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Macroeconomics-at-Risk

We estimate Value-at-Risk of output using quantile regressions. Our objective is to gauge dynamically the tail risk of real activity. We find that the shape of the distribution of output evolves over time and not only its location and its dispersion. Moreover, financial intermediation stress has a significantly stronger elasticity with real activity at the lower tail of the distribution.

JEL codes: C31, C53, E3, G2.
Keywords: Quantile regression, density forecasts, VaR, macroeconomic risks.

Since at least Engle (1982) and Stock and Watson (2002), we know that the conditional variance of future output and inflation evolves over time. However, in these seminal contributions, the risk of real activity and inflation is implicitly considered as symmetric. In this paper, we investigate the time evolution of the conditional distribution of macroeconomics variables with a special interest on the extreme tails of the output.

The conduct of monetary policy has been recently associated to a risk management practice both in monetary policy statements (Greenspan, 2003; Mishkin, 2008) and in academic research (Kilian and Manganelli, 2008). This risk management perspective of the monetary policy is directly inspired by the literature on robust

The first author thanks the *Banque de France* Foundation and the second one the Europlace Institute of Finance for their financial supports. The authors are also grateful to Florian Ielpo and Chrisophe Hurlin for precious comments and suggestions when preparing this piece of work.

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control (Hansen and Sargent, 2003 and 2007). The key idea of robust control is that policy-making should aim at minimizing the consequences of worst-case scenarios[1].

Thus Federal Reserve Board Chairman Alan Greenspan in 2003 declares that "A central bank seeking to maximize its probability of achieving its goals is driven, I believe, to a risk-management approach to policy. By this I mean that policymakers need to consider not only the most likely future path for the economy but also the distribution of possible outcomes about that path" (Greenspan 2003).

The common practice of risk management requires controlling the probability of catastrophe. For a financial intermediary, the focus is on reducing the risk of significant monetary loss. For a central banker, it means acting to reduce the chances that output or the price level will be substantially below trend. Because of their focus on the conditional mean of the quantities being models, traditional time-series econometric tools are ill-equipped to address the questions that are foremost in the minds of policymakers who adopt such a risk management perspective.

To control risk in financial institutions, risk managers employ the concept of Value-at-Risk (VaR). VaR measures the worst possible loss over a specific time horizon, at a given probability[2]. Hence, our objective is to propose such VaR estimates on output to gauge and explain tail macroeconomic risks.

We pay a special attention to financial stress factors in our estimates. Indeed, the recent financial turmoil featured a risk in the ability of financial institutions to ensure their financial intermediary role between lenders and borrowers for the non-financial sector (households and businesses) but also between financial institutions themselves.

The two reference models developed to analyze business cycle fluctuations in developed economies – the real business cycle models and dynamic neo-Keynesian model – confer to financial intermediaries a minor role, and the macroeconomic

1. Even if the required policy eventually appears sub-optimal considering ex post that the large-scale shocks have not materialized, a risk-management approach assesses that the associated cost of buying an insurance is small compared to the alternative

2. The VaR has been widely accepted since the 1990s. It was first popularized by JP Morgan and later by Risk-Metrics Group in their risk management software. VaR became so popular that it was approved by bank regulators as a valid approach for calculating risk charges. There are two well known limitations of VaR measures: (a) they not take into account the size of tail losses; and (b) they lack "coherence" in the sense of Artzner et al. (1999), since they do not satisfy the sub-additivity property required for consistent risk ordering. This means that VaR may be incapable of identifying diversification opportunities. Although there has been a good deal of criticism of VaR in the literature because of these shortcomings, it remains a widely used method for risk measurement by practitioners mainly because it has an intuitive interpretation, it can be easily back-tested, and it is required by regulation.

literature revealed little about the relationship between financial intermediation and macroeconomic volatility.

In recent years however, many contributions have emerged to (1) attempt to link theoretical financial factors – including, but not limited to, financial intermediation – to macroeconomic fluctuations and the optimal response of monetary policy financial shocks, (2) assess the cost of failures of financial intermediaries generally are of direct relevance to the costs of banking and financial crises.

The idea that the financial sector can amplify the business cycle dating at least to Fisher (1933). Traditionally, financial shocks were apprehended through the channel of the cost of credit (or the interest rate channel) and wealth effects (see, e.g., Lettau and Ludvigson, 2004). Since the work developed by Bernanke and Blinder (1988) and Bernanke and Gertler (1995 and 1996), it is apparent that financial imperfections resulting from information asymmetries, contribute to the transmission but also the amplification of monetary shocks, real or financial. More recently, studies have shown that the analytical framework of the financial accelerator could be extended agents, non-financial intermediaries. This new financial accelerator describes how the financial system amplifies the impact of the real economy.

The new financial accelerator mechanism has been clearly illustrated by Adrian and Shin (2008) - a negative shock to asset prices depleted bank capital and leverage increases. Since it is difficult to raise new capital in times of crisis, when banks tend to liquidate their assets. These disposals impacting asset prices then propagating the initial shock. This mechanism may have a strong impact on economic activity, especially when several banks simultaneously shock, which is typical of systemic events. In this context, the multiplication factor is leverage - when banks are themselves indebted, the initial shock and reducing negative asset price follows can lead to massive liquidations of assets, which accentuates the lower prices and possibly trigger a vicious circle, especially if banks want to restore a target debt level.

This is the meaning of the concerns raised in 2008-2009 on the risk of a credit crunch, that is to say a rationing of credit following the blocking of the interbank market.

We estimate dynamically, using quantile regressions, the probability distribution of future output, as opposed to mean and/or variance point estimates. This framework allows the shape of the distribution of output to be assessed conditionally on the current state of the economy and is totally model based and judgement free[3].

Quantile regression (Koenker and Basset, 1978; Koenker, 2005) may be considered as a natural extension of classical least squares estimation of conditional mean models to the estimation of an ensemble of models for conditional quantile functions. The central special case is the median regression estimator that minimizes a sum of absolute errors. The remaining conditional quantile functions are estimated by minimizing an asymmetrically weighted sum of absolute errors. Altogether the ensemble of estimated conditional quantile functions offers a much more complete view of the effect of covariates on the location, scale and shape of the distribution of the response variable.

The rest of the paper is organized as follows. In section 1, we present the empirical framework. In particular, Section 1.1 briefly exposes the quantile regression methodology. Section 1.2 presents the data and Section 1.3 discusses some preliminary analyses based on a simple VAR methodology. Section 2 presents the empirical results from quantile regressions. Section 3 summarizes our main conclusions.

1. THE EMPIRICAL FRAMEWORK

1.1 Quantile Regression

In order to address how changes in a set of conditioning variables influence the shape of the distribution of a dependent variable, Koenker and Bassett (1978)

[3] A number of institutions construct indicators of forecast uncertainty that are related to the current state of the economy by skewing and rescaling measures of past-forecast performance using assessment of risk and simulations. The BoE produces asymmetric fan charts for its inflation and GDP forecasts, by skewing and rescaling past forecast errors based on the MPC members' judgment of risks. In a somewhat different manner the Bank of Japan aggregates distribution forecasts of its board members. The IMF global growth forecasts for the World Economic Outlook are not based on an explicit model (being an aggregate of individual country forecasts); hence asymmetric fan charts are based on an automated assessment of risks related to four global risk factors: financial conditions (term spread and stock market returns), oil prices and global interest rates (Elekdag and Kannan, 2009). The volatility and market expectations on developments of these risk factors are used to rescale and skew the past forecast errors to arrive at a probability distribution. Alternatively, the Norges Bank, the Bank of Canada (for longer horizons) and on some occasions the CPB (Lansen and Krankendonk, 2008), use model-based stochastic simulations, where the confidence intervals are derived from shocking the underlying variables and model coefficients.

developed the concept of "quantile regression". Quantile regression is designed to answer the following question: When a conditioning variable X changes, what happens to the τ^{th} quantile of the distribution of Y?

Quantile regression can be viewed as an extension of classical Ordinary Least Squares (OLS hereafter). In quantile regression, the estimation of the conditional mean by OLS is extended to the similar estimation of an ensemble of models of various conditional quantile functions for a data distribution. Then, quantile regression can better quantify conditional distribution of $(Y \mid x)$. The central special case is the median regression estimator that minimizes a sum of absolute errors. The estimates of remaining conditional quantile functions are obtained by minimizing an asymmetrically weighted sum of absolute errors where the weights are the function of the quantile of interest. Taken together, the ensemble of estimated conditional quantile functions of $(y \mid x)$ offers a more complete view of the effect of covariates on the location, scale and shape of the distribution of the response variable. In the classical approach of OLS regression the conditional mean function, the function that describes how the mean of y changes with the vector of covariates x, is (almost) all we need to know about the relationship between y and x. Then, classical OLS is considered as a pure location shift model since it assumes that x affects only the location of the conditional distribution of y, not its scale, or any other aspect of its distributional shape.

Covariates may influence the conditional distribution of the response in myriad other ways: expanding its dispersion as in traditional models of heteroscedasticity, stretching one tail of the distribution, compressing the other tail, and even inducing multimodality. Explicit investigation of these effects via quantile regression can provide a more nuanced view of the stochastic relationship between variables, and therefore a more informative empirical analysis.

Parameter estimation in quantile regression is the result of an optimization problem. To see how this works, recall that we can write down an OLS problem as an optimization problem where we minimize the sum of squared deviations of the fitted values for the dependent variable from the data. In the same way, the median quantile (0.5) in quantile regressions is defined through the problem of minimizing the sum of absolute residuals. The symmetrical piecewise linear absolute value function assures the same number of observations above and below the median of the distribution.

The other quantiles values can be obtained by minimizing a sum of asymmetrically weighted absolute residuals, thereby giving different weights to positive and negative residuals. Solving

$$\underset{\xi \in \mathbf{R}}{\arg\min} \sum_{i=1}^{n} \rho_{\tau}\left(y_i - \xi\right) \tag{1}$$

where $\rho_{\tau}(\cdot)$ is the tilted absolute value function (usually called "pinball loss function"), as illustrated in Figure 1, gives the τ^{th} sample quantile with its solution. Depending on the exact shape of the function $\rho_{\tau}(\cdot)$, the optimization problem yields an estimate at a particular quantile. This quantile depends on the relative slopes on the two sides of the origin.

Taking the directional derivatives of the objective function with respect to ξ (from left to right) shows that this problem yield the sample quantile as its solution.

After defining the unconditional quantiles as an optimization problem, it is easy to define conditional quantiles similarly. Taking the least squares regression model for a random sample, $y_1, y_2, ..., y_n$, we solve

$$\underset{\mu \in \mathbf{R}}{\arg\min} \sum_{i=1}^{n} \left(y_i - \mu\right)^2 \tag{2}$$

which gives the sample mean, an estimate of the unconditional population mean. Replacing the scalar, μ, by a parametric function $\mu(x, \beta)$, and then solving

$$\underset{\mu \in \mathbf{R^p}}{\arg\min} \sum_{i=1}^{n} \left(y_i - \mu\left(x_i, \beta\right)\right)^2 \tag{3}$$

gives an estimate of the conditional expectation function $E\left(y \mid x\right)$.

Proceeding the same way for quantile regression, to obtain an estimate of the conditional median function, the scalar ξ in the first equation is replaced by the parametric function $\xi(x, \beta)$, and τ is set to ½. Finally, the estimation of the 99 percentile lines in addition to the standard “mean” line makes possible the production of not only a mean forecast, but a distribution of forecasts around this mean. Further insights into this robust regression technique can be obtained from Koenker and Basset (2005).

Quantile regression has been applied in a variety of economic and financial problems. Applications include investigations of wage structure (Buchinsky and Leslie, 2010), wage mobility (Buchinsky and Hunt 1996), and educational attainment (Eide and Showalter 1998). Financial applications include Chan and Lakonishok (1992) and Engle and Manganelli (2004) to the problems of robust beta estimation and VaR respectively.

1.2 Data

Quantile regressions are implemented using monthly time series of the US for the period March 1975 - July 2012. All the series come from the FRED II Database of the Federal Reserve Bank of St-Louis and Datastream. The sample is constrained by the availability of the house price index.

The main variables considered are: the index of industrial production, IP_t, the index of consumer prices, CPI_t, the 3-month interbank rate, $LIBOR_t$, the 10 year interest rate, $GB10_t$, a house price index[4], HP_t, and equity prices (the S&P500 index), PSP_t.

In addition to these "traditional" variables, we considered several variables reflecting stress/health of financial intermediaries: a stock market index of the US banking sector (market capitalization weighted), $PBKS_t$, the volatility of this index (quadratic monthly returns), $RBKS2_t$, an interbank spread (the Ted spread), TED_t, the default spread (defined as the yield difference between Moody’s BAA and AAA corporate bonds), DEF_t, the implied volatility of the S&P equity index, VIX_t, and two

4. Note that the house price index is built from the Case-Shiller index and the OFHEO index before January 1987.

aggregate indicators of financial stress calculated by the Federal Reserve Bank of St. Louis and the Federal Reserve Bank of Kansas City, denoted SL_t and KC_t [5].

1.3 Preliminary analyses

We investigate, as a first step, causality and relationships between the set of macroeconomic and financial conditions variables.

The VAR model is estimated with 7 lags selected based on the AIC information criterion. Variables that include a (stochastic) tendency were detrending using a high-pass filter (the industrial production index, the consumer price index, the stock price index and the house price index) since we focus on cyclical fluctuations. Given the strong correlation of the two aggregated indicators of financial stress (SL_t and KC_t), we only consider the Stress index of the Kansas City Federal Reserve in our estimates of the VAR model[6].

Simple Granger causality tests appear in Table 1. It appears that financial stress indicators and industrial production have a double causality at the 1% and 5% significance level. Several variables also cause financial stress except the VIX, which is most often caused by other indicators of financial stress. Furthermore, some impulse response functions confirm the significant impact of financial shocks on output.

Figure 2 presents generalized impulse response functions of the industrial production growth and the equity index to a Ted spread shock. We used the method proposed by Pesaran and Shin (1998), which unlike traditionally used Cholesky decomposition, does not require orthogonalization of shocks and is independent of the order of the variables. For each variable, the shock is equal to one standard deviation. The time horizon of responses is 120 months which is about the time required for the variables return to their equilibrium levels.

This analysis indicates that the effects of stress on the interbank market are significant on the activity and the stock market at the horizon of a few months. After

[5] See the appendix for some details about data reconstruction for some variables.
[6] The correlation matrix of variables is shown in the appendix. Results obtained with the Stress index of the St Louis Federal Reserve are qualitatively similar. These results are available upon request.

this horizon, the shocks fade gradually although the confidence intervals are wide enough. Note that the impact on output is more durable than the stock price.

For forecasters, it has become customary to present the point forecasts accompanied by a forecast density (fan chart)[7]. This realistic approach implicitly recognizes that it is impossible to predict with certainty. Confidence intervals and density forecasts were increasingly used to describe the uncertainty of any point forecast (see e.g., Tay and Wallis, 2000).

Forecast densities are most often computed based on the dispersion of past forecast errors of the estimated model. They permit to view, from a fan chart, the uncertainty associated to predictions. Figure 3 shows such a fan chart of industrial growth forecasts calibrated on the standard deviation of past forecast errors of the VAR model.

However, this kind of methodology as well as survey-based density forecasts do not provide a conditional, semiparametric or reproducible fan chart. On the one hand, most of the fan charts are unconditional: whatever the economic situation, the magnitude of the uncertainty represented is constant. On the other hand, the fan chart of the Bank of England (BOE) is not reproducible because it introduces subjectivity members of the BOE.

2. EMPIRICAL RESULTS

To overcome the difficulties of traditional density forecasts, we led, from quantile regressions, estimates of the density of output.

Table 2 to 4 presents the results of quantile regressions for three quantiles (5%, 50% and 95%) of the industrial production growth. Several multivariate regressions are examined. All variables are considered with a delay.

Student statistics of the estimated coefficients are reported in parentheses and the last column presents two statistics to assess the relevance of the regressions carried out: the first one measures the frequency of hits for the VaR estimated and the second

7. Since 1996, the Bank of England publishes a density forecast for inflation in its quarterly Inflation Report, called “fan chart”. In France, INSEE publishes a fan chart forecast as part of the Gross Domestic Product (GDP) in his “Note de Conjoncture”.

one, the sum of the absolute value of these hits (shown in brackets). Hits are defined as exceedances of the estimated VaR.

These results from Table 2 indicate that the introduction of financial health variables significantly impact the VaR95% of industrial production (quantile 5%). These variables appear to be significant and the measures of relevance predictions are improved. It appears, however, that model only including the default spread (DEF_t) as a stress financial indicator achieves 5% quantile forecasts of industrial production equally satisfying. This result may be related to the smaller weight of the direct banking intermediation in the US than it is in the euro area.

Figure 4 shows the evolution of the industrial production growth and 95% VaR estimated from the conditional specification including and not including, respectively, a financial stress indicator (here the regressions # 14 and # 16 in Table 2). This figure shows that the estimated quantile 5% in industrial production growth is significantly improved by the introduction of a financial factor (here the default spread, DEF_t).

The observation that the financial stress variables are significant is confirmed by examining the absolute value of Hits of VaR estimated using two specifications # 14 and # 16 in Table 1.

Figure 5 shows the absolute values exceeding the 95% VaR conditional real activity without (upper figure) and with (lower figure) financial stress indicators. Hits appear less frequent and smaller amplitude when a financial stress indicator is introduced in the specification of the quantile regression.

Moreover, a test of inequality between the estimated coefficients for different quantiles and a comparison of estimated quantiles in two different states of nature suggest that the first extreme quantile estimates (less than 15%) are more sensitive to financial health variables than other quantiles. For example, within specifications # 4 and # 6 (Table 2) which predict the 5% quantile of industrial production growth, the estimated coefficients of variables TED_t and DEF_t are respectively -0.4% and -0.7% (and significant at the 1% level). The same regression coefficients in a predictive quantile 50% regression are estimated both at 0.1%. Moreover, the coefficient for TED_t is not significant at 5%. Hence, financial intermediation stress has a significantly stronger elasticity with real activity at the lower tail of the distribution.

Figure 6 presents the conditional quantiles of 2.5% to 50% of the output in two different states of nature (quantiles estimated for March 2006 and October 2008) and their difference. It appears that financial stress impacts not only the location but also the shape of the conditional distribution of activity with an extreme risk of bad outputs (recession) more pronounced.

3. CONCLUSION

We apply quantile regressions to estimate VaR of output. Our objective is to gauge dynamically the tail risk of real activity. Our results, based on monthly data from the US over the period 1975M3-2012M7, suggest that the shape of the distribution of output evolves over time and not only its location and its dispersion. Moreover, financial intermediation stress has a significantly stronger elasticity with real activity at the lower tail of the distribution.

Hence, dysfunctions of financial intermediaries lead to extreme risk of negative output, *i.e.* higher probability of severe recession.

These results strongly suggest that monetary policy should not neglected financial intermediation disruptions, in a risk management framework, since they can be responsible, or at least early warning indicators, of output tail risks.

Our analyzes obtained over the US, where banking intermediation is relatively less developed than direct one, should now be extended to other countries in Europe in order to confirm our results.

LITERATURE CITED

Adrian, Tobias and Hyun Shin (2008). “Financial Intermediaries, Financial Stability, and Monetary Policy”, *Federal Reserve Bank of New York Staff Report* 346, 39 pages.

Artzner, Philippe, Freddy Delbaen, Jean-Marc, Eber and David Heath (1998). “Coherent Measures of Risk”, Mathematical Finance 6, 203-228.

Barell, Ray, Philip Davis and Olga Pomerantz (2006). “Cost of Financial Stability, Household Sector Balance Sheets and Consumption”, *Journal of Financial Stability* 2, 194-216.

Bean Charles, Larsen Jens and Kalin Nikolov (2002). “Financial Frictions and the Monetary Transmission Mechanism: Theory, Evidence and Policy Implications”, *European Central Bank Working Paper,* 67 pages.

Bernanke, Ben and Alan Blinder (1988). “Credit, Money, and Aggregate Demand”, *American Economic Review* 2, 435-439.

Bernanke Ben, Gertler Mark and Svi Gilchrist (1996). “The Financial Accelerator and the Flight to Quality”, *Review of Economics and Statistics*, 1, 1-15.

Buchinsky, Moshe and Phillip Leslie (2010). “Educational Attainment and the Changing U.S. Wage Structure: Dynamic Implications Without Rational Expectations”, *Journal of Labor Economics* 28, 3, 541-94.

Buchinsky, Moshe and Jennifer Hunt (1996). “Wage Mobility in the United States.” National Bureau of Economic Research, Working Paper No. 5455. Cambridge, MA: N.B.E.R.

Chan, Louis K.C. and Joseph Lakonishok, (1992). “Robust Measurement of Beta Risk”, *The Journal of Financial and Quantitative Analysis*, 27, 2, pp:265-282

Christiano, Lawrence, Motto Roberto and Massimo Rostagno (2010). “Financial Factors in Economic Fluctuations”, ECB working paper 1192, ECB, 132 pages.

Curdi,Vasco and Michael Woodford M. (2010). “The Central-Bank Balance Sheet as an Instrument of Monetary Policy”, *Federal Reserve Bank of New York* 26, 83 pages.

De Bandt, Olivier and Phillip Hartmann (2000). “Systemic risk: A survey”, European Central Bank Working Paper 35, 77 pages.

Eide, Eric and Mark Showalter (1998). “The Effect of School Quality on Student Performance: A Quantile Regression Approach”, Economics Letters, Elsevier, vol. 58(3), pages 345-350, March.

Engle, Robert and Simone Manganelli, (2004). “CAViaR: Conditional Value at Risk by Quantile Regression”, Journal of Business & Economic Statistics, 22, 4, 367-381

Fisher Irving (1933). “The Debt-Deflation Theory of Great Depressions”, *Econometrica* 1(4), 337-357.

Gertler, Mark and Nobuhiro Kiyotaki (2009). “Financial Intermediation and Credit Policy in Business Cycle Analysis”, *Handbook of Monetary Economics* 3A, 68 pages.

Hansen, Lars, and Thomas Sargent (2003). “Robust Control of Forward-Looking Models”, *Journal of Monetary Economics* 50, 581–604.

Hansen, Lars and Thomas Sargent (2007). *Robustness*. Princeton University Press.

Kindleberger Charles (1978). “Manias, Panics and Crashes: a History of Financial Crises”, *New York: Basic Books*, 320 pages.

Koenker Roger and Gilbert Bassett (1978). “Regression Quantiles”, *Econometrica* 46:1, 33-50.

Lettau Martin and Syndey Ludvigson (2004). “Understanding Trend and Cycle in Asset Values: Reevaluating the Wealth Effect on Consumption”, *American Economic Review* 94, 276-299.

Mishkin Frederic (1999). “International Experiences with Different Monetary Policy Regimes”, *Journal of Monetary Economics* 43, 579-605.

Peek, Joe and Eric Rosengren (1995). “Bank Regulation and the Credit Crunch”, *Journal of Banking and Finance* 1, 679-692.

Pesaran, Hashem and Yongcheol Shin (1998). “Generalized Impulse Response Analysis in Linear Multivariate Models”, *Economic Letters* 58, 17-29.

Tay Anthony and Kenneth Wallis (2000). “Density Forecasting: A Survey”, *Journal of Forecasting* 19, 235-254.

TABLE 1.

GRANGER CAUSALITY TESTS

Null hypothesis	F-Stat.	p-Stat.	Null hypothesis	F-Stat.	p-Stat.	Null hypothesis	F-Stat.	p-Stat.
CPI $\nRightarrow$ IP	4,65	**0,00**	KC $\nRightarrow$ CPI	3,00	**0,02**	PSP $\nRightarrow$ TED	0,87	0,48
IP $\nRightarrow$ CPI	5,65	**0,00**	CPI $\nRightarrow$ KC	3,25	**0,01**	TED $\nRightarrow$ PSP	0,56	0,69
LIBOR $\nRightarrow$ IP	2,56	**0,04**	HP $\nRightarrow$ LIBOR	2,50	**0,04**	GB10 $\nRightarrow$ TED	10,75	**0,00**
IP $\nRightarrow$ LIBOR	4,88	**0,00**	LIBOR $\nRightarrow$ HP	0,79	0,53	TED $\nRightarrow$ GB10	2,65	**0,03**
HP $\nRightarrow$ IP	6,70	**0,00**	TED $\nRightarrow$ LIBOR	16,24	**0,00**	VIX $\nRightarrow$ TED	1,04	0,38
IP $\nRightarrow$ HP	2,57	**0,04**	LIBOR $\nRightarrow$ TED	11,56	**0,00**	TED $\nRightarrow$ VIX	1,29	0,27
TED $\nRightarrow$ IP	2,41	0,05	DEF $\nRightarrow$ LIBOR	5,42	**0,00**	KC $\nRightarrow$ TED	0,42	0,79
IP $\nRightarrow$ TED	2,98	**0,02**	LIBOR $\nRightarrow$ DEF	10,03	**0,00**	TED $\nRightarrow$ KC	13,39	**0,00**
DEF $\nRightarrow$ IP	9,06	**0,00**	PSP $\nRightarrow$ LIBOR	0,95	0,43	PSP $\nRightarrow$ DEF	7,60	**0,00**
IP $\nRightarrow$ DEF	4,31	**0,00**	LIBOR $\nRightarrow$ PSP	0,38	0,82	DEF $\nRightarrow$ PSP	0,36	0,84
PSP $\nRightarrow$ IP	14,03	**0,00**	GB10 $\nRightarrow$ LIBOR	8,68	**0,00**	GB10 $\nRightarrow$ DEF	9,63	**0,00**
IP $\nRightarrow$ PSP	6,72	**0,00**	LIBOR $\nRightarrow$ GB10	3,50	**0,01**	DEF $\nRightarrow$ GB10	1,80	0,13
GB10 $\nRightarrow$ IP	4,46	**0,00**	VIX $\nRightarrow$ LIBOR	0,51	0,73	VIX $\nRightarrow$ DEF	2,65	**0,03**
IP $\nRightarrow$ GB10	0,33	0,86	LIBOR $\nRightarrow$ VIX	0,88	0,48	DEF $\nRightarrow$ VIX	6,78	**0,00**
VIX $\nRightarrow$ IP	6,48	**0,00**	DEF $\nRightarrow$ TED	1,42	0,23	KC $\nRightarrow$ DEF	11,94	**0,00**
IP $\nRightarrow$ VIX	2,51	**0,04**	TED $\nRightarrow$ DEF	12,90	**0,00**	DEF $\nRightarrow$ KC	2,87	**0,02**
KC $\nRightarrow$ IP	9,25	**0,00**	KC $\nRightarrow$ LIBOR	5,01	**0,00**	GB10 $\nRightarrow$ PSP	0,35	0,85
IP $\nRightarrow$ KC	3,28	**0,01**	LIBOR $\nRightarrow$ KC	10,98	**0,00**	PSP $\nRightarrow$ GB10	3,36	**0,01**
LIBOR $\nRightarrow$ CPI	0,55	0,70	TED $\nRightarrow$ HP	1,63	0,16	VIX $\nRightarrow$ PSP	1,87	0,12
CPI $\nRightarrow$ LIBOR	3,88	**0,00**	HP $\nRightarrow$ TED	0,90	0,46	PSP $\nRightarrow$ VIX	21,07	**0,00**
HP $\nRightarrow$ CPI	0,55	0,70	DEF $\nRightarrow$ HP	0,90	0,47	KC $\nRightarrow$ PSP	0,40	0,81
CPI $\nRightarrow$ HP	2,04	0,09	HP $\nRightarrow$ DEF	3,79	**0,00**	PSP $\nRightarrow$ KC	4,18	**0,00**
TED $\nRightarrow$ CPI	0,83	0,50	PSP $\nRightarrow$ HP	11,94	**0,00**	VIX $\nRightarrow$ GB10	0,90	0,46
CPI $\nRightarrow$ TED	3,56	**0,01**	HP $\nRightarrow$ PSP	2,08	0,08	GB10 $\nRightarrow$ VIX	1,18	0,32
DEF $\nRightarrow$ CPI	2,42	0,05	GB10 $\nRightarrow$ HP	0,67	0,61	KC $\nRightarrow$ GB10	3,31	**0,01**
CPI $\nRightarrow$ DEF	5,62	**0,00**	HP $\nRightarrow$ GB10	0,36	0,84	GB10 $\nRightarrow$ KC	6,81	**0,00**
PSP $\nRightarrow$ CPI	7,03	**0,00**	VIX $\nRightarrow$ HP	2,16	0,07	KC $\nRightarrow$ VIX	99,60	**0,00**
CPI $\nRightarrow$ PSP	4,52	**0,00**	HP $\nRightarrow$ VIX	5,83	**0,00**	VIX $\nRightarrow$ KC	3,67	**0,01**
GB10 $\nRightarrow$ CPI	0,65	0,63	KC $\nRightarrow$ HP	1,65	0,16	VIX $\nRightarrow$ DEF	2,65	**0,03**
CPI $\nRightarrow$ GB10	5,90	**0,00**	HP $\nRightarrow$ KC	2,48	**0,04**	DEF $\nRightarrow$ VIX	6,78	**0,00**
VIX $\nRightarrow$ CPI	0,67	0,61	DEF $\nRightarrow$ TED	1,42	0,23	KC $\nRightarrow$ DEF	11,94	**0,00**
CPI $\nRightarrow$ VIX	2,67	**0,03**	TED $\nRightarrow$ DEF	12,90	**0,00**	DEF $\nRightarrow$ KC	2,87	**0,02**

Source: *Datastream, Bloomberg* and *FRED II database*, monthly data from 1975M03 to 2012M07. The symbol A $\nRightarrow$ B indicates that under the null hypothesis the variable *A* does not Granger cause the variable *B*. Significant p-values appear in bold face. Calculations by the authors.

TABLE 2

PREDICTIVE REGRESSIONS OF THE INDUSTRIAL PRODUCTION GROWTH (VAR95%)

#	*Const.* (*t*-stat)	CPI_t (*t*-stat)	ΔIP_t (*t*-stat)	$LIBOR_t$ (*t*-stat)	$GB10_t$ (*t*-stat)	HP_t (*t*-stat)	PSP_t (*t*-stat)	TED_t (*t*-stat)	DEF_t (*t*-stat)	SR_t (*t*-stat)	Hit Freq. [Hit Size]
					Panel A: models with autoregressive term						
1	**-0.008**	0.000	**0.529**	0.000							0.047
	(-5.399)	(-0.826)	(4.519)	(-1.292)							[0.101]
2	**-0.010**	-0.001	**0.530**	-0.001	0.001						0.042
	(-4.821)	(-1.534)	(4.299)	(-1.375)	(0.979)						[0.091]
3	**-0.003**	0.000	**0.231**	**-0.001**	0.000	**0.000**	0.000				0.065
	(-2.069)	(-0.825)	(2.493)	(-4.138)	(1.247)	(2.128)	(1.493)				[0.120]
4	**-0.004**	0.000	**0.275**	0.000	0.000	0.000	0.000	**-0.004**			0.060
	(-3.363)	(-0.817)	(3.128)	(0.982)	(-1.046)	(1.552)	(1.562)	(-3.721)			[0.090]
5	**-0.003**	**-0.001**	0.061	0.000	0.000	0.000		**-0.006**			0.065
	(-2.400)	(-2.096)	(0.736)	(1.261)	(-0.747)	(0.752)		(-3.524)			[0.125]
6	0.000	0.000	0.138	-0.001	**0.001**	0.000	0.000	-0.001	**-0.007**		0.056
	(-0.785)	(-1.477)	(1.710)	(-1.908)	(1.980)	(1.456)	(0.906)	(-1.063)	(-4.851)		[0.089]
7	0.000	**-0.001**	0.078	**-0.001**	**0.001**	0.000		-0.001	**-0.007**		0.058
	(0.483)	(-2.461)	(0.894)	(-2.909)	(2.854)	(1.408)		(-0.683)	(-4.830)		[0.099]
8	-0.001	0.000	**0.243**	0.000	0.000	0.000	(0.000)	-0.002	**-0.004**	0.000	0.058
	(-0.641)	(-1.323)	(2.589)	(-0.791)	(0.713)	(0.817)	0.620	(-1.319)	(-2.448)	(-0.588)	[0.103]
9	**-0.006**	-0.001	**0.325**	-0.001	0.001	0.000	(0.000)	-0.001	-0.001	-0.001	0.058
	(-2.860)	(-1.857)	(3.546)	(-1.753)	(1.863)	(0.599)	1.870	(-0.589)	(-0.591)	(-1.778)	[0.094]
10	0.000	0.000	**0.175**	-0.001	**0.001**	0.000	(0.000)	-0.001	**-0.007**	0.005	0.058
	(0.687)	(-0.966)	(2.001)	(-1.772)	(1.970)	(0.696)	0.789	(-1.016)	(-4.810)	(0.757)	[0.095]
11	0.000	0.000	0.144	**-0.001**	**0.001**	0.000	(0.000)	-0.001	**-0.007**	-0.039	0.054
	(0.887)	(-1.585)	(1.826)	(-2.113)	(2.095)	(1.118)	-0.674	(-0.875)	(-5.494)	(-0.857)	[0.085]
12	0.000	-0.001	0.089	-0.001	**0.001**	0.000	(0.000)	-0.002	**-0.006**	0.000	0.054
	(0.592)	(-1.816)	(1.209)	(-1.726)	(2.213)	(1.729)	0.712	(-1.245)	(-4.509)	(-0.732)	[0.095]
					Panel B: models without autoregressive term						
13	**-0.006**	0.000		0.000							0.051
	(-3.217)	(-0.736)		(-0.923)							[0.177]
14	**-0.016**	-0.001		**-0.002**	**0.003**						0.049
	(-6.791)	(-1.852)		(-4.590)	(4.884)						[0.122]
15	**-0.006**	0.000		**-0.001**	**0.001**	**0.000**	0.000				0.056
	(-2.971)	(-0.789)		(-3.732)	(2.262)	(2.799)	(0.852)				[0.126]
16	**-0.008**	0.000		0.000	**0.001**	**0.000**	0.000	**-0.005**			0.049
	(-5.181)	(-0.711)		(-0.902)	(3.278)	(2.058)	(1.510)	(-3.859)			[0.104]
17	**-0.010**	-0.001		0.000	**0.001**	**0.000**		**-0.008**			0.047
	(-6.787)	(-1.632)		(1.111)	(4.681)	(3.093)		(-6.573)			[0.090]
18	0.000	-0.001		**-0.001**	**0.001**	0.000	0.000	0.000	**-0.007**	0.056	0.056
	(0.684)	(-1.899)		(-4.246)	(3.475)	(0.690)	(1.706)	(0.787)	(-5.974)	(0.097)	[0.097]
19	0.000	-0.001		**-0.001**	**0.001**	**0.000**		-0.002	**-0.006**		0.058
	(-0.796)	(-1.868)		(-2.011)	(2.361)	(2.799)		(-1.358)	(-4.236)		[0.096]
20	0.000	**-0.001**		**-0.001**	**0.001**	0.000	0.000	-0.002	**-0.007**	0.000	0.056
	(0.798)	(-2.650)		(-2.078)	(2.706)	(0.606)	(1.345)	(-1.104)	(-5.130)	(-0.793)	[0.089]
21	0.000	**-0.001**		-0.001	**0.001**	0.000	0.000	-0.002	**-0.007**	0.000	0.054
	(0.849)	(-2.658)		(-1.715)	(2.430)	(0.809)	(0.866)	(-1.246)	(-5.481)	(0.756)	[0.090]
22	0.000	**-0.001**		**-0.001**	**0.001**	0.000	0.000	-0.002	**-0.007**	0.001	0.056
	(0.721)	(-2.214)		(-2.096)	(2.648)	(1.346)	(0.679)	(-1.019)	(-4.913)	(0.641)	[0.091]
23	0.000	**-0.001**		0.000	0.001	0.000	0.000	-0.003	**-0.006**	-0.003	0.054
	(0.941)	(-2.072)		(-1.086)	(1.664)	(1.209)	(0.898)	(-1.941)	(-4.214)	(-0.747)	[0.091]
24	0.000	**-0.001**		**-0.001**	**0.001**	0.000	0.000	0.000	**-0.008**	0.000	0.054
	(0.475)	(-2.976)		(-3.368)	(2.997)	(0.668)	(1.639)	(-0.498)	(-5.902)	(-0.608)	[0.089]

Source: *Datastream*, *Bloomberg* and *FRED II database*, monthly data from 1975M3 to 2012M07. Significant coefficients (at 5%) appear in bold face. The column *RS* corresponds respectively to the variables *SL*, *KC*, *PBKS*, *RBKS2* and *VIX* . Computations by the authors.

TABLE 3

PREDICTIVE REGRESSIONS OF THE INDUSTRIAL PRODUCTION GROWTH (VAR50%)

#	*Const.* (*t*-stat)	CPI_t (*t*-stat)	ΔIP_t (*t*-stat)	$LIBOR_t$ (*t*-stat)	$GB10_t$ (*t*-stat)	HP_t (*t*-stat)	PSP_t (*t*-stat)	TED_t (*t*-stat)	DEF_t (*t*-stat)	SR_t (*t*-stat)	Hit Freq. [Hit Size]
					Panel A: models with autoregressive term						
1	**0.002**	**-0.001**	**0.298**	**0.000**							0.500
	(4.408)	(-4.654)	(6.773)	(-1.978)							[1.092]
2	-0.001	**-0.001**	**0.261**	**-0.001**	**0.001**						0.498
	(-0.887)	(-5.045)	(6.805)	(-5.328)	(4.985)						[1.055]
3	-0.001	**-0.001**	**0.219**	**-0.001**	**0.002**	**0.000**	**0.000**				0.500
	(-1.907)	(-5.56)	(4.919)	(-8.012)	(7.725)	(2.401)	(2.628)				[1.008]
4	-0.001	**-0.001**	**0.211**	**-0.001**	**0.001**	0.000	0.000	-0.001			0.502
	(-1.428)	(-4.721)	(4.706)	(-4.499)	(6.977)	(1.943)	(1.794)	(-1.756)			[1.021]
5	-0.001	**-0.001**	**0.245**	**-0.001**	**0.001**	**0.000**		-0.001			0.500
	(-1.128)	(-4.708)	(5.96)	(-3.686)	(6.127)	(2.457)		(-1.701)			[1.034]
6	0.000	**-0.001**	**0.209**	**-0.001**	**0.002**	0.000	0.000	-0.001	**-0.001**		0.500
	(-0.674)	(-4.4)	(4.536)	(-5.485)	(7.835)	(1.37)	(1.497)	(-0.968)	(-2.308)		[0.996]
7	0.000	**-0.001**	**0.184**	**-0.001**	**0.001**	0.000		-0.001	**-0.002**		0.496
	(0.943)	(-3.698)	(4.01)	(-4.341)	(5.878)	(1.664)		(-0.924)	(-2.573)		[1.015]
8	-0.001	**-0.001**	**0.172**	**-0.001**	**0.002**	0.000	0.000	-0.001	-0.001	0.000	0.498
	(-0.922)	(-4.532)	(3.887)	(-4.407)	(7.052)	(1.013)	(1.378)	(-1.074)	(-1.257)	(-0.916)	[0.994]
9	0.000	**-0.001**	**0.164**	**-0.001**	**0.002**	0.000	0.000	0.000	-0.001	-0.001	0.500
	(-1.003)	(-4.922)	(3.704)	(-5.342)	(6.528)	(0.967)	(1.319)	(0.758)	(-1.793)	(-1.36)	[0.998]
10	0.000	**-0.001**	**0.185**	**-0.001**	**0.002**	0.000	0.000	-0.001	**-0.002**	-0.002	0.502
	(-1.106)	(-5.098)	(4.39)	(-5.022)	(7.448)	(1.45)	(1.469)	(-1.046)	(-2.336)	(-0.828)	[0.971]
11	0.000	**-0.001**	**0.169**	**-0.001**	**0.002**	0.000	0.000	-0.001	**-0.002**	-0.023	0.498
	(0.953)	(-4.875)	(3.687)	(-5.437)	(7.748)	(1.03)	(1.69)	(-0.845)	(-2.698)	(-0.904)	[0.97]
12	0.000	**-0.001**	**0.205**	**-0.001**	**0.002**	0.000	0.000	0.000	**-0.002**	0.000	0.496
	(0.747)	(-4.505)	(4.601)	(-5.422)	(7.055)	(1.369)	(1.552)	(-0.641)	(-2.377)	(-0.664)	[0.979]
					Panel B: models without autoregressive term						
13	**0.003**	**-0.001**		0.000							0.496
	(5.819)	(-3.184)		(-1.946)							[1.15]
14	-0.001	**-0.001**		**-0.001**	**0.001**						0.498
	(-1.04)	(-5.314)		(-7.152)	(7.016)						[1.07]
15	**-0.002**	**-0.001**		**-0.002**	**0.002**	**0.000**	**0.000**				0.493
	(-3.347)	(-6.938)		(-11.15)	(11.24)	(2.949)	(3.684)				[0.994]
16	**-0.002**	**-0.001**		**-0.001**	**0.002**	**0.000**	**0.000**	**-0.002**			0.502
	(-2.396)	(-5.62)		(-6.05)	(10.32)	(2.525)	(2.775)	(-2.651)			[1.017]
17	-0.001	**-0.001**		**-0.001**	**0.002**	**0.000**		**-0.002**			0.500
	(-1.849)	(-5.616)		(-4.675)	(8.284)	(2.517)		(-2.69)			[1.025]
18	0.000	**-0.001**		**-0.001**	**0.002**	0.000	0.000	**-0.001**	**-0.002**	0.502	0.502
	(1.695)	(-4.865)		(-6.383)	(10.26)	(1.834)	(1.741)	(-1.983)	(-3.653)	(0.967)	[0.967]
19	0.001	**-0.001**		**-0.001**	**0.002**	0.000		-0.001	**-0.003**		0.498
	(1.478)	(-3.806)		(-4.095)	(7.09)	(1.263)		(-1.586)	(-4.114)		[1.014]
20	0.000	**-0.001**		**-0.001**	**0.002**	0.000	0.000	-0.001	**-0.003**	0.000	0.496
	(1.446)	(-4.385)		(-5.979)	(9.68)	(1.307)	(1.53)	(-1.366)	(-3.71)	(-1.311)	[0.974]
21	-0.001	**-0.001**		**-0.001**	**0.002**	0.000	0.000	0.000	**-0.002**	-0.001	0.498
	(-1.038)	(-4.378)		(-7.119)	(8.728)	(1.056)	(1.752)	(0.978)	(-2.067)	(-1.999)	[0.988]
22	0.000	**-0.001**		**-0.001**	**0.002**	0.000	**0.000**	-0.001	**-0.002**	0.003	0.498
	(1.177)	(-4.455)		(-5.878)	(9.195)	(1.723)	(1.994)	(-1.713)	(-3.418)	(1.054)	[0.978]
23	0.000	**-0.001**		**-0.002**	**0.002**	**0.000**	**0.000**	0.000	**-0.003**	0.002	0.500
	(0.872)	(-4.957)		(-10.58)	(11.12)	(2.147)	(2.095)	(0.822)	(-5.004)	(0.844)	[0.945]
24	0.000	**-0.001**		**-0.001**	**0.002**	0.000	0.000	-0.001	**-0.002**	0.000	0.507
	(1.188)	(-4.695)		(-5.18)	(8.75)	(1.785)	(1.702)	(-1.555)	(-3.127)	(-1.274)	[0.983]

Source: *Datastream*, *Bloomberg* and *FRED II database*, monthly data from 1975M3 to 2012M07. Significant coefficients (at 5%) appear in bold face. The column *RS* corresponds respectively to the variables *SL*, *KC*, *PBKS*, *RBKS2* and *VIX* . Computations by the authors.

TABLE 4

PREDICTIVE REGRESSIONS OF THE INDUSTRIAL PRODUCTION GROWTH (VAR05%)

#	*Const.* (*t*-stat)	CPI_t (*t*-stat)	ΔIP_t (*t*-stat)	$LIBOR_t$ (*t*-stat)	$GB10_t$ (*t*-stat)	HP_t (*t*-stat)	PSP_t (*t*-stat)	TED_t (*t*-stat)	DEF_t (*t*-stat)	SR_t (*t*-stat)	Hit Freq. [Hit Size]
					Panel A: models with autoregressive term						
1	**0.011**	0.000	-0.020	0.000							0.049
	(8.101)	(-0.153)	(-0.219)	(1.254)							[0.066]
2	0.000	0.000	-0.042	**-0.003**	**0.004**						0.060
	(0.436)	(0.431)	(-0.538)	(-6.535)	(8.514)						[0.079]
3	**0.004**	0.000	-0.072	**-0.003**	**0.004**	0.000	0.000				0.036
	(1.977)	(-0.74)	(-1.213)	(-5.972)	(6.668)	(1.815)	(1.849)				[0.035]
4	0.001	0.000	**-0.224**	**-0.003**	**0.004**	**0.000**	0.000	0.000			0.056
	(0.521)	(-1.605)	(-2.748)	(-8.437)	(11.20)	(3.226)	(0.514)	(-0.441)			[0.064]
5	**0.004**	0.000	-0.116	**-0.002**	**0.002**	0.000		0.002			0.054
	(2.205)	(-0.941)	(-1.537)	(-4.116)	(5.878)	(0.818)		(1.132)			[0.067]
6	0.000	0.000	**-0.181**	**-0.002**	**0.003**	0.000	0.000	-0.002	0.002		0.069
	(-0.537)	(-0.961)	(-2.236)	(-3.71)	(8.437)	(0.631)	(0.59)	(-1.317)	(1.49)		[0.072]
7	0.000	0.000	-0.055	**-0.001**	**0.002**	**0.000**		-0.001	**0.005**		0.058
	(0.729)	(-1.56)	(-0.961)	(-3.61)	(6.227)	(2.328)		(-1.039)	(3.951)		[0.079]
8	0.001	**-0.001**	-0.129	**-0.002**	**0.003**	0.000	**0.000**	**-0.002**	**0.004**	-0.001	0.054
	(1.043)	(-2.36)	(-1.677)	(-4.193)	(7.215)	(1.017)	(2.53)	(-1.199)	(2.664)	(-1.03)	[0.061]
9	0.002	0.000	-0.083	**-0.002**	**0.004**	0.000	**0.000**	-0.001	-0.001	-0.001	0.058
	(1.054)	(-0.968)	(-0.933)	(-4.453)	(7.549)	(0.909)	(2.688)	(-0.769)	(-0.74)	(-1.55)	[0.073]
10	0.000	0.000	-0.108	**-0.002**	**0.003**	**0.000**	0.000	0.000	**0.003**	0.009	0.054
	(-0.968)	(-1.545)	(-1.593)	(-7.417)	(8.077)	(2.128)	(1.532)	(1.332)	(2.823)	(1.516)	[0.077]
11	0.000	-0.001	-0.095	**-0.002**	**0.003**	**0.000**	0.000	0.001	**0.004**	-0.024	0.056
	(0.663)	(-1.935)	(-1.303)	(-6.469)	(8.141)	(2.298)	(1.228)	(0.975)	(3.021)	(-0.863)	[0.079]
12	0.000	0.000	-0.172	**-0.002**	**0.004**	0.000	0.000	-0.002	0.001	0.000	0.058
	(0.716)	(-0.941)	(-1.884)	(-4.267)	(9.537)	(1.131)	(0.826)	(-1.582)	(0.902)	(-0.623)	[0.069]
					Panel B: models without autoregressive term						
13	**0.012**	0.000		0.000							0.049
	(9.055)	(-0.687)		(0.856)							[0.07]
14	**0.007**	0.000		0.000	**0.001**						0.054
	(4.262)	(-0.897)		(-1.274)	(2.995)						[0.054]
15	0.000	0.000		-0.003	**0.004**	**0.000**	0.000				0.056
	(1.544)	(-1.099)		(-8.167)	(11.97)	(2.625)	(1.728)				[0.079]
16	0.000	0.000		**-0.003**	**0.004**	0.000	0.000	0.001			0.060
	(1.191)	(-1.799)		(-7.516)	(11.73)	(0.961)	(1.944)	(1.332)			[0.073]
17	**0.004**	0.000		**-0.002**	**0.003**	0.000		0.001			0.054
	(2.058)	(0.879)		(-4.519)	(5.436)	(1.499)		(1.176)			[0.062]
18	0.000	-0.001		**-0.003**	**0.004**	**0.000**	**0.000**	**0.003**	0.002	0.051	0.051
	(-1.501)	(-1.699)		(-8.403)	(11.28)	(3.179)	(2.361)	(2.717)	(1.626)	(0.071)	[0.071]
19	0.002	0.000		**-0.001**	**0.003**	**0.000**		**-0.003**	0.002		0.054
	(1.214)	(-1.653)		(-2.753)	(5.763)	(1.969)		(-2.486)	(1.961)		[0.068]
20	0.000	0.000		**-0.002**	**0.003**	0.000	**0.000**	0.000	0.000	0.000	0.063
	(1.379)	(0.813)		(-5.818)	(10.74)	(-1.617)	(2.659)	(-1.808)	(1.438)	(1.685)	[0.084]
21	0.001	0.000		**-0.002**	**0.003**	0.000	0.000	-0.001	**0.003**	**-0.002**	0.049
	(1.247)	(-1.052)		(-4.124)	(6.862)	(1.326)	(0.932)	(-1.023)	(2.265)	(-2.296)	[0.066]
22	0.000	0.000		**-0.002**	**0.004**	**0.000**	0.000	0.001	**0.002**	0.014	0.054
	(-0.645)	(-1.135)		(-7.467)	(9.382)	(2.166)	(1.009)	(1.075)	(1.516)	(1.489)	[0.072]
23	0.001	0.000		**-0.002**	**0.003**	0.000	0.000	-0.002	**0.003**	-0.112	0.051
	(1.043)	(-1.059)		(-3.437)	(6.642)	(1.371)	(1.575)	(-1.554)	(2.228)	(-1.809)	[0.07]
24	0.000	0.000		**-0.002**	**0.002**	0.000	0.000	0.000	**0.003**	0.000	0.058
	(-1.308)	(-1.047)		(-5.037)	(6.85)	(1.486)	(1.449)	(1.582)	(3.08)	(-1.346)	[0.081]

Source: *Datastream*, *Bloomberg* and *FRED II database*, monthly data from 1975M3 to 2012M07. Significant coefficients (at 5%) appear in bold face. The column *RS* corresponds respectively to the variables *SL*, *KC*, *PBKS*, *RBKS2* and *VIX* . Computations by the authors.

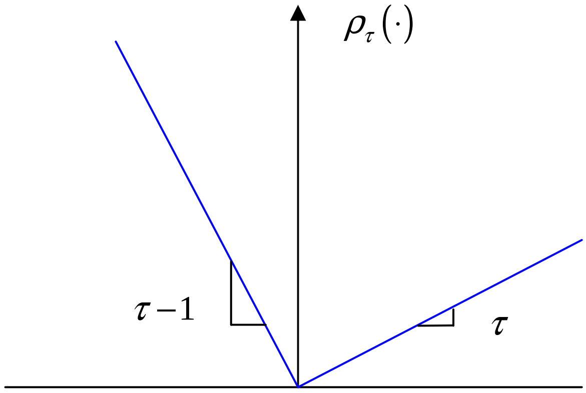

Fig. 1. Quantile regression function $\rho_\tau(\cdot)$
Source: Illustration by the authors.

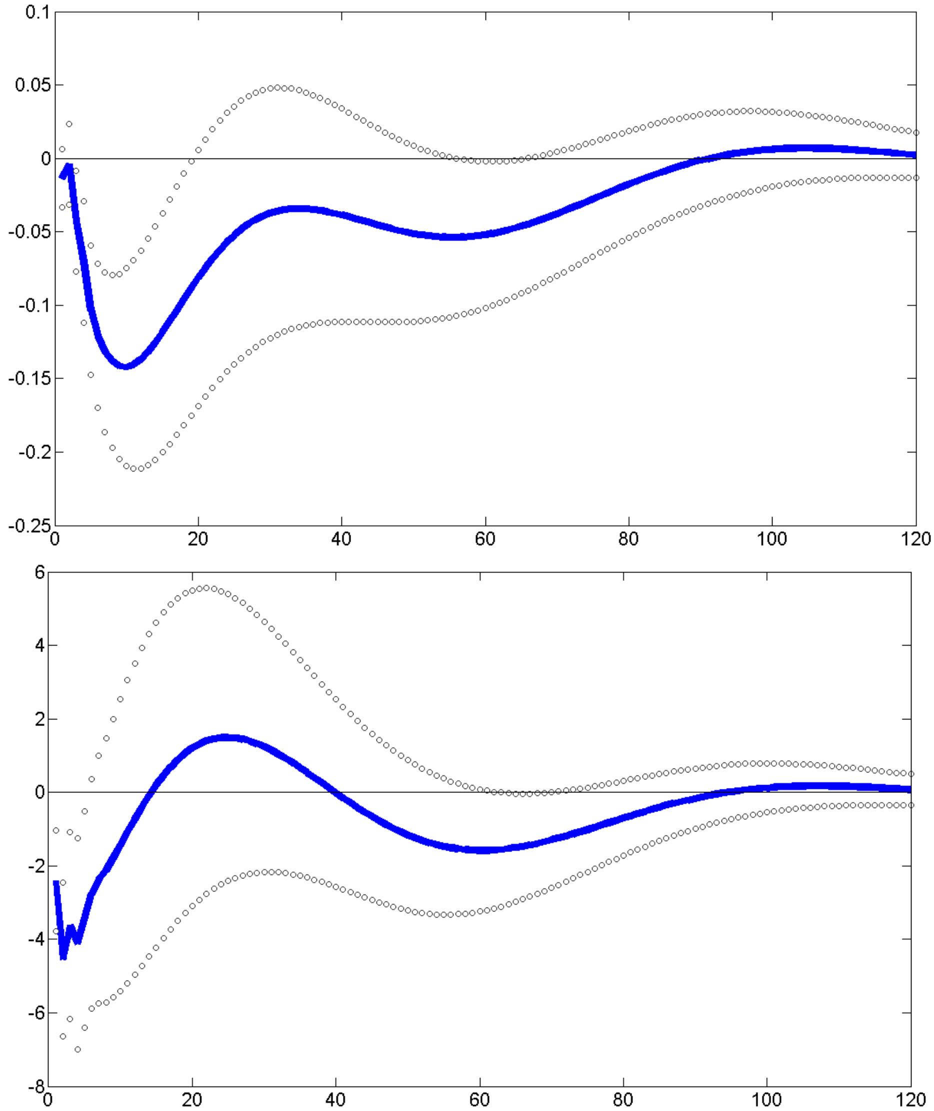

Fig. 2. Generalized impulse response functions of the industrial production growth and the equity index to a Ted spread shock
Source: *Datastream*, *Bloomberg* and *FRED II database*, monthly data from 1975M3 to 2012M07. The grey points represent the response at +/- 2 standard errors. Computations by the authors.

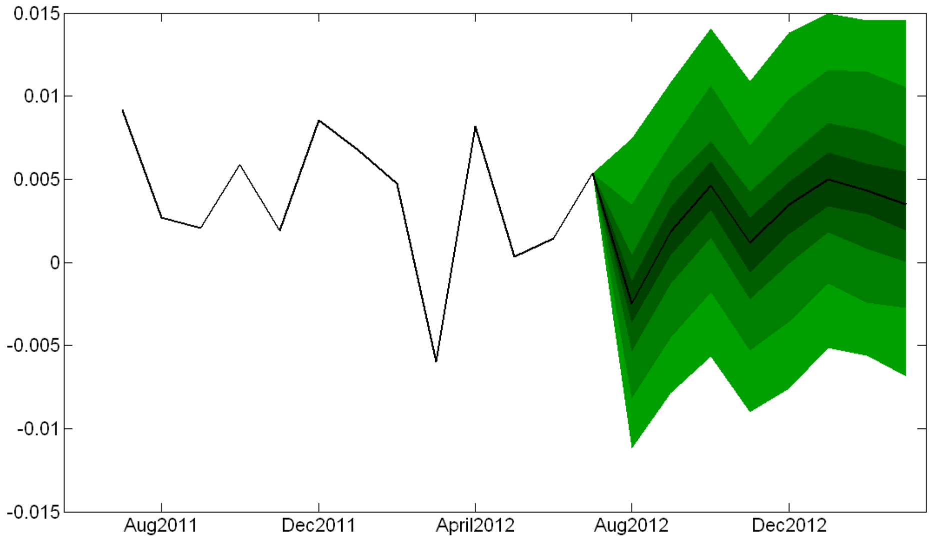

Fig. 3. Industrial production growth and out-of-sample density forecasting (VAR model)

Source: *Datastream*, *Bloomberg* and *FRED II database*, monthly data from 1975M3 to 2012M07. Computations by the authors.

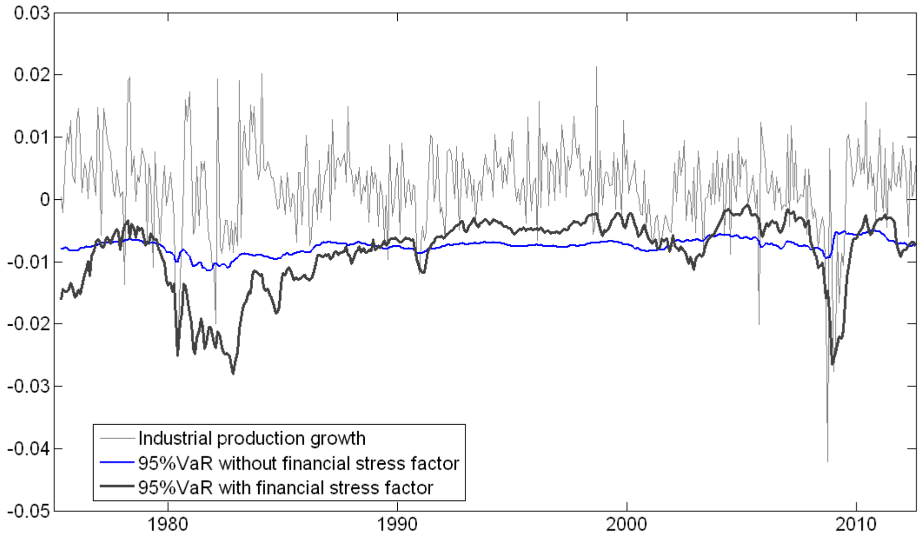

Fig. 4. Industrial production growth and its 95% estimated VaR (models with/without financial health variables)
Source: *Datastream*, *Bloomberg* and *FRED II database*, monthly data from 1975M3 to 2012M07. Computations by the authors.

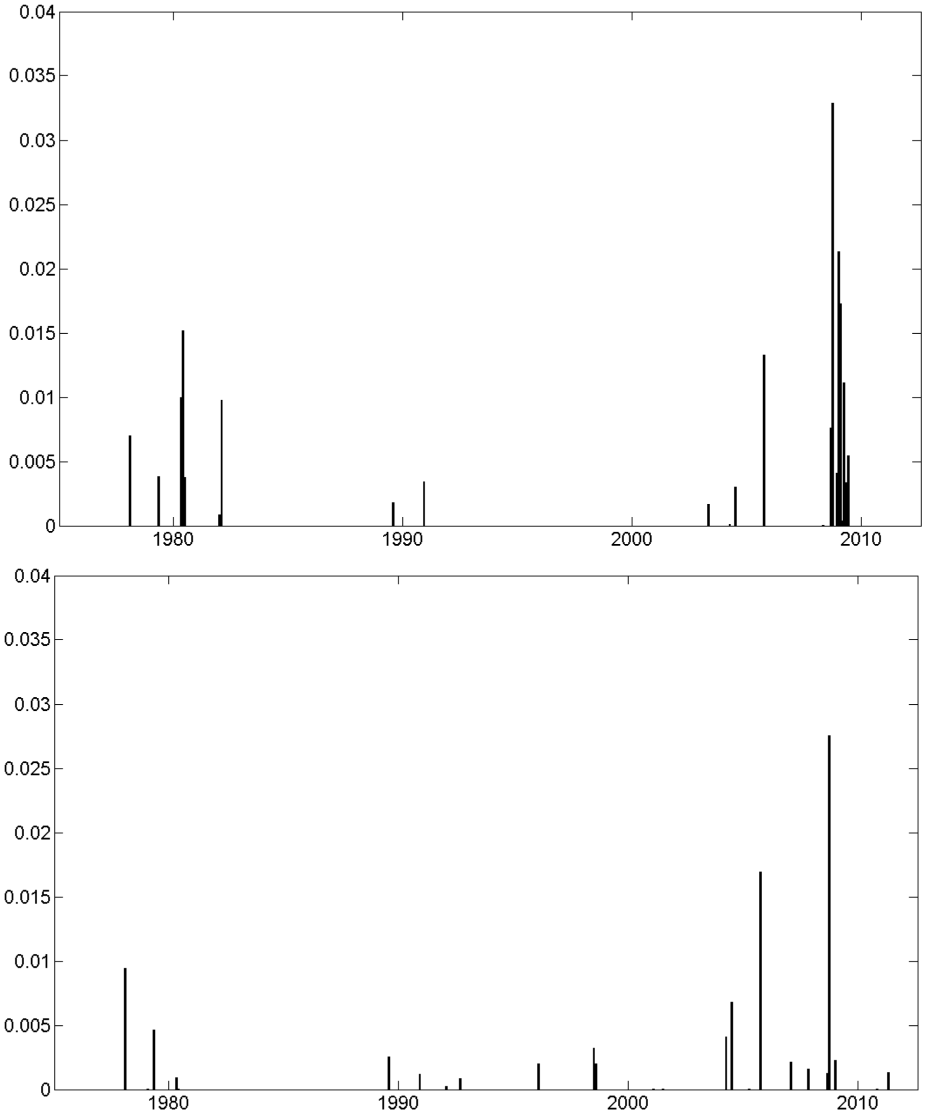

Fig. 5. Absolute value of the Hits of the predicted 95%VaR for the industrial production growth without (upper figure) and with (lower figure) the financial health variables

Source: *Datastream*, *Bloomberg* and *FRED II database*, monthly data from 1975M3 to 2012M07. Computations by the authors.

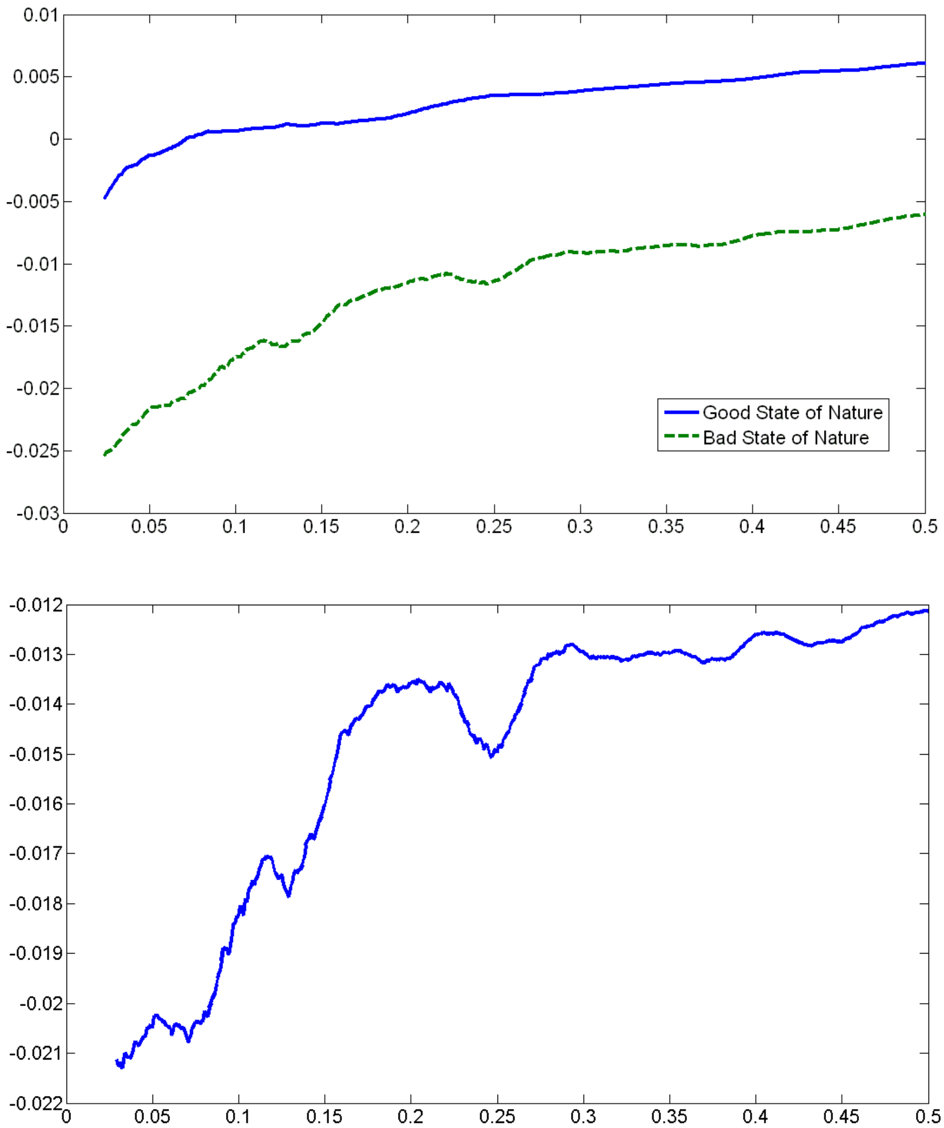

Fig. 6. Predicted quantiles (from 2.5% to 50%) of the industrial production growth in two states of the nature and their difference

Source: *Datastream*, *Bloomberg* and *FRED II database*, monthly data from 1975M3 to 2012M07. The "good state of nature" and the "bad state of nature" correspond respectively to the predicted VaR in March 2006 and October 2008. Computations by the authors.

Appendix 1. Complementary Results

TABLE A.1.

CORRELATION MATRIX

	IP	*CPI*	*LIBOR*	*HP*	*PSP*	*GB10*	*PBKS*	*RBKS2*	*TED*	*DEF*	*VIX*	*KC*	*SL*
IP	1.00	-0.08	0.28	0.55	0.72	0.07	0.64	-0.14	0.21	-0.38	-0.16	-0.12	-0.21
CPI	-0.08	1.00	0.05	-0.07	0.15	0.13	0.04	0.05	0.04	0.24	-0.07	0.14	0.14
LIBOR	0.28	0.05	1.00	0.26	0.22	0.92	0.22	-0.14	0.82	0.30	-0.07	0.58	0.56
HP	0.55	-0.07	0.26	1.00	0.33	0.14	0.76	-0.37	0.04	-0.37	-0.51	-0.33	-0.36
PSP	0.72	0.15	0.22	0.33	1.00	0.07	0.68	-0.17	0.12	-0.26	-0.18	-0.05	-0.18
GB10	0.07	0.13	0.92	0.14	0.07	1.00	0.12	-0.17	0.69	0.34	-0.11	0.53	0.56
PBKS	0.64	0.04	0.22	0.76	0.68	0.12	1.00	-0.42	0.05	-0.38	-0.45	-0.28	-0.34
RBKS2	-0.14	0.05	-0.14	-0.37	-0.17	-0.17	-0.42	1.00	0.06	0.35	0.35	0.29	0.25
TED	0.21	0.04	0.82	0.04	0.12	0.69	0.05	0.06	1.00	0.51	0.13	0.78	0.77
DEF	-0.38	0.24	0.30	-0.37	-0.26	0.34	-0.38	0.35	0.51	1.00	0.44	0.85	0.86
VIX	-0.16	-0.07	-0.07	-0.51	-0.18	-0.11	-0.45	0.35	0.13	0.44	1.00	0.46	0.42
KC	-0.12	0.14	0.58	-0.33	-0.05	0.53	-0.28	0.29	0.78	0.85	0.46	1.00	0.97
SL	-0.21	0.14	0.56	-0.36	-0.18	0.56	-0.34	0.25	0.77	0.86	0.42	0.97	1.00

Source: *Datastream*, *Bloomberg and FRED II database*, monthly data from 1975M03 to 2012M07. *IP*: industrial production, *CPI*: consumer price index, *LIBOR*: Libor 3 month rate, *HP*: house price index, *PSP*: S&P500 index, *GB10*: 10 year Treasury rate, *PBKS*: banking sector equity index, *RBKS2*: volatility of the banking sector equity index return (monthly squared returns), *TED*: Ted spread, *DEF*: Moody's BAA – AAA spread), *VIX*: implied volatility of the S&P index (*VIX*), *KC*: Financial stress index of the Kansas-City Fed, *SL*: Financial stress index of the Saint-Louis Fed. Computations by the authors.

Appendix 2. Data reconstruction

The VIX was rebuilt before 1990 from the cross-sectional volatility of the S & P 500. Figure A.1 shows on the period of availability of the VIX, the VIX itself and its reconstruction from the cross-volatility.

Composite indicators of financial stress of the Federal Reserve of St. Louis and Federal Reserve Bank of Kansas City are calculated by Principal Component Analysis (PCA). The weekly index Fed Saint-Louis is constructed from 18 data sets including data from 1994 interest rate (effective rate of the Federal Reserve rate 2 years, 10 years, 30-year U.S. Treasury etc..) data rate spreads (yield curve Treasury yield curve corporate, Ted spread, etc..) and various data (VIX volatility index bond market, etc.).. The monthly index of the Kansas City Fed is itself constructed from 11 data sets since February 1990 including data rate spreads means (Ted spread, spread AAA and 10-year Treasury, etc..) and measures based on current or anticipated behaviour of asset prices (VIX correlation between stock returns and yields of Treasury bonds, etc.).. These two indicators were reconstructed until the early 1990s from a principal components analysis on our other indicators of financial stress. The comparison of these two indicators with their reconstruction that appears in Figure A.2 shows these indicators are highly correlated in periods of stress even if level differences appear in situations "normal".

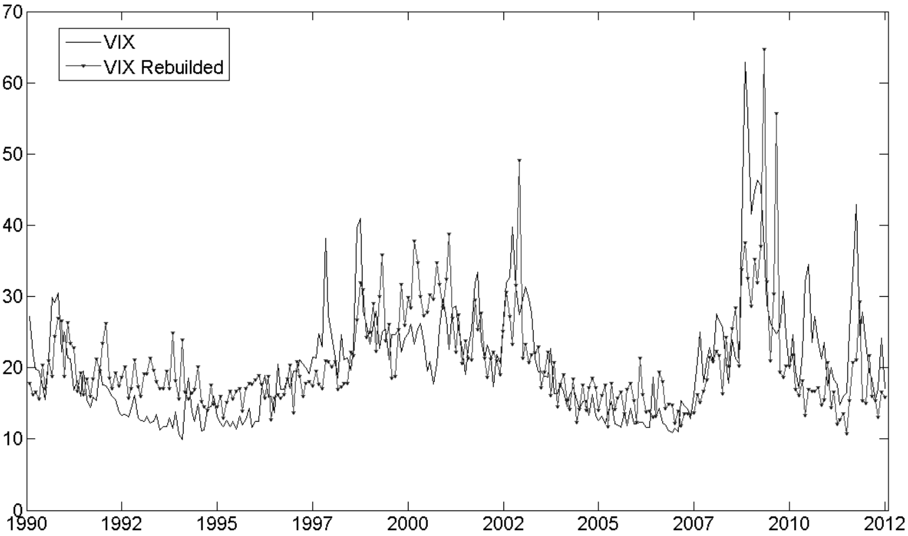

Fig. A.1. Implied volatility (VIX) and its completion based on the cross-volatility of the S&P500 equity index over the period 1990M01-2012M07
Source: *Datastream*, *Bloomberg* and *FRED II database*, monthly data from 1975M3 to 2012M07. Computations by the authors.

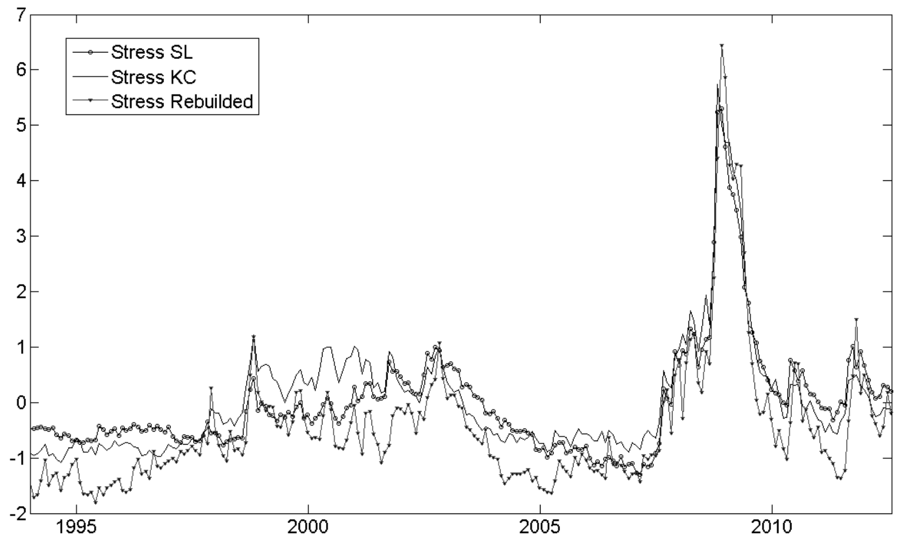

Fig. A.2. Financial stress indices (Saint-Louis fed and Kansas City Fed) and their completion over the period 1994M01-2012M07
Source: *Datastream*, *Bloomberg* and *FRED II database*, monthly data from 1975M3 to 2012M07. Computations by the authors.