecasting methods become

equivalent when the MF-VAR model is used in forecasting. In the table we report the $25^{th}, 50^{th}$ and 75^{th} quantiles of the relative RMSPE.

In general, Table 3.3.1 shows that in most cases the forecasting accuracy of point forecasts obtained from the MF-VAR outperforms those obtained from the LF-VAR. When $h = 1$ we can observe that the difference between the forecasting accuracy of the two models is smaller than the cases where $h = 2/3$ and $h = 1/3$. Thus, the ability of the MF-VAR model to make use of the within quarter information allows it to enhance its forecasting accuracy in nowcasting horizons in comparison to the LF-VAR. We can also notice that the persistence parameter ρ has a significant role in the forecast comparison. When $\rho = 0.1$ the two models provide very comparable forecasts. On the other hand, larger values of ρ enhance the relative performance of the MF-VAR for all forecast horizons. That result might imply that when the data has more useful information for forecasting, the MF-VAR is better suited for exploiting this information in forecasting. In addition, we observe that larger values for δ_L magnify the relative gains between the two models due to nowcasting. Therefore, when the HF variable has a larger influence on the LF-variable, nowcasting becomes more useful. Table 3.3.1 also shows that both direct and iterative forecasting methods provide comparable forecasting results. However, in some cases when $h = 2/3$, iterative forecasting provides slightly better results. One possible reason is that the DGP used to generate the data is not very different from the MF-VAR model and so the iterative forecasting method provides slightly better results as the model's misspecification is only related to the low frequency variable.

In a similar fashion, Table 3.3.2 reports the relative LPDS of the MF-VAR in comparison to the LF-VAR model. The computations are, however, more intensive as we compute 1000 forecast replications for each forecast in each simulation. Although higher values of LPDS suggest better performance in density forecasting, the values obtained for LPDS have a negative sign. Thus, values below 1 indicate that the MF-VAR provides better density forecasts; while values above 1 favor the LF-VAR. For each set of parameters, the table displays the 25^{th}, 50^{th}, and 75^{th} quantiles for the relative LPDS for $h = 1$, $2/3$ and $1/3$. In the first block, the forecasts of the MF-VAR are obtained using direct forecasting, while iterative forecasting is used in the lower part of the table.

The results in Table 3.3.2 are consistent with those obtained from Table 3.3.1. In general, the MF-VAR provides better or at least comparable density forecasts in comparison to the LF-VAR model. For smaller values of the persistence parameter ρ, the two models show similar accuracy in density forecasting for $h = 1$ and $h = 2/3$. When more within-quarter information is available, $h = 1/3$, the difference between the density forecasting accuracy of the two models in favor of the MF-VAR is largest, even for smaller values of ρ. For larger values of ρ, the MF-VAR outperforms the LF-VAR for all forecasting/nowcasting horizons. Moreover, larger values of the parameter δ_L proliferate the relative gains due to nowcasting. Similar to relative RMSPE, iterative forecasting provides slightly better

Table 3.3.2: Relative LPDS of MF-VAR compared to LF-VAR

Direct Forecasting										
Parameters		$h=1$			$h=2/3$			$h=1/3$		
ρ	δ_l	25^{th}	50^{th}	75^{th}	25^{th}	50^{th}	75^{th}	25^{th}	50^{th}	75^{th}
0.1	0.1	0.99	1.00	1.01	0.99	1.00	1.01	0.98	1.00	1.02
0.1	0.5	0.99	1.00	1.01	0.99	1.00	1.01	0.88	0.92	0.96
0.1	1.0	0.99	1.00	1.01	0.99	1.00	1.01	0.70	0.75	0.81
0.5	0.1	0.99	1.00	1.01	0.99	1.00	1.01	0.98	1.00	1.01
0.5	0.5	0.97	0.99	1.01	0.92	0.95	0.98	0.82	0.87	0.92
0.5	1.0	0.95	0.97	1.00	0.84	0.84	0.91	0.56	0.62	0.69
0.9	0.1	0.98	1.00	1.02	0.97	0.99	1.02	0.96	0.99	1.02
0.9	0.5	0.91	0.94	0.98	0.85	0.89	0.94	0.76	0.82	0.87
0.9	1.0	0.81	0.85	0.88	0.61	0.66	0.70	0.45	0.50	0.54
Iterative Forecasting										
0.1	0.1				0.99	1.00	1.01	0.98	1.00	1.01
0.1	0.5				0.99	1.00	1.01	0.88	0.92	0.96
0.1	1.0				0.98	1.00	1.01	0.69	0.75	0.80
0.5	0.1				0.98	1.00	1.01	0.98	0.99	1.01
0.5	0.5				0.89	0.93	0.97	0.82	0.86	0.92
0.5	1.0				0.79	0.84	0.89	0.56	0.61	0.69
0.9	0.1				0.96	0.99	1.02	0.95	0.98	1.02
0.9	0.5				0.83	0.88	0.93	0.76	0.81	0.86
0.9	1.0				0.56	0.60	0.65	0.44	0.49	0.54

The table shows the Monte Carlo experiment results using 1000 simulations based on a bivariate HF-VAR model in equation (3.24). It contains the 25^{th}, 50^{th}, and 75^{th} percentiles of the relative LPDS of MF-VAR compared to LF-VAR at different forecast horizons for different sets of parameters. Values below/above 1 indicate better/worse performance of the MF-VAR model as compared to the LF-VAR model.In the first tab forecasts for the MF-VAR are obtained using direct forecasting while in the second tab iterative forecasting is used. For $h = 1$ we only report results using direct forecasting since both forecasting methods are equivalent.

relative density forecasts compared to direct forecasting. Thus, in general, the results in Table 3.3.2 are inline with and confirm the results from Table 3.3.1.

Although similar simulation experiments have been used in the literature, the above Monte Carlo simulations have three main contributions to the literature. First, the comparison between the two models using different forecasting/nowcasting horizons allow us to understand the role of the different parameters in affecting the relative forecasting accuracy of the two models. Although one might argue that it is not fair to compare two models that make use of different information sets, it is still very useful to quantify the relative gains that the MF-VAR model can achieve due to nowcasting. Second, the simulations compare two forecasting methods that can be used for forecasting using MF-VAR and highlight that the iterative forecasting method can slightly outperform the direct forecasting method when the model's misspecification is only related to the low-frequency

variable. Third, the results obtained suggest that the conclusions drawn from the simulations are not only limited to point forecasts, but also extend to density forecasts.

3.4 Empirical study

3.4.1 Data description

Despite the tremendous growth of available economic and financial time series, the GDP growth, especially for the US, is considered by many as one of the most important economic indicators. Therefore, for both academics as well as market participants, there is a lot of interest in forecasting it. In the empirical study we evaluate the forecasting performance of the MF-VAR model using US data. We forecast the quarterly GDP growth - measured using the log-difference of the real GDP - of the US using six different monthly indicators -namely, Industrial Production (IP), Purchasing Managers index (PM), total non-farm Employment (EM), Capacity utilization (CA), Philadelphia Fed outlook survey for general business activity (PF), and the Chicago Fed national activity index (CF)[6]. The predictors used are similar to the ones in Aastveit et al. (2014). The three indicators IP, EM, and CA are transformed to stationarity (monthly growth rates) by means of taking log-differences. PM, PF, and CF are stationary survey-based measures and thus, no further transformation is needed. PM includes information about production, inventories, employment, new orders, and inflation. PF is a survey that questions manufacturers on general business conditions. CF is a weighted average of 85 indicators related to economic activity and inflation. The data is collected from 1967M7 to 2014M6, where the starting date is determined by the availability of all the predictors.

3.4.2 Design of the empirical study

We compare the point and density forecasts of a number of competing models. Since one main goal is to assess the possible gains due to the use of mixed-frequency data in VARs, we compare the LF-VAR model to a number of MF-VAR models. For $h = 1$, we evaluate the performance of both parametric mixed-frequency VAR (MF-VAR) as well as a Bayesian mixed-frequency VAR (MF-BVAR). For nowcasting horizons, $h = 2/3$ and $h = 1/3$, we compare the forecasts obtained from MF-VAR and MF-BVAR using both direct and iterative forecasting methods.

We use data from 1967Q3 to 1999Q4 for in-sample estimation and keep the data from 2000Q1 to 2014Q2 for forecast evaluation. A rolling-window of size 130 quarterly observations and 390 monthly observations is used to obtain point and density forecasts for $h = 1$, $2/3$, and $1/3$. In the Bayesian approach,the density forecasts' results are based

[6]The data is obtained from Datastream.

on 5000 draws from the posterior that are obtained after discarding the first 10000 draws. Similarly, in the bootstrap approach, density forecasts are constructed using 5000 bootstrap replications. The forecast evaluation period is divided into two periods; a pre-crisis period (Pre) from 2000Q1 to 2007Q2, and a crisis and post-crisis period (Post) from 2007Q3 to 2014Q2. This allows us to understand how the forecasting performance of the competing models varies in different forecasting periods. In addition, we also report the forecasting performance for the whole forecast evaluation period from 2000Q1 to 2014Q2. We report both RMSPE and LPDS for all the competing models.

It is worth noting that in the Monte Carlo experiment our choice of DGP is based on our interest to compare the forecasting performance of both LF-VAR and MF-VAR and hence, presenting the relative RMSPE and LPDS is a natural choice as it allows us to summarize the results from the simulations in a meaningful way. In the empirical study, we are also interested in comparing the forecasting performance of both forecasting models as well. However, forecasting the GDP growth is a more general question and as a result, we present the absolute RMPSE and LPDS to allow future studies to replicate our own results as well as to compare them with results obtained from other forecasting models if needed.

We use each of the six predictors separately to forecast the GDP growth. Then we use all possible combinations of 2, 3 and 4 predictors in the forecasting equation using IP, PM, EM, and CF. The choice of these 4 predictors is mainly based on their relatively good performance in forecasting the GDP growth. Finally we use all 6 predictors at a time for forecasting. First, we would like to assess the performance of the different predictors. Second, it is important to understand whether adding more predictors to the forecasting equation improve the forecasts or not. Third, adding more predictors to the forecasting equation allows us to investigate how the increase in the dimension of the MF-VAR model affects its forecasting performance. This is quite useful given that the MF-VAR model is prone to parameters proliferation.

3.4.3 Results

The RMSPE results using single predictors are shown in Table 3.4.1. The first column shows the model used in forecasting. When LF-VAR is used, the monthly predictor is aggregated to a quarterly frequency using an equal weighting scheme. Thus, for LF-VAR, a bivariate VAR is used. On the other hand, the dimension of the MF-VAR is $K = 4$ as the MF-VAR includes quarterly GDP growth and three monthly lags for the monthly predictor used. All the forecasting models are estimated using 4 quarterly lags and 12 monthly lags. The second column contains the forecasting method used, while the third column includes the forecast/nowcast horizon. The LF-VAR cannot make use of the within quarter information and thus, is only used for $h = 1$. When $h = 1$, both direct

and iterative forecasting methods are equivalent and thus we do not report the forecasting method. The fourth column shows the forecasting period evaluated. Columns 5 to 10 show the predictor used in forecasting.

The results in Table 3.4.1 show that CF provides lower RMSPE compared to other predictors. This is true for all the models, forecast horizons, and evaluation periods. On the other hand, when $h = 1$, PF seems to provide worse point forecasts in comparison to others. However, for nowcasting horizons, PF's forecasting performance improves relative to other monthly indicators. IP and CA show very similar RMSPE for all the different forecast horizons and evaluation periods and their point forecasts are very comparable to those obtained from PM and EM. As expected, in the post-crisis period, all the predictors provide equal or worse forecasting performance compared to the pre-crisis period. In general, for each predictor the differences in RMSPE between pre-crisis and post-crisis periods are more pronounced in nowcasting horizons compared to the case when $h = 1$. This may suggest that in several cases, the gains due to nowcasting are better observed in the pre-crisis period.

In order to assess the point forecast performance of the different models, we compare their RMSPEs for each indicator. For $h = 1$, in most cases, the MF-VAR shows slightly lower RMSPE compared to LF-VAR. However, for both $h = 2/3$ and $h = 1/3$, the MF-VAR's RMSPEs are lower than the RMSPEs obtained for $h = 1$. Thus, the MF-VAR does not only outperform LF-VAR due to the way it makes use of high-frequency data, but most importantly due to its ability to utilize available within quarter information. In Table 3.4.1, the results of both MF-VAR and MF-BVAR are almost identical. This is mainly because the dimension of the MF-BVAR model is not large, and so minimum shrinkage has been applied implying that the estimated parameters obtained from OLS and Bayesian estimation are quite similar. For most of the indicators used in forecasting, direct and iterative forecasting methods provide comparable RMSPEs. Unlike the results for the Monte Carlo experiment, it is difficult to suggest that either of the forecasting methods outperforms the other.

In a similar fashion, Table 3.4.2 reports the LPDS for the single indicators. In general, for the case of one monthly indicator, the results from Table 3.4.2 are consistent with those from Table 3.4.1. Similarly, CF provides better density forecasts according to the LPDS criteria and again the different variants of the MF-VAR outperform the LF-VAR model. Also sizable gains can be observed in density nowcasts in comparison to density forecasts when $h = 1$. However, we observe small differences between the LPDSs obtained from the MF-BVAR and the MF-VAR. Both the bootstrap and the Bayesian method provide slightly different results, but none of the two methods consistently provide higher LPDS values. Again, direct and iterative forecasting methods also provide comparable LPDS values for all the different indicators at each forecast horizon and evaluation period.

In addition, we also evaluate forecasting performance using more than one predictor. Ta-

Table 3.4.1: RMSPE for single predictors

Model	Method	h	Period	IP	PM	EM	CA	PF	CF
		1	Pre	0.58	0.58	0.52	0.59	0.58	0.51
LF-VAR		1	Post	0.76	0.76	0.77	0.74	0.82	0.62
		1	Whole	0.67	0.67	0.65	0.67	0.70	0.57
		1	Pre	0.65	0.60	0.54	0.65	0.54	0.56
MF-VAR		1	Post	0.64	0.74	0.70	0.63	0.88	0.54
		1	Whole	0.64	0.67	0.63	0.64	0.73	0.55
		1	Pre	0.65	0.60	0.54	0.65	0.54	0.56
MF-BVAR		1	Post	0.64	0.74	0.70	0.63	0.88	0.54
		1	Whole	0.64	0.67	0.63	0.64	0.73	0.55
		2/3	Pre	0.51	0.57	0.52	0.51	0.50	0.47
MF-VAR	Direct	2/3	Post	0.69	0.71	0.66	0.69	0.80	0.56
		2/3	Whole	0.61	0.64	0.60	0.61	0.67	0.51
		1/3	Pre	0.50	0.52	0.51	0.50	0.49	0.46
MF-VAR	Direct	1/3	Post	0.69	0.65	0.62	0.68	0.75	0.56
		1/3	Whole	0.60	0.59	0.57	0.60	0.63	0.51
		2/3	Pre	0.51	0.57	0.51	0.51	0.51	0.47
MF-BVAR	Direct	2/3	Post	0.69	0.71	0.67	0.69	0.80	0.56
		2/3	Whole	0.60	0.64	0.60	0.61	0.67	0.51
		1/3	Pre	0.50	0.52	0.50	0.50	0.5	0.46
MF-BVAR	Direct	1/3	Post	0.68	0.65	0.62	0.68	0.75	0.55
		1/3	Whole	0.60	0.59	0.56	0.60	0.63	0.51
		2/3	Pre	0.51	0.49	0.54	0.51	0.53	0.47
MF-VAR	Iterative	2/3	Post	0.71	0.62	0.66	0.71	0.72	0.58
		2/3	Whole	0.62	0.56	0.60	0.62	0.63	0.53
		1/3	Pre	0.51	0.52	0.51	0.51	0.49	0.47
MF-VAR	Iterative	1/3	Post	0.70	0.64	0.63	0.70	0.65	0.57
		1/3	Whole	0.61	0.58	0.57	0.61	0.58	0.52
		2/3	Pre	0.51	0.49	0.51	0.51	0.52	0.46
MF-BVAR	Iterative	2/3	Post	0.70	0.62	0.67	0.70	0.72	0.57
		2/3	Whole	0.61	0.56	0.59	0.61	0.63	0.52
		1/3	Pre	0.50	0.52	0.50	0.51	0.50	0.47
MF-BVAR	Iterative	1/3	Post	0.69	0.64	0.62	0.69	0.65	0.56
		1/3	Whole	0.60	0.58	0.56	0.60	0.58	0.52

The table shows the out-of-sample RMSPE obtained from forecasting the GDP growth of the US in different periods using different variants of the MF-VAR as well as the LF-VAR model for different forecast horizons by means of different single predictors. The first column includes the forecasting model, the second column shows the forecasting method, and the forecast horizon is reported in the third column. The evaluation period is highlighted in the fourth column. 'Pre' refers to the evaluation period from 2000Q1 to 2007Q2, 'Post' refers to the period from 2007Q3 to 2014Q2, while 'Whole' covers the whole evaluation period from 2000Q1 to 2014Q2. The RMSPEs for each of the six predictors are reported in columns 5 to 10. The point forecasts are obtained using a rolling window of 130 quarterly observations and 390 monthly observations where the in-sample estimation starts from 1967Q3 to 1999Q4. All models use 4 quarterly lags.

bles 3.A.1 and 3.A.3 in Appendix 3.A report the RMSPE results for two predictors and

Table 3.4.2: LPDS for single predictors

Model	Method	h	Period	IP	PM	EM	CA	PF	CF
		1	Pre	-0.95	-0.97	-0.90	-0.96	-0.98	-0.87
LF-VAR		1	Post	-1.12	-1.16	-1.17	-1.11	-1.23	-0.99
		1	Whole	-1.04	-1.07	-1.03	-1.03	-1.11	-0.93
		1	Pre	-1.00	-0.96	-0.88	-1.00	-0.96	-0.87
MF-VAR		1	Post	-1.00	-1.14	-1.09	-0.99	-1.31	-0.86
		1	Whole	-1.00	-1.05	-0.99	-1.00	-1.14	-0.86
		1	Pre	-1.00	-0.95	-0.89	-1.00	-0.96	-0.88
MF-BVAR		1	Post	-0.97	-1.10	-1.04	-0.97	-1.30	-0.83
		1	Whole	-0.98	-1.02	-0.97	-0.98	-1.13	-0.85
		2/3	Pre	-0.79	-0.87	-0.80	-0.80	-0.89	-0.71
MF-VAR	Direct	2/3	Post	-1.01	-1.05	-1.05	-1.02	-1.24	-0.86
		2/3	Whole	-0.90	-0.96	-0.92	-0.91	-1.06	-0.78
		1/3	Pre	-0.77	-0.81	-0.77	-0.78	-0.81	-0.70
MF-VAR	Direct	1/3	Post	-0.99	-0.96	-0.98	-0.99	-1.04	-0.84
		1/3	Whole	-0.88	-0.88	-0.88	-0.88	-0.93	-0.77
		2/3	Pre	-0.77	-0.90	-0.82	-0.77	-0.90	-0.69
MF-BVAR	Direct	2/3	Post	-1.03	-1.03	-1.01	-0.99	-1.19	-0.81
		2/3	Whole	-0.90	-0.97	-0.91	-0.88	-1.04	-0.75
		1/3	Pre	-0.76	-0.80	-0.79	-0.75	-0.87	-0.68
MF-BVAR	Direct	1/3	Post	-1.05	-0.98	-0.94	-1.03	-1.10	-0.83
		1/3	Whole	-0.90	-0.89	-0.86	-0.89	-0.99	-0.75
		2/3	Pre	-0.79	-0.78	-0.80	-0.80	-0.88	-0.70
MF-VAR	Iterative	2/3	Post	-1.02	-0.96	-1.05	-1.03	-1.11	-0.86
		2/3	Whole	-0.90	-0.87	-0.93	-0.91	-0.99	-0.78
		1/3	Pre	-0.77	-0.87	-0.77	-0.77	-0.81	-0.69
MF-VAR	Iterative	1/3	Post	-1.00	-0.97	-0.99	-1.00	-1.00	-0.85
		1/3	Whole	-0.88	-0.87	-0.88	-0.89	-0.91	-0.77
		2/3	Pre	-0.79	-0.79	-0.82	-0.77	-0.88	-0.68
MF-BVAR	Iterative	2/3	Post	-1.02	-0.93	-1.02	-1.02	-1.10	-0.84
		2/3	Whole	-0.90	-0.86	-0.92	-0.90	-0.99	-0.76
		1/3	Pre	-0.77	-0.79	-0.79	-0.76	-0.84	-0.68
MF-BVAR	Iterative	1/3	Post	-1.00	-0.96	-0.95	-1.05	-0.98	-0.84
		1/3	Whole	-0.88	-0.87	-0.87	-0.90	-0.91	-0.76

The table shows the out-of-sample LPDS obtained from forecasting the GDP growth of the US in different periods using different variants of the MF-VAR as well as the LF-VAR model for different forecast horizons by means of different single predictors. The first column includes the forecasting model, the second column shows the forecasting method, and the forecast horizon is reported in the third column. The evaluation period is highlighted in the fourth column. 'Pre' refers to the evaluation period from 2000Q1 to 2007Q2, 'Post' refers to the period from 2007Q3 to 2014Q2, while 'Whole' covers the whole evaluation period from 2000Q1 to 2014Q2. The LPDS for each of the six predictors are reported in columns 5 to 10. For the MF-BVAR, the density forecasts are based on 5000 draws from the posterior, while for the MF-VAR and the LF-VAR density forecasts are constructed using 5000 bootstrap replications. A rolling window of 130 quarterly observations and 390 monthly observations is used where the in-sample estimation starts from 1967Q3 to 1999Q4. All models use 4 quarterly lags.

more than two predictors respectively, while Tables 3.A.2 and 3.A.4 in Appendix 3.A report the LPDS results for two predictors and more than two predictors respectively. Adding more predictors to the forecasting equation allow us to assess the usefulness of using more than one predictor in improving the forecasts. Moreover, this is a very important exercise to evaluate the forecasting performance of the different variants of the MF-VAR model as they are prone to parameters proliferation.

Table 3.A.1 reports the forecasting performance using two different predictors at a time. In general, in comparison to Table 3.4.1, we observe that adding more predictors to the forecasting equation does not improve the accuracy of the point forecasts. For instance, adding either of IP or PM or EM to CF in the forecasting equation lead to higher values of RMSPE compared to using CF as a single predictor. This is true for both the LF-VAR as well as all the variants of the MF-VAR; therefore, the deterioration in forecasting performance cannot be attributed to the increase in the dimension of the MF-VAR. Moreover, we observe that combining CF with another predictor provide more accurate forecasts compared to IP-PM and IP-EM; in addition, in most cases PM-EM provide the most accurate forecasts compared to the other 5 combinations. Thus, combining the best two single predictors in the forecasting equation does not guarantee a more accurate forecasts. We also notice some differences in the forecasting performance of both the MF-VAR and the MF-BVAR as the MF-VAR outperforms its Bayesian counterpart for most of the cases, and therefore the use of Bayesian estimation is not justified when 2 predictors are included in the MF-BVAR model. Both direct and iterative forecasting methods provide very comparable forecasting accuracy. Also, in the majority of the cases, the different variants of the MF-VAR models provide better point forecasts compared to the LF-VAR. The density forecasts results for two predictors in Table 3.A.2 are consistent with the point forecasts results in Table 3.A.1.

The results for using 3 or 4 predictors in Table 3.A.3 show that the forecasting accuracy of both the LF-VAR and the MF-VAR is quite similar when $h = 1$; however there are some gains due to nowcasting when $h = 2/3$ and $h = 1/3$. In addition, both MF-VAR and MF-BVAR show similar forecasting accuracy. However, when all predictors are included in the forecasting equation, we observe that the LF-VAR provides much better forecasts compared to the MF-VAR where combining PM-EM-CF in the forecasting equation provides the most accurate predictions compared to other combinations of 3 predictors. On the hand, non of the 4 different combinations of 3 predictors provide superior forecasts in comparison to the other competitors when MF-VAR is used. We also notice that using the MF-BVAR for $h = 2/3$ and $h = 1/3$ strongly enhances the forecasting accuracy. This result highlights the unsuitability of using the MF-VAR model for large dimensions and strongly supports the use of Bayesian estimation with shrinkage when several predictors are used in the forecasting equation. With few exceptions, the results for the LPDS in Table 3.A.4 are inline with the RMSPE results in Table 3.A.3. Moreover, Table 3.A.4

also shows the gains in density nowcasting that can be achieved by MF-BVAR when the forecasting equation includes several predictors.

3.5 Conclusion

With the increasing availability of economic and financial time series observed at different frequencies, there is an urgent need of time series models that make use of mixed-frequency data and be able to provide accurate forecasts. This paper provides a methodology that allows the use of a MF-VAR class of models to obtain point and density forecasts/nowcasts. We outline both a bootstrap approach as well as a Bayesian approach that can be used to calculate the forecasts. Moreover, we also describe how nowcasts can be obtained using both direct forecasting as well as iterative forecasting methods.

We use Monte Carlo simulations to compare both point and density forecasts of the MF-VAR relative to the LF-VAR model. In general, the results show that the MF-VAR outperforms the LF-VAR especially when the persistence parameter used in the DGP is large. The results also document the gains that can be achieved in nowcasting horizons due to the ability of the MF-VAR model to utilize within quarter information. Moreover, we also show how the different parameters of the DGP can affect the relative gains due to nowcasting. In addition, we compare the forecasting performance of both direct and iterative forecasting methods and show that when the true DGP is close to the MF-VAR model, the iterative forecasting method can provide more accurate forecasts. The results from relative density forecasts are consistent with the point forecast results.

Using an empirical study, we assess the forecasting performance of the different variants of the MF-VAR in comparison to the LF-VAR. We use different monthly predictors to forecast the US GDP growth. In general, the MF-VAR model provides better point and density forecasts. The results highlight that adding more than one predictor to the forecasting equation does not improve the forecasting accuracy; on the contrary, using a single predictor in most of the cases provides better forecasts. Among the set of predictors used, the Chicago Fed national activity index seems to provide the most accurate forecasts. As expected, the different models and predictors show more accurate point and density forecasts in the pre-crisis period. Moreover, in many cases, the gains due to nowcasting are more pronounced in the pre-crisis period. When the forecasting equation includes 6 predictors, the forecasting accuracy of the MF-VAR deteriorates significantly as the model is prone to parameters proliferation. In this case, the MF-BVAR provides much better forecasts due to Bayesian shrinkage. Both direct and iterative forecasting methods show very comparable forecasting accuracy. In general, the empirical study shows and quantifies the gains of using HF predictors in forecasting the GDP growth rate using the MF-VAR model; however, when the frequentist approach is used in estimation, these forecast gains are only achieved when a small number of predictors are included in the forecasting equa-

tion. Moreover, the results highlight the suitability of using Bayesian estimation when the number of predictors used in the MF-VAR model is large.

Bibliography of Chapter 3

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3.A Appendix

Table 3.A.1: RMSPE for 2 predictors

Model	M	h	Period	IP-PM	IP-EM	IP-CF	PM-EM	PM-CF	EM-CF
		1	Pre	0.65	0.56	0.58	0.54	0.54	0.50
LF-VAR		1	Post	0.84	0.89	0.86	0.67	0.60	0.67
		1	Whole	0.76	0.73	0.72	0.61	0.58	0.60
		1	Pre	0.66	0.60	0.54	0.57	0.65	0.60
MF-VAR		1	Post	0.75	0.72	0.72	0.65	0.64	0.59
		1	Whole	0.71	0.67	0.64	0.61	0.64	0.60
		1	Pre	0.63	0.61	0.60	0.65	0.62	0.60
MF-BVAR		1	Post	0.82	0.78	0.71	0.87	0.78	0.76
		1	Whole	0.73	0.70	0.66	0.77	0.70	0.68
		2/3	Pre	0.56	0.50	0.49	0.53	0.57	0.50
MF-VAR	D	2/3	Post	0.79	0.72	0.66	0.63	0.67	0.62
		2/3	Whole	0.69	0.62	0.58	0.58	0.62	0.57
		1/3	Pre	0.51	0.49	0.49	0.50	0.53	0.50
MF-VAR	D	1/3	Post	0.81	0.67	0.64	0.58	0.69	0.61
		1/3	Whole	0.68	0.59	0.57	0.54	0.61	0.56
		2/3	Pre	0.54	0.51	0.52	0.62	0.55	0.52
MF-BVAR	D	2/3	Post	0.86	0.79	0.69	0.87	0.69	0.70
		2/3	Whole	0.72	0.67	0.61	0.75	0.62	0.62
		1/3	Pre	0.50	0.49	0.50	0.56	0.51	0.51
MF-BVAR	D	1/3	Post	0.84	0.76	0.66	0.70	0.67	0.68
		1/3	Whole	0.69	0.64	0.58	0.64	0.60	0.60
		2/3	Pre	0.51	0.50	0.48	0.52	0.56	0.50
MF-VAR	I	2/3	Post	0.76	0.73	0.68	0.56	0.67	0.64
		2/3	Whole	0.65	0.63	0.59	0.54	0.62	0.57
		1/3	Pre	0.52	0.50	0.49	0.51	0.53	0.49
MF-VAR	I	1/3	Post	0.75	0.69	0.65	0.56	0.68	0.62
		1/3	Whole	0.65	0.60	0.57	0.54	0.61	0.56
		2/3	Pre	0.51	0.53	0.53	0.56	0.54	0.55
MF-BVAR	I	2/3	Post	0.84	0.85	0.75	0.76	0.68	0.73
		2/3	Whole	0.70	0.71	0.65	0.67	0.62	0.65
		1/3	Pre	0.52	0.52	0.53	0.57	0.53	0.54
MF-BVAR	I	1/3	Post	0.80	0.80	0.67	0.69	0.66	0.70
		1/3	Whole	0.68	0.67	0.61	0.63	0.60	0.62

The table shows the out-of-sample RMSPE obtained from forecasting the GDP growth of the US in different periods using different variants of the MF-VAR as well as the LF-VAR model for different forecast horizons by means of different combinations of two predictors. The first column includes the forecasting model, the second column shows the forecasting method 'M' where 'D' is direct and 'I' is iterative, and the forecast horizon is in the third column. The evaluation period is highlighted in the fourth column. 'Pre' refers to the evaluation period from 2000Q1 to 2007Q2, 'Post' refers to the period from 2007Q3 to 2014Q2, while 'Whole' covers the whole period. The RMSPEs for each of the six different combinations of two predictors are reported in columns 5 to 10. The point forecasts are obtained using a rolling window of 130 quarterly observations and 390 monthly observations where the in-sample estimation starts from 1967Q3 to 1999Q4.

Table 3.A.2: LPDS for 2 predictors

Model	M	h	Period	IP-PM	IP-EM	IP-CF	PM-EM	PM-CF	EM-CF
		1	Pre	-1.04	-0.93	-0.95	-0.92	-0.91	-0.87
LF-VAR		1	Post	-1.18	-1.25	-1.20	-1.06	-0.96	-1.03
		1	Whole	-1.11	-1.09	-1.08	-0.99	-0.94	-0.95
		1	Pre	-1.03	-0.95	-0.85	-0.91	-1.01	-0.94
MF-VAR		1	Post	-1.14	-1.10	-1.06	-1.04	-1.00	-0.93
		1	Whole	-1.09	-1.03	-0.96	-0.98	-1.00	-0.93
		1	Pre	-0.99	-0.98	-0.95	-1.02	-0.98	-0.96
MF-BVAR		1	Post	-1.17	-1.12	-1.03	-1.25	-1.11	-1.10
		1	Whole	-1.08	-1.05	-0.99	-1.13	-1.05	-1.03
		2/3	Pre	-0.89	-0.79	-0.77	-0.81	-0.88	-0.78
MF-VAR	D	2/3	Post	-1.14	-1.03	-0.96	-0.99	-1.03	-0.91
		2/3	Whole	-1.01	-0.91	-0.86	-0.90	-0.95	-0.86
		1/3	Pre	-0.82	-0.77	-0.73	-0.77	-0.82	-0.77
MF-VAR	D	1/3	Post	-1.03	-0.97	-0.95	-0.90	-0.97	-0.91
		1/3	Whole	-0.93	-0.87	-0.84	-0.83	-0.90	-0.84
		2/3	Pre	-0.84	-0.80	-0.80	-0.98	-0.88	-0.81
MF-BVAR	D	2/3	Post	-1.27	-1.20	-1.03	-1.22	-1.03	-1.08
		2/3	Whole	-1.06	-1.00	-0.91	-1.10	-0.95	-0.95
		1/3	Pre	-0.78	-0.76	-0.77	-0.88	-0.83	-0.79
MF-BVAR	D	1/3	Post	-1.23	-1.17	-1.00	-1.05	-1.00	-1.06
		1/3	Whole	-1.01	-0.77	-0.88	-0.97	-0.92	-0.93
		2/3	Pre	-0.79	-0.80	-0.76	-0.74	-0.79	-0.78
MF-VAR	I	2/3	Post	-1.09	-1.03	-0.98	-0.92	-1.00	-0.91
		2/3	Whole	-0.94	-0.91	-0.87	-0.83	-0.90	-0.86
		1/3	Pre	-0.78	-0.78	-0.72	-0.75	-0.79	-0.77
MF-VAR	I	1/3	Post	-1.04	-0.98	-0.96	-0.89	-0.99	-0.91
		1/3	Whole	-0.91	-0.88	-0.84	-0.82	-0.89	-0.84
		2/3	Pre	-0.79	-0.83	-0.82	-0.89	-0.83	-0.84
MF-BVAR	I	2/3	Post	-1.24	-1.25	-1.07	-1.09	-0.98	-1.08
		2/3	Whole	-1.02	-1.04	-0.95	-0.99	-0.91	-0.96
		1/3	Pre	-0.79	-0.80	-0.82	-0.88	-0.81	-0.82
MF-BVAR	I	1/3	Post	-1.22	-1.20	-0.99	-1.02	-0.98	-1.05
		1/3	Whole	-1.00	-1.00	-0.90	-0.95	-0.89	-0.94

The table shows the out-of-sample LPDS obtained from forecasting the GDP growth of the US in different periods using different variants of the MF-VAR as well as the LF-VAR model for different forecast horizons by means of different combinations of two predictors. The first column includes the forecasting model, the second column shows the forecasting method 'M' where 'D' is direct and 'I' is iterative, and the forecast horizon is reported in the third column. The evaluation period is highlighted in the fourth column. 'Pre' refers to the evaluation period from 2000Q1 to 2007Q2, 'Post' refers to the period from 2007Q3 to 2014Q2, while 'Whole' covers the whole evaluation period from 2000Q1 to 2014Q2. The LPDS for each of the six different combinations of two predictors are reported in columns 5 to 10. For the MF-BVAR, the density forecasts are based on 5000 draws from the posterior, while for the MF-VAR and the LF-VAR density forecasts are constructed using 5000 bootstrap replications. A rolling window of 130 quarterly observations and 390 monthly observations is used where the in-sample estimation starts from 1967Q3 to 1999Q4. All models use 4 quarterly lags.

Table 3.A.3: RMSPE for more than 2 predictors

Model	M	h	Period	IP-PM-EM	IP-PM-CF	IP-CF-EM	PM-EM-CF	Best 4	ALL
		1	Pre	0.61	0.58	0.57	0.54	0.58	0.61
LF-VAR		1	Post	0.90	0.87	0.86	0.69	0.88	0.86
		1	Whole	0.76	0.73	0.73	0.62	0.75	0.74
		1	Pre	0.68	0.65	0.63	0.68	0.70	0.88
MF-VAR		1	Post	0.78	0.78	0.74	0.74	0.80	0.96
		1	Whole	0.73	0.71	0.68	0.71	0.75	0.92
		1	Pre	0.64	0.63	0.61	0.64	0.67	0.75
MF-BVAR		1	Post	0.85	0.79	0.76	0.82	0.85	1.06
		1	Whole	0.75	0.72	0.69	0.73	0.77	0.92
		2/3	Pre	0.57	0.56	0.55	0.58	0.60	0.90
MF-VAR	D	2/3	Post	0.80	0.82	0.69	0.76	0.85	1.05
		2/3	Whole	0.69	0.70	0.62	0.68	0.73	0.97
		1/3	Pre	0.54	0.52	0.55	0.56	0.58	1.07
MF-VAR	D	1/3	Post	0.80	0.81	0.66	0.75	0.92	0.97
		1/3	Whole	0.68	0.68	0.61	0.66	0.77	1.02
		2/3	Pre	0.56	0.56	0.53	0.57	0.58	0.60
MF-BVAR	D	2/3	Post	0.87	0.82	0.72	0.69	0.79	0.78
		2/3	Whole	0.73	0.70	0.63	0.63	0.69	0.69
		1/3	Pre	0.50	0.55	0.50	0.53	0.51	0.55
MF-BVAR	D	1/3	Post	0.83	0.76	0.68	0.68	0.75	0.70
		1/3	Whole	0.68	0.66	0.60	0.61	0.64	0.63
		2/3	Pre	0.55	0.49	0.55	0.57	0.58	1.06
MF-VAR	I	2/3	Post	0.78	0.74	0.70	0.77	0.78	0.96
		2/3	Whole	0.67	0.63	0.63	0.68	0.69	1.01
		1/3	Pre	0.55	0.53	0.55	0.56	0.59	1.02
MF-VAR	I	1/3	Post	0.74	0.75	0.67	0.76	0.76	1.08
		1/3	Whole	0.66	0.65	0.61	0.66	0.68	1.05
		2/3	Pre	0.51	0.53	0.53	0.53	0.57	0.58
MF-BVAR	I	2/3	Post	0.83	0.76	0.78	0.69	0.83	0.83
		2/3	Whole	0.69	0.65	0.67	0.61	0.71	0.72
		1/3	Pre	0.52	0.52	0.52	0.53	0.56	0.54
MF-BVAR	I	1/3	Post	0.77	0.71	0.69	0.65	0.77	0.69
		1/3	Whole	0.66	0.62	0.61	0.59	0.67	0.62

The table shows the out-of-sample RMSPE obtained from forecasting the GDP growth of the US in different periods using different variants of the MF-VAR as well as the LF-VAR model for different forecast horizons by means of 3, 4 and 6 predictors. The first column includes the forecasting model, the second column shows the forecasting method 'M' where 'D' is direct and 'I' is iterative, and the forecast horizon is reported in the third column. The evaluation period is highlighted in the fourth column. 'Pre' refers to the evaluation period from 2000Q1 to 2007Q2, 'Post' refers to the period from 2007Q3 to 2014Q2, while 'Whole' covers the whole evaluation period from 2000Q1 to 2014Q2. The RMSPEs for the different combinations of predictors are reported in columns 5 to 10. The point forecasts are obtained using a rolling window of 130 quarterly observations and 390 monthly observations where the in-sample estimation starts from 1967Q3 to 1999Q4. All models use 4 quarterly lags.

Table 3.A.4: LPDS for more than 2 predictors

Model	M	h	Period	IP-PM-EM	IP-PM-CF	IP-CF-EM	PM-EM-CF	Best 4	ALL
		1	Pre	-1.01	-0.97	-0.96	-0.93	-0.98	-0.98
LF-VAR		1	Post	-1.24	-1.20	-1.20	-1.06	-1.21	-1.21
		1	Whole	-1.12	-1.08	-1.08	-0.99	-1.09	–1.09
		1	Pre	-1.07	-1.01	-0.98	-1.06	-1.08	-1.35
MF-VAR		1	Post	-1.18	-1.16	-1.08	-1.13	-1.18	-1.42
		1	Whole	-1.13	-1.09	-1.03	-1.10	-1.13	-1.38
		1	Pre	-.1.01	-0.99	-0.96	-1.00	-1.04	-1.16
MF-BVAR		1	Post	-1.23	-1.15	-1.12	-1.19	-1.22	-1.44
		1	Whole	-1.12	-1.07	-1.04	-1.10	-1.13	-1.30
		2/3	Pre	-0.93	-0.94	-0.86	-0.89	-0.99	-1.23
MF-VAR	D	2/3	Post	-1.14	-1.16	-0.96	-1.10	-1.11	-1.25
		2/3	Whole	-1.04	-1.05	-0.91	-0.99	-1.05	-1.24
		1/3	Pre	-0.86	-0.84	-0.83	-0.85	-0.93	-1.20
MF-VAR	D	1/3	Post	-1.00	-1.10	-0.95	-1.05	-1.06	-1.39
		1/3	Whole	-0.93	-0.97	-0.89	-0.95	-0.99	-1.30
		2/3	Pre	-0.87	-0.94	-0.81	-0.86	-0.89	-0.92
MF-BVAR	D	2/3	Post	-1.24	-1.16	-1.05	-0.99	-1.03	-1.05
		2/3	Whole	-1.06	-1.05	-0.93	-0.93	-0.98	-0.99
		1/3	Pre	-0.79	-0.84	-0.76	-0.81	-0.79	-0.85
MF-BVAR	D	1/3	Post	-1.18	-1.04	-1.00	-0.98	-1.04	-1.01
		1/3	Whole	-0.98	-0.94	-0.88	-0.90	-0.91	-0.93
		2/3	Pre	-0.87	-0.76	-0.87	-0.86	-0.97	-1.37
MF-VAR	I	2/3	Post	-1.00	-1.03	-1.00	-1.04	-1.07	-1.19
		2/3	Whole	-0.98	-0.89	-0.93	-0.95	-1.02	-1.28
		1/3	Pre	-0.83	-0.81	-0.83	-0.82	-0.90	-1.28
MF-VAR	I	1/3	Post	-1.01	-1.10	-0.97	-1.07	-1.06	-1.40
		1/3	Whole	-0.92	-0.96	-0.90	-0.95	-0.98	-1.34
		2/3	Pre	-0.81	-0.82	-0.84	-0.84	-0.92	-0.95
MF-BVAR	I	2/3	Post	-1.19	-1.05	-1.11	-0.99	-1.13	-1.08
		2/3	Whole	-1.00	-0.94	-0.97	-0.91	-1.02	-1.02
		1/3	Pre	-0.80	-0.80	-0.82	-0.82	-0.87	-0.84
MF-BVAR	I	1/3	Post	-1.15	-0.99	-1.01	-0.96	-1.06	-0.99
		1/3	Whole	-0.97	-0.90	-0.92	-0.89	-0.97	-0.92

The table shows the out-of-sample LPDS obtained from forecasting the GDP growth of the US in different periods using different variants of the MF-VAR as well as the LF-VAR model for different forecast horizons by means of 3, 4 and 6 predictors. The first column includes the forecasting model, the second column shows the forecasting method 'M' where 'D' is direct and 'I' is iterative, and the forecast horizon is reported in the third column. The evaluation period is highlighted in the fourth column. 'Pre' refers to the evaluation period from 2000Q1 to 2007Q2, 'Post' refers to the period from 2007Q3 to 2014Q2, while 'Whole' covers the whole evaluation period from 2000Q1 to 2014Q2. The LPDS for the different combinations of predictors are reported in columns 5 to 10. For the MF-BVAR, the density forecasts are based on 5000 draws from the posterior, while for the MF-VAR and the LF-VAR density forecasts are constructed using 5000 bootstrap replications. A rolling window of 130 quarterly observations and 390 monthly observations is used where the in-sample estimation starts from 1967Q3 to 1999Q4. All models use 4 quarterly lags.

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Abgrenzung

Ich versichere hiermit, dass ich Kapitel 1 und 3 der vorliegenden Arbeit ohne Hilfe Dritter und ohne Benutzung anderer als der angegebenen Hilfsmittel verfasst habe.

Kapitel 2 entstammt einer gemeinsamen Arbeit mit Sandra Stankiewicz von der Universität Konstanz. Meine individuelle Leistung bei der Erstellung des Kapitel 2 beträgt 50%.