Banks, Risk, and the Business Cycle: An Analysis Based on Real-Time Data

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An important question for stock market investors and bank supervisors is to which extent the stock returns of banks reflect business-cycle-sensitive risk in the banking industry. In order to answer this question, we used the stochastic discount factor model to derive a multivariate exponential GARCH-in-mean model. We used monthly U.S. data for the period from 1980 to 2006, for both real-time and revised macroeconomic data to estimate the model. Our empirical results show that using real-time rather than revised macroeconomic data can significantly alter estimates of the risk premium that stock market investors require for bearing business-cycle-sensitive risk in the banking industry.
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1. Introduction

Several arguments can be made that the business cycle plays a major role for the amount of risk lurking in the banking industry. One argument states that a business-cycle downturn is likely to deteriorate households' and firms' balance sheets, which, in turn, should increase the risk of default of outstanding loans. Another argument implies that this risk is aggravated because problems due to an asymmetric distribution of information among banks and their borrowers give rise to procyclical agency costs. Procyclical agency costs may reflect that problems due to adverse selection among borrowers are likely to get worse during business-cycle downturns. Yet another argument stipulates that problems due to an asymmetric distribution of information may imply that moral hazard and excessive risk-taking behavior on the side of banks' borrowers become more of a problem in bad times than in good times. Finally, excessive risk-taking on the side of banks may also be a problem. A common argument is that deposit insurance schemes may imply that banks choose a risky asset portfolio and gamble on resurrection, implying that risks in the banking industry exacerbate during business-cycle downturns. Profound theoretical analyses of these arguments can be found in Diamond (1983), Bernanke and Gertler (1989), Rajan (1994), and Kiyotaki and Moore (1997), to name just a few.

The results reported in the theoretical literature have led researchers to ask whether and, if so, how risk in the banking industry varies over the business cycle. In a rapidly growing empirical literature, researchers have addressed these questions by analyzing the sensitivity of stock returns of banks to potentially important risk factors like, for example, interest rates and other macroeconomic variables (Dewenter and Hess 1989, Song 1994, Elyasiani and Mansur 1998, Baele et al. 2004). Our contribution to this strand of the empirical literature is that we show that, when analyzing the link between stock returns of banks and the business cycle, it may be important to account for the fact that macroeconomic data available to researchers typically differ from the macroeconomic data available to stock market investors, bank supervisors, and monetary authorities in real time. Researchers have access to accurate macroeconomic data that have been revised many times. In contrast, when reaching decisions in real time, stock market investors, bank supervisors, and monetary authorities have access only to preliminary first-releases of macroeconomic data. In real time, the issue arises that investors and authorities can base their inferences regarding business-cycle-sensitive risk in the banking industry only on the then latest release of publicly available macroeconomic data. Given the enormous importance of this issue, it is surprising that only few studies report evidence of the implications of using real-time macroeconomic data for research in empirical finance (see, for example, Christoffersen et al. 2002, Evans and Speight 2006, Pierdzioch et al. 2008).

Our empirical analysis can be summarized as follows. In a first step, we used the stochastic discount factor (SDF) model to analyze the link between risk in the banking industry and the business cycle. The SDF model provides a general framework for pricing of assets in arbitrage-free markets (Smith and Wickens 2002). The model implies that the risk premium that stock market investors demand for bearing business-cycle-sensitive risk should be proportional to the covariance of returns on stocks of banks with the business cycle. In a second step, we used the SDF model to derive a multivariate exponential GARCH-in-mean (MEGARCH-M) model. In recent years, the multivariate GARCH-M model has been popular among researchers to study the macroeconomic determinants of the risk premium in stock markets (Scruggs 1998, Smith et al. 2009). In the earlier literature, univariate GARCH models have been used by Song (1994) and Elyasiani and Mansur (1998) to study the dynamics of stock returns of banks. Our MEGARCH-M model provides a unified framework to model the joint distribution of the stock returns of banks and macroeconomic variables over the business cycle. In a third step, we used data on industrial production and data on the term spread to measure the business cycle. We estimated our MEGARCH-M model using monthly U.S. data for the period from 1980 to 2006. (We deliberately decided not to analyze very recent data because the recent collapse of the U.S. banking industry is likely to have resulted in a structural break in the data generating process.)

Our results show that using real-time rather than revised macroeconomic data yields estimates of business-cycle-sensitive systematic risk in the banking industry that are significantly different from estimates that are based on revised macroeconomic data. This difference between estimates is economically interesting for several reasons. For example, bank supervisors should account for this difference between estimates of systematic risk when measuring and controlling systematic risk in the banking industry in real time. As witnessed by the financial crisis of 2007/2009, banking supervisors and monetary authorities hardly can wait until revised macroeconomic data become available when deciding on important banking-regulation issues in times of market jitters and financial turmoil. What is needed in such turbulent times is a model that links business-cycle-sensitive systematic risk to real-time macroeconomic data. In a similar vein, because the risk premium fluctuates over time, our estimates may provide useful information for banks' CEOs. If CEOs use real-time macroeconomic data rather than revised macroeconomic data for estimating business-cycle-sensitive-systematic risk in the banking industry, this may have profound implications for decisions regarding the rebalancing of asset portfolios and the underwriting of new capital. Finally, our results are useful in terms of economic model building. Our results reveal that the conditional variance of output growth is a significant component of the risk premium. In line with, for example, models of procyclical agency costs, our results indicate that the risk premium investors required for investing in stocks of banks fluctuated more strongly over the business cycle than the risk premium on the market portfolio.

Our research goes beyond earlier empirical studies in empirical finance based on real-time macroeconomic data in several respects. First, Christoffersen et al. (2002) and Evans and Speight (2006) use cross-sectional risk-factor regressions to study the pricing of macroeconomic risk factors. Our empirical study, in contrast, is explicitly based on the SDF asset-pricing model. Our study, thus, differs from earlier studies in terms of the theoretical model that we use to motivate our empirical analysis. The SDF model encompasses various micro-founded asset pricing models and can be interpreted as an application of the Arrow-Debreu model to the pricing of risky assets in arbitrage free markets.

Second, we used the SDF model to study time-varying business-cycle-sensitive risk in the banking industry by means of a MEGARCH-M model. Our empirical study, thus, differs in an important way from earlier real-time-data-based studies with respect to the empirical model that we used to study real-time macroeconomic data. In our model, macroeconomic innovations can affect the time-varying mean and the time-varying conditional volatility of stock returns. In addition, the MEGARCH-M model embeds a vector autoregressive model that captures potential feedback effects of stock market developments on macroeconomic data. The global financial market crisis of 2007/2009 witnesses the potential importance of such feedback effects. The potential importance of feedback effects also follows from models of the "financial accelerator" tracing back to the research of, for example, Bernanke and Gertler (1989), and others.

Third, the way we measured real-time macroeconomic data differs from the approaches taken in earlier studies. For example, Pierdzioch et al. (2008) use real-time and revised macroeconomic data to analyze the out-of-sample predictability of stock returns. They use a recursive modelling approach that needs as data input entire vintages of real-time macroeconomic data. For our empirical study, in contrast, we constructed a time series of the real-time growth rate of macroeconomic data by using the last two observations from a vintage of macroeconomic data. This construction of the data implies that our analysis sheds light on how innovations in macroeconomic data affect time-varying business-cycle-sensitive risk in the banking industry rather than on the longer-run equilibrium link between the stock returns of banks and macroeconomic variables.

In addition, in our empirical analyses, we were not interested in the type of out-of-sample predictability of stock returns analyzed by Pierdzioch et al. (2008). Rather, we studied the in-sample pricing of macroeconomic risk factors. The MEGARCH-M model is particularly suited to study the in-sample pricing of macroeconomic risk factors because it renders it possible to invoke several theoretically well-founded economic restrictions. Finally, our study goes beyond earlier studies in that we explicitly focus on the banking industry.

We organize the remainder of this paper as follows. In Section 2, we lay out how we used the SDF model to derive our MEGARCH-M model. In Section 3, we describe the data we used in our empirical analysis. In Section 4, we report our empirical results. In Section 5, we offer some concluding remarks.

2. The Empirical Model

The stochastic discount factor (SDF) model provides a general framework for the pricing of assets in arbitrage-free markets. The SDF model stipulates that the expected stock returns of banks between period t and period $t+1$ satisfy the no-arbitrage condition

$$E_t(M_{t+1}R_{t+1}) = 1\,, \tag{1}$$

where E_t denotes the conditional-expectations operator and M_{t+1} denotes the SDF. The (gross) stock returns in the banking industry are defined as $R_{t+1} = 1 + r_{t+1}$, where r_{t+1} denotes net returns. The SDF can be thought of as an application of the Arrow-Debreu general equilibrium model to arbitrage-free asset pricing (Campbell 2000). In the Arrow-Debreu general equilibrium model, uncertainty is modeled in terms of future states of nature, which will realize according to some probability law. In the absence of arbitrage opportunities, there exists a set of positive state prices, implying that the SDF is a random variable with positive realizations. If complete markets exist, then both the SDF and state prices are uniquely determined (Campbell 2000). The generality of the SDF model, as defined by Equation (1), implies that it encompasses various micro-founded asset-pricing models, and more flexible asset-pricing models based on a multidimensional modeling of risk factors. An example of the former is the standard capital asset pricing model (CAPM) (for survey of CAPM and CCAPM applications, see Smith and Wickens 2002). An example of the latter is the arbitrage pricing theory developed by Ross (1976) (for a survey, see Connors and Korajczyk 1995).
Assuming log-normality and taking logarithms gives

$$E_t(m_{t+1}) + E_t(r_{t+1}) + \tfrac{1}{2}V_t(m_{t+1}) + \tfrac{1}{2}V_t(r_{t+1}) + Cov_t(m_{t+1}, r_{t+1}) = 0\,, \tag{2}$$

where $m_{t+1} = \ln M_{t+1}$, and V_t and Cov_t denote the conditional variance and covariance operators. A risk-free asset that yields a rate of return of r^f_{t+1} must satisfy the equation

$$E_t(m_{t+1}) + r^f_{t+1} + \tfrac{1}{2}V_t(m_{t+1}) = 0 \,. \tag{3}$$

Upon combining Equations (2) and (3), one gets

$$E_t(r_{t+1} - r^f_{t+1}) + \tfrac{1}{2}V_t(r_{t+1}) = -Cov_t(m_{t+1}, r_{t+1}) \,. \tag{4}$$

The right-hand side of Equation (4) represents the risk premium that stock market investors demand for bearing the risk in the banking industry. The term $\frac{1}{2}V_t(r_{t+1})$ captures a time-varying effect that arises because of Jensen's inequality.

We assume that the SDF can be expressed as a linear function of macroeconomic variables, $-m_{t+1} = \beta' z_{t+1}$, where β denotes a 2×1 vector of parameters to be estimated, and z_t denotes a 2×1 vector that contains data on the growth rate of output (industrial production) and data on the term spread. Equation (4) can then be rewritten as

$$E_t(r_{t+1} - r^f_{t+1}) = -\tfrac{1}{2}V_t(r_{t+1}) + \sum_{i=1}^{2} \beta_i Cov_t(z_{i,t+1}, r_{t+1}) \,. \tag{5}$$

The unrestricted version of Equation (5) that we used in our empirical analysis is given by

$$E_t(r_{t+1} - r^f_{t+1}) = \beta_0 V_t(r_{t+1}) + \sum_{i=1}^{2} \beta_i Cov_t(z_{i,t+1}, r_{t+1}) \,. \tag{6}$$

We opted for the MEGARCH-M model to estimate Equation (6). A key advantage of the MEGARCH-M model is that it can be used to estimate the time-varying conditional variance and covariances that feature prominently in Equation (6). The conditional mean equation of the MEGARCH-M model, written in the form of a vector autoregressive model (VAR), is given by

$$Y_t = A + BY_{t-1} + \Gamma \Sigma_t j_r + u_t \,, \tag{7}$$

where A is a 3×1 vector, B and Γ are 3×3 matrices, $Y_t = (\Delta y_t, s_t, r_t)'$ is a 3×1 vector of variables, j_r is a 3×1 selection vector that selects the third column of Σ_t, and u_t denotes a normally distributed zero-mean 3×1 error vector with a time-varying conditional variance-covariance matrix, Σ_t. The vector Y_t contains the growth rate of output, Δy_t, the term spread, s_t, and (excess) returns on stocks of banks, r_t. Consistency with the SDF model requires that the third element of the vector A and the third-row elements of the matrix B are zero. The third row of the matrix Γ contains both the effect capturing Jensen's inequality and the time-varying covariances, and its first row and second row are zero.

We used a triangular factorization to model the conditional variance-covariance matrix, Σ_t (Tsay 2002). The triangular factorization uses the fact that the Choleski decomposition of the positive-definite conditional variance-covariance matrix is given by $\Sigma_t = LG_tL'$, where L denotes a 3×3 lower triangular matrix with unit diagonal elements, and G_t denotes a 3×3 matrix with positive diagonal elements and zero off-diagonal elements. The matrices L and G_t are given by

$$L = \begin{pmatrix} 1 & 0 & 0 \\ l_{21} & 1 & 0 \\ l_{31} & l_{32} & 1 \end{pmatrix}, \qquad G_t = \begin{pmatrix} g_{11,t} & 0 & 0 \\ 0 & g_{22,t} & 0 \\ 0 & 0 & g_{33,t} \end{pmatrix}, \tag{8}$$

where the elements l_{ij} represent the Choleski factors and the elements $g_{ii,t}$ can be interpreted as structural variances.

The triangular factorization is based on a identification scheme that makes use of a recursive ordering of the endogenous variables in the VAR (Sims 1980). According to this identification scheme the residuals of a reduced-form VAR can be decomposed into a series of structural residuals by invoking a set of restrictions on the contemporaneous relations among the endogenous variables of the VAR. Conceptually, the Choleski decomposition of the variance and covariance matrix of the innovations to the VAR is based on the idea that financial markets exhibit forward-looking behavior and may instantaneously react if new information regarding the stance of the business cycle become publicly available. Based on new information on the stance of the business cycle, investors can immediately reassess the risk of equity market investments. In contrast, output growth reacts only with a lag to innovations in financial market variables. In order to formalize this idea, a triangular factorization of the conditional variance and covariance matrix implies that an innovation to excess returns on stocks of banks is restricted to have no contemporaneous effect on the conditional variance of output growth and the term spread. An innovation to output growth, in contrast, can exert a contemporaneous effect on the conditional variances of the term spread and excess equity return. Moreover, an innovation to the term spread can have a contemporaneous effect on the conditional variance of excess equity returns, but not on the conditional variance of output growth. Finally, it should be noted that the Jensen effect indirectly accounts for the contribution to excess returns on stocks of banks of both the time-varying structural conditional variances of innovations to excess equity returns and the time-varying structural conditional variances of innovations to the macroeconomic variables.

The triangular factorization ensures positive-definiteness of Σ_t as long as the elements $g_{ii,t}$ are positive. In addition, the triangular factorization is an orthogonal transformation. This implies that the resulting likelihood function is extremely simple. The log-likelihood function to be maximized is given by (Tsay 2002):

$$LL = -\frac{1}{2}\sum_t \sum_i \left[\ln(g_{ii,t}) + \frac{v_{i,t}^2}{g_{ii,t}}\right], \tag{9}$$

where we have dropped a constant term. Estimation by quasi-maximum likelihood (QML) gives consistent estimates under weak assumptions even if the standardized residuals are not normally distributed (Bollerslev and Wooldridge 1992). We computed robust standard errors from the diagonal elements of the QML estimator.

An EGARCH model (Nelson 1991), captures the dynamics of the structural variances, $g_{ii,t}$ by means of the following equation:

$$g_{ii,t} = \exp\left(\alpha_{i0} + \alpha_{i1}\ln(g_{ii,t-1}) + \alpha_{i2}\frac{v_{i,t-1}}{\sqrt{g_{ii,t-1}}} + \alpha_{i3}\left(\left|\frac{v_{i,t-1}}{\sqrt{g_{ii,t-1}}}\right| - \sqrt{\frac{2}{\pi}}\right)\right), \tag{10}$$

where we have used the orthogonal transformations $v_{1,t} = u_{1,t}$, $v_{2,t} = u_{2,t} - l_{21}u_{1,t}$, and $v_{3,t} = u_{3,t} - l_{31}u_{1,t} - l_{32}u_{2,t}$.

The EGARCH model has been used by Scruggs (1998) and Adrian and Rosenberg (2008) to model the equity risk premium. Consistent with the findings reported by Engle and Ng (1993), the EGARCH model implies that a negative realization of $v_{i,t}$ increases variances more than a positive realization of the same magnitude, provided $\alpha_{i2} < 0$. Moreover, a large negative (positive) realization of $v_{i,t}$ raises variances more than a small negative (positive) shock, provided $\alpha_{i3} > 0$.

3. The Data

We collected monthly U.S. data for the sample period 1980–2006 on the growth rate of output (total industrial production), Δy_t, the term spread, s_t, and excess returns of the stocks of banks, r_t.

The data we used to calculate s_t and r_t are from Thompson Financial Datastream. Returns are defined as the annualized month-to-month capital gain on the Datastream-calculated banking-sector index plus dividend yield. In order to compute excess returns, we subtracted from returns the 3-month Treasury Bill rate. We used the latter together with the 10-year government bond yield to calculate the term spread. Chen et al. (1986) and Campbell (1987) analyze the term structure as a predictor of the variation in expected returns over time. Fama and French (1989) study the cyclical variation of the term spread over the business cycle. In a similar vein, Fama (1990) argues that the term structure captures cyclical variation in expected returns on stocks. The term spread in our model is similar to the excess bond return analyzed by Scruggs (1998).

We calculated output growth as the annualized month-to-month rate of change in an industrial production index. To this end, we retrieved publicly available real-time data on industrial production from the website of the Federal Reserve Bank of Philadelphia (2006). As described in detailed in Croushore and Stark (2001), the real-time macroeconomic data are organized in vintages. A vintage contains the data that would have been available to equity market investors, regulators of the banking industry, and monetary authorities in real time. Successive vintage differ because (i) new data become available over time, and (ii) historical data are retroactively revised.

The last vintage in our sample, released in January 2007, contains the most recent available macroeconomic data, also called "revised data". We used the last vintage in our sample to compute the revised growth rate of output. In contrast, we computed a time series of the real-time growth rate of output by extracting from every vintage in our sample the last two observations. This computation is built on the notion that, in real time, stock market investors, bank supervisors, and monetary authorities use the most recent release of data to make inferences regarding the business-cycle sensitive risk in the banking industry. Our computation implies that a release in April of data on the growth rate of output in March affects the risk premium in April, not in March.

Table 1 summarizes descriptive statistics. The sample mean of the growth rate of output measured with revised data is greater than the sample mean of the growth rate measured of output with real-time data. The sample standard deviation is comparable across the revised and the real-time growth rates. With regard to the coefficient of asymmetry, the data in general are negatively skewed, where excess equity returns are an exception. The negative skewness supports our decision to estimate a MEGARCH-M as a means to model the asymmetric sign and size effects in the data. The excess equity returns are positively but not significantly skewed. The data also appear to have leptokurtic (except for the term spread) and non-normal distributions. The quasi-maximum likelihood estimator produces consistent estimates even in case of deviations from normality.

Table 1
Summary of Descriptive Statistics

Row	Diagnostic Statistic	Output Growth (Real-Time)	Output Growth (Revised)	Term Spread	Excess Return
1	Mean	1.8144	2.5405	1.7776	15.419
2	Median	2.7170	3.1746	1.7900	16.697
3	Maximum	24.911	26.837	4.4200	268.46
4	Minimum	-35.983	-31.746	-2.6500	-250.68
5	Std. Dev.	7.7424	7.6478	1.2897	65.273
6	Skewness	-1.0044	-0.2651	-0.5890	-0.1864
7	Kurtosis	6.3261	4.6863	3.1996	4.6901
8	Jarque-Bera	0.0000	0.0000	0.0001	0.0000
9	Q(12)	0.0000	0.0000	0.0000	0.0000

Notes: This table summarizes descriptive statistics for output growth rate (measured with real-time and revised macroeconomic data), the term spread, and the excess returns on an index of the U.S. banking industry. Jarque-Bera represents the p-value of the test for non-normality of the distribution. Q(12) represents the p-value of the Ljung-Box Q-Test for autocorrelation of order 12 in squared values.

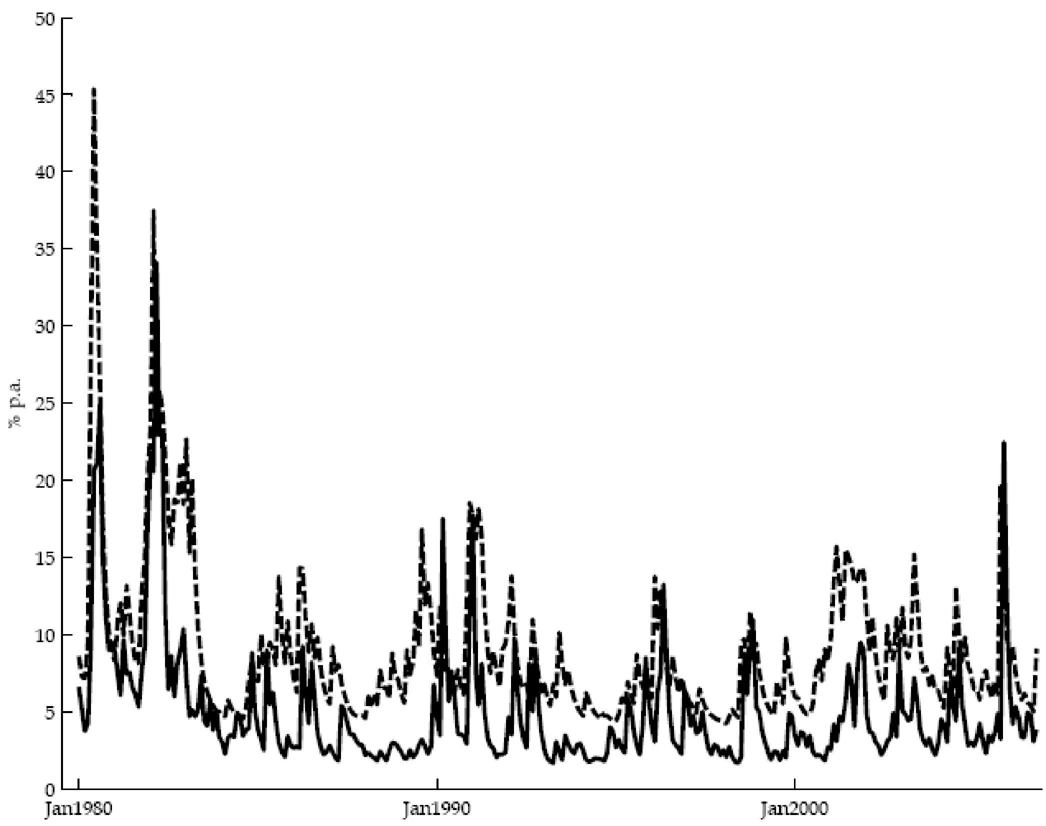
4. Empirical Results

We present our empirical results in two steps. In a first step, we present results on the risk premium. In a second step, we report results on the conditional variances and the conditional-mean model implied by our MEGARCH-M model.

4.1 The Risk Premium

The solid line shown in Figure I shows the risk premium for investing in bank stocks that we obtained when we used real-time macroeconomic data to estimate our MEGARCH-M model. The dashed line shows the risk premium that we obtained when we used revised macroeconomic data. Consistent with Merton's (1980) analysis, both the solid and the dashed lines are positive over the whole sample period. A comparison of the dashed line with the solid line reveals that estimates of the risk premium based on real-time macroeconomic data can substantially differ from estimates on revised macroeconomic data. This difference can have important implications for investors' real-time assessment of the business-cycle-sensitive risk arising from investments in bank stocks. The difference can also be important for bank supervisors who seek to measure and control systematic risk in the banking industry. The difference between estimates of the risk premium based on real-time and revised macroeconomic data may also be important for banks' CEOs, who may use estimates of the risk premium for deciding whether to rebalance asset portfolios and to underwrite new capital.

Figure I
The Risk Premium



Note: Solid lines (dashed lines) represent the real-time (revised) data.

As regards the link between the risk in the banking industry and the business cycle, a few more remarks are in order. The risk premium was relatively large at the beginning of the sample period, which follows the recession phase in the first half of the 1980 in the United States. The second half of the 1980s was a phase that witnessed a relatively low risk premium and a strong expansion of the economy. This phase, however, also saw months of a relatively large risk premium during and after the stock market crash in 1987. The recession of the U.S. economy in 1990/1991 is clearly marked by a rise in the risk premium. The risk premium was relatively small during the subsequent prolonged expansion until 2001. The risk premium substantially increased thereafter when the economy entered the recession of 2001. The estimated increase in the risk premium is somewhat stronger when revised rather than real-time macroeconomic data are used.

Table 2 summarizes our results on the link between the risk premium and the business cycle. Panel A of Table 2 shows the average risk premium during expansions and during recessions. We defined expansions and recessions according to the NBER business-cycle-dating system. When estimates of our MEGARCH-M model are based on real-time macroeconomic data, the risk premium is 3.65 percentage points lower in expansions than in recessions. The risk premium is 6.86 percentage points lower in expansions than in recessions when revised macroeconomic data are used for estimation.

Panel B of Table 2 shows the results that we obtained when we used data for the period 1980–2006 on the returns on the S&P500 index to estimate our MEGARCH-M model. The risk premium is smaller when the S&P500 index is used for estimation, which is likely to reflect diversification effects. More interesting is the result that, as compared to the results for the banking industry, the increase in the risk premium during a recession is much smaller in the case of the S&P500 index. If real-time macroeconomic data are used for estimation, the risk premium only increases by approximately 1.3 percentage points. If revised macroeconomic data are used for estimation, the risk premium increases by about 3.6 percentage points. Thus, the cyclical variation in the risk premium investors require for investing in the S&P500 index is much smaller than the cyclical variation in the risk premium investors require for investing in the banking industry. The differences between the results reported for the S&P500 index and the banking industry may reflect, apart from diversification effects, that the risk of investing in the banking industry is particularly sensitive to business-cycle fluctuations.

Table 2
Expansions, Recessions, and the Risk Premium

Panel A

Banking Industry	Expansion	Recession
Real-time data	4.34	7.99
Revised data	9.76	16.62

Panel B

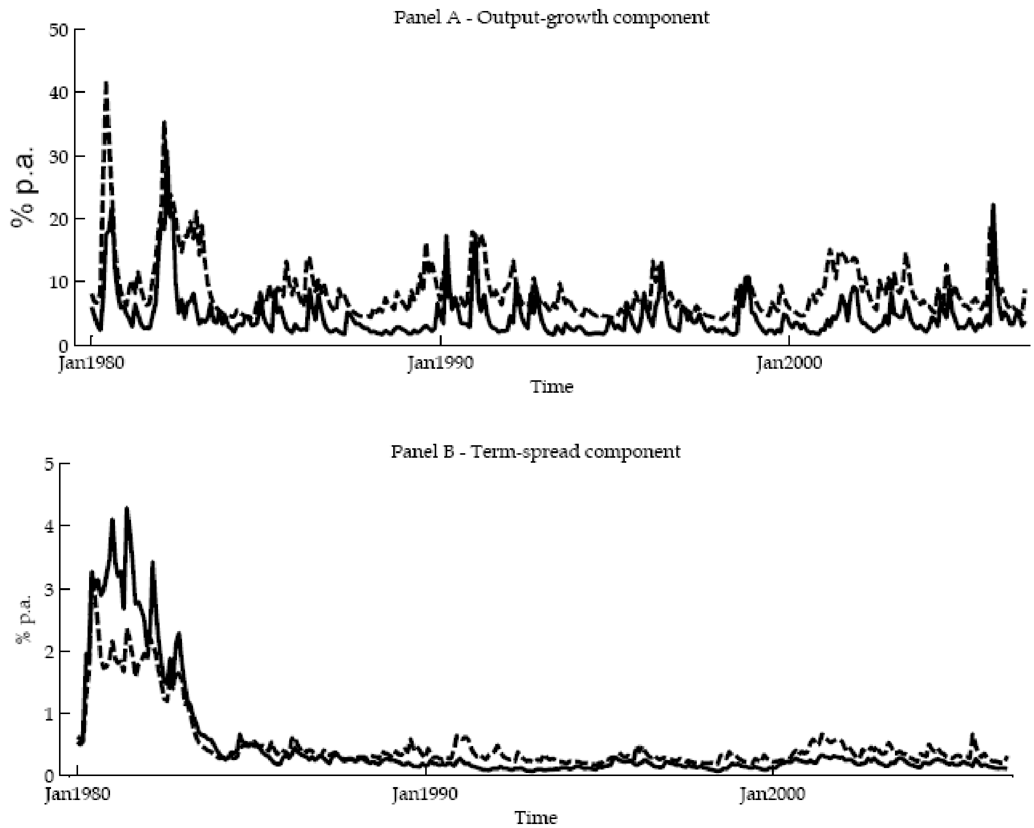
S&P500	Expansion	Recession
Real-time data	2.55	3.86
Revised data	7.98	11.62

Notes: This table summarizes the average risk premium (based on real-time macroeconomic data and based on revised macroeconomic data) in economic expansions and recessions. Economic expansions and recessions are defined according to the NBER business-cycle dating system.

Table 2 further shows that the risk premium that investors demand for investing in the stocks of banks is lower when real-time macroeconomic data are used for estimation than when revised macroeconomic data are used. This result holds irrespective of whether the economy experienced an expansion or a recession.

A closer look at the components of the risk premium yields further interesting insights. The two components of the risk premium shown in Figure II are the output-growth component and the term-spread component.

Figure II
Components of the Risk Premium



Note: Solid lines (dashed lines) represent the real-time (revised) data.

Panel A graphs the output-growth component and Panel B sketches the term-spread component. The output-growth component was on average larger than the term-spread component. Moreover, both components of the risk premium were lower when estimated with real-time rather than with revised macroeconomic data. Only at the beginning of the 1980s was the term-spread component estimated based on real-time macroeconomic data larger than the term-spread component estimated based on revised macroeconomic data. During the first years of the 1980s, bond-market volatility was considerably higher than during the rest of the sample, probably reflecting uncertainty about the stance of monetary policy (Elyasiani and Mansur 1998).

The estimation results summarized in Tables 3 and 4 show that the output-growth component is significant when real-time macroeconomic data are used to estimate our MEGARCH-M model. The term-spread component is insignificant, irrespective of whether real-time or revised macroeconomic data are used for estimation. The coefficient capturing Jensen's inequality is significant when estimates are based on real-time macroeconomic data.

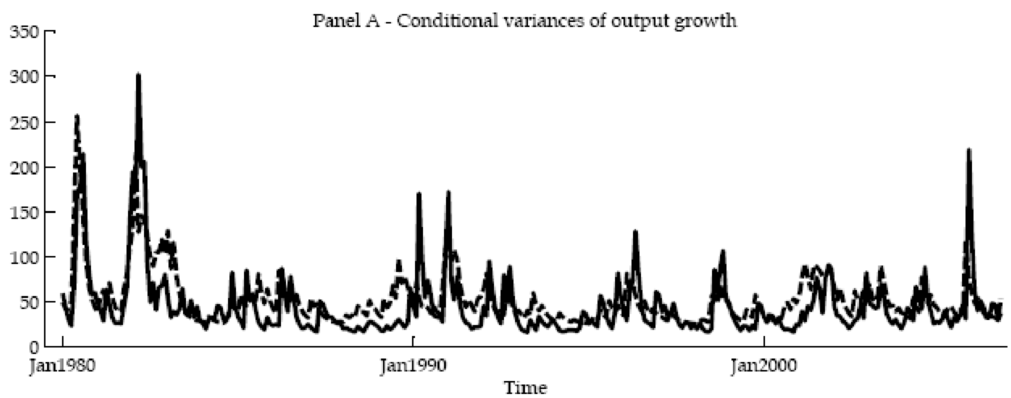
4.2 The Conditional Variances and the Conditional-Mean Model

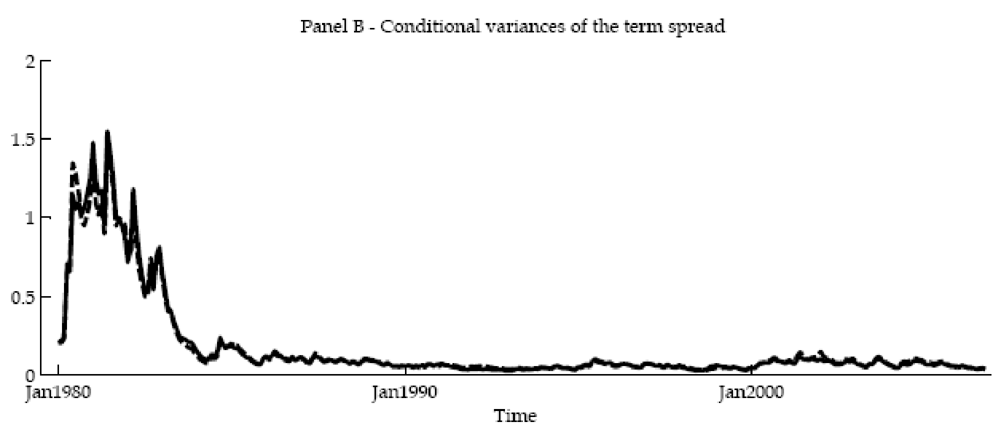
The estimated time-varying conditional variances graphed in Figure III suggest that the risk premium was mainly determined by the conditional variance of the growth rate of output. The conditional variance of the term spread may have contributed to the risk premium at the beginning of the sample, following the monetary regime change that took place in 1979. During the remainder of the sample, the conditional variance of the term spread was small.

The conditional variance of output growth is often larger when it is estimated with revised rather than with real-time macroeconomic data. Furthermore, in periods of high output volatility and, thus, large uncertainty about the stance of the business cycle potential problems due to, for example, asymmetric information and moral hazard are likely to aggravate, which, in turn, may be reflected in estimates of the risk premium.

The parameter estimates summarized in Tables 3 and 4 suggest that the GARCH effects are close to unity, suggesting that changes in the conditional variances are very persistent. The size effect is significant and the corresponding coefficient has the expected positive sign. This result implies that a large shock increases the conditional variances more than a small shock. The asymmetric sign effect has the expected negative sign. The sign effect is less precisely estimated than the size effect, particularly when the estimates are based on revised macroeconomic data. The conditional means of the growth rate of output and the term spread are primarily determined by their respective lags.
The term spread follows a highly persistent autoregressive process. Moreover, when real-time macroeconomic data are used for estimation, the term spread exerts a significant positive effect on the growth rate of output. This result is consistent with the results reported by Estrella (2005). The estimated conditional mean-model further reveals that the growth rate of output exerts a significant negative effect on the term spread. Finally, the excess returns on the stocks of banks do not appear to be a significant factor driving the conditional means of the growth rate of output and the term spread.

Figure III
Conditional Variances





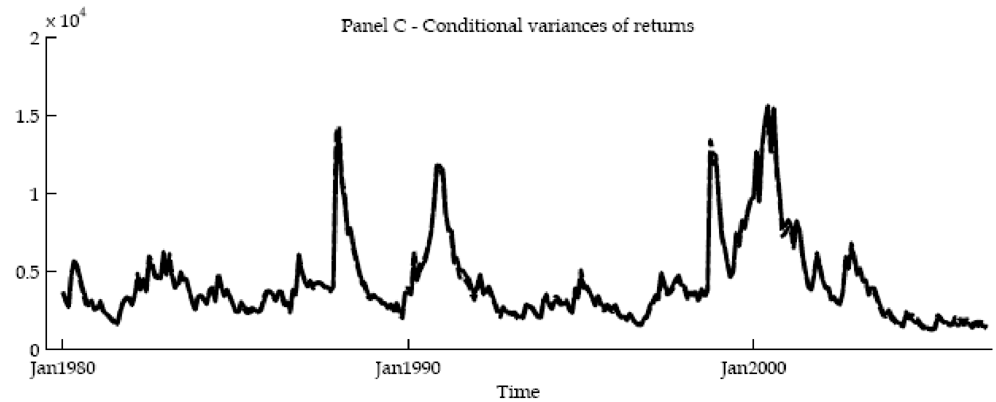


Table 3
The MEGARCH-M Model with Real-Time Macroeconomic Data

Row	Variable	Output Growth	Term Spread	Excess Return
			Conditional means	
1	Constant	0.2134 (0.4565)	0.0336 (0.0013)	
2	Δy_{t-1}	0.4428 (0.0000)	-0.0097 (0.0017)	
3	s_{t-1}	0.4764 (0.0006)	0.9837 (0.0000)	
4	r_{t-1}	0.0032 (0.4653)	0.0001 (0.7416)	
5	$V_{t-1}(r_t)$			0.0027 (0.0006)
6	$Cov_{t-1}(r_t, \Delta y_t)$			19.860 (0.0577)
7	$Cov_{t-1}(r_t, s_t)$			-23.8848 (0.7164)
			Conditional variances	
8	Constant	1.1174 (0.0000)	-0.0224 (0.0055)	0.5593 (0.0000)
9	GARCH	0.6928 (0.0000)	0.9911 (0.0000)	0.9316 (0.0000)
10	Sign ARCH	-0.2041 (0.0010)	-0.0582 (0.0348)	-0.0612 (0.1780)
11	Size ARCH	0.5307 (0.0000)	0.2627 (0.0000)	0.2670 (0.0016)
			Conditional correlations	
12	Chol \ Corr	1.0000 (1.0000)	-0.1184 (0.0200)	0.0006 (0.0156)
13	Chol \ Corr	-0.0052 (0.0102)	1.0000 (1.0000)	-0.0007 (0.1526)
14	Chol \ Corr	0.0051 (0.0562)	-0.1153 (0.7213)	1.0000 (1.0000)
15	LogL		-1993.90	

Notes: This table shows estimates of our MEGARCH-M model (corresponding p-values are given in parentheses) based on real-time data on industrial production. We estimated the model using monthly data spanning the period from 1980/1 to 2006/11. We performed a triangular factorization of the variance-covariance matrix to identify the structural innovations of the model. We ordered the growth rate of industrial production first, the term spread second, and excess equity returns third. In Rows 1-7, we report estimates of the conditional mean model. In Rows 8-11, we report estimates of the conditional variance model. In Rows 12-14, we report estimates of the off-diagonal elements l_{ij} of the Choleski factor matrix (lower triangular matrix) and the implied correlations (upper triangular matrix) with the corresponding asymptotic p-values in parentheses. The implied correlations are given by the sample mean of the time-varying correlations. In Row 15, we report the value of the log-likelihood function. We performed the estimation of the model using the robust quasi-maximum likelihood (QML) estimation of the variance-covariance matrix suggested by Bollerslev and Wooldridge (1992).

Table 4
The MEGARCH-M Model with Revised Macroeconomic Data

Row	Variable	Output Growth	Term Spread	Excess Return
			Conditional means	
1	Constant	1.3864 (0.1012)	0.0214 (0.4643)	
2	Δy_{t-1}	0.1728 (0.0034)	-0.0045 (0.0215)	
3	s_{t-1}	0.5109 (0.1163)	0.9874 (0.0000)	
4	r_{t-1}	0.0036 (0.4146)	0.0001 (0.6638)	
5	$V_{t-1}(r_t)$			0.0017 (0.2687)
6	$Cov_{t-1}(r_t, \Delta y_t)$			0.3888 (0.4389)
7	$Cov_{t-1}(r_t, s_t)$			65.9158 (0.3105)
			Conditional variances	
8	Constant	0.9393 (0.2283)	-0.0287 (0.4464)	0.6160 (0.0290)
9	GARCH	0.7565 (0.0001)	0.9881 (0.0000)	0.9246 (0.0000)
10	Sign ARCH	-0.2097 (0.0034)	-0.0270 (0.5963)	-0.0786 (0.0709)
11	Size ARCH	0.2185 (0.0406)	0.2744 (0.0341)	0.2748 (0.0000)
			Conditional correlations	
12	Chol \ Corr	1.0000 (1.0000)	0.0045 (0.0042)	0.0505 (0.0012)
13	Chol \ Corr	0.0002 (0.9212)	1.0000 (1.0000)	0.0004 (0.0062)
14	Chol \ Corr	0.4222 (0.3339)	0.0221 (0.8978)	1.0000 (1.0000)
15	LogL		-2040.88	

Notes: This table shows estimates of our MEGARCH-M model (corresponding p-values are given in parentheses) based on revised data on industrial production. We estimated the model using monthly data spanning the period from 1980/1 to 2006/11. We performed a triangular factorization of the variance-covariance matrix to identify the structural innovations of the model. We ordered the growth rate of industrial production first, the term spread second, and excess equity returns third. In Rows 1-7, we report estimates of the conditional mean model. In Rows 8-11, we report estimates of the conditional variance model. In Rows 12-14, we report estimates of the off-diagonal elements l_{ij} of the Choleski factor matrix (lower triangular matrix) and the implied correlations (upper triangular matrix) with the corresponding asymptotic p-values in parentheses. The implied correlations are given by the sample mean of the time-varying correlations. In Row 15, we report the value of the log-likelihood function. We performed the estimation of the model using the robust quasi-maximum likelihood (QML) estimation of the variance-covariance matrix suggested by Bollerslev and Wooldridge (1992).

The diagnostic tests summarized in Table 5 indicate that the MEGARCH-M model does a reasonably good job in capturing the dynamics of the conditional variance-covariance matrix. The diagnostic tests suggest that there is no remaining autocorrelation in the squared standardized residual up to order 12. The validity of the specification of the model is further corroborated by the Sign bias, Negative bias, Positive bias, and Joint tests, proposed by Engle and Ng (1993). Moreover, the MEGARCH-M model is supported by the orthogonality conditions for the first, second, third, and fourth moments (Nelson 1991). It should also be noted that the MEGARCH-M model fits well the dynamics of both the real-time and the revised macroeconomic data.

We further studied whether the risk premium based on real-time macroeconomic data is statistically different from the risk premium estimated from revised macroeconomic data. To this end, we used a t-test (Wilcoxon/Mann-Whitney test, F-test) to test for differences between the means (medians, variances) of the estimates of the risk premium. Table 6 summarizes the results. The mean, median, and variance of the risk premium estimated based on real-time macroeconomic data significantly differ from the mean, median, and variance estimated based on revised macroeconomic data. In economic terms, differences between the estimates of the risk premium based on real-time and revised macroeconomic data can arise because, when an investor uses real-time data to make inferences about the risk premium, he or she must take into account that the then available real-time data will be revised a number of times and more data will become available in the future. The results of tests for significance suggest that investor's ex-ante (i.e., using real-time macroeconomic data) evaluation of the risk of equity market investments in the banking sector significantly differs from the ex-post evaluation of risk, which can be evaluated based on revised macroeconomic data.

Table 5
Diagnostic Statistics for the MEGARCH-M Model

Panel A: Real-Time Macroeconomic Data

Row	Diagnostic Statistic	Output Growth	Term Spread	Excess Return
1	Q(12)	0.3456	0.1119	0.9970
2	Sign Bias	0.8684	0.3935	0.2209
3	Neg. Size Bias	0.9227	0.5842	0.5106
4	Pos. Size Bias	0.4820	0.1849	0.2574
5	Joint	0.8816	0.6208	0.6404
6	$E(z)=0$	0.9253	0.5069	0.9849
7	$E(z^2)=0$	0.9931	0.7037	>0.9999
8	$E(z^3)=0$	0.8020	0.4130	0.1876
9	$E(z^4)=0$	0.7170	0.2203	0.4756

Panel B: Revised Macroeconomic Data

Row	Diagnostic Statistic	Output Growth	Term Spread	Excess Return
1	Q(12)	0.3195	0.1208	0.9954
2	Sign Bias	0.9512	0.1614	0.1941
3	Neg. Size Bias	0.2414	0.2120	0.5789
4	Pos. Size Bias	0.4908	0.1464	0.2441
5	Joint	0.2902	0.4410	0.5794
6	$E(z)=0$	0.8117	0.6675	0.9335
7	$E(z^2)=0$	0.9803	0.7162	0.9864
8	$E(z^3)=0$	0.4320	0.4564	0.1673
9	$E(z^4)=0$	0.3764	0.2238	0.4872

Notes: This table summarizes diagnostic statistics for the standardized residuals, z, of the MEGARCH-M model (p-values). Q(12) denotes the results of a Ljung-Box Q-Test for autocorrelation of order 12 in squared standardized residuals. The Sign bias, Negative bias, Positive Bias, and Joint tests were computed as described by Engle and Ng (1993). The orthogonality conditions for the first four moments of standardized residuals were computed as described by Nelson (1991). We estimated the model using monthly data for the period 1980/1-2006/11. Panel A summarizes the diagnostic statistics using real-time macroeconomic data. Panel B summarizes the diagnostic statistics using revised macroeconomic data.

5. Concluding Remarks

Our main result is that using real-time rather than revised macroeconomic data can have profound implications for estimates of the risk premium investors require for investing in the stocks of banks. This main result illustrates that the risk premium that stock market investors, based on real-time macroeconomic data, require for investing in the stocks of banks may be significantly different from the risk premium derived in retrospect by researchers based on revised macroeconomic data. As one would have expected, another result of our empirical analysis is that the risk premium that is required for investing in the banking industry is more sensitive to business-cycle fluctuations than the risk premium on investments in a more diversified portfolio, such as the S&P500 stock index. In light of this result, the choice between real-time data or revised macroeconomic data is of particular relevance for studying the risk premium in empirical analyses of the banking industry.

A natural question to be explored in future research is whether the finding that using real-time rather than revised macroeconomic data can give rise to significantly different estimates of the risk premium can be corroborated for other countries other than the United States.

Table 6
Differences between Estimates of the Risk Premium

Differences Between Means			
Sample Period	Real-Time Macroeconomic Data	Revised Macroeconomic Data	t-test
1980/01–2006/11	5.0438	9.1124	10.9731***
Differences Between Medians			
Sample Period	Real-Time Macroeconomic Data	Revised Macroeconomic Data	Wilcoxon/Mann-Whitney-test
1980/01–2006/11	3.6383	7.6560	14.7775***
Differences Between Variances			
Sample Period	Real-Time Macroeconomic Data	Revised Macroeconomic Data	F-test
1980/01–2006/11	4.1700	5.1844	1.5457***

Notes: This table summarizes results of tests for significance of the differences between the mean, median, and variance of the risk premium in the banking sector based on real-time macroeconomic data and the mean, median, and variance of the risk premium in the banking sector based on revised macroeconomic data. The test for significance of the difference in the means (medians, variances) is a t-test (Wilcoxon/Mann-Whitney test, F-test). We report the results of our MEGARCH-M model that features the growth rate of industrial production, the term spread, and excess equity returns in the banking sector. We estimated the models using monthly data for the period from 1980/1 to 2006/11. We performed a triangular factorization of the variance-covariance matrix to identify the structural innovations of the model. We performed the estimation of the model using the robust quasi-maximum likelihood (QML) estimation of the variance-covariance matrix suggested by Bollerslev and Wooldridge (1992). An asterisk *** denotes significance at the one percent level.

Specifically, it would be interesting to study whether the differential effect of using real-time versus revised macroeconomic data on the risk premium depends upon financial architecture. Many researchers have examined the relative performance of bank-based and market-based economies and have concluded that financial architecture may matter for long-term economic growth (Levine 2002, Levine and Zervos 1998, Tadesse 2006, among others). Future research could benefit from studying whether (i) the response of the risk premium in the banking industry to changes in the stance of the business cycle depends upon financial architecture, and (ii) whether the differential effect of using real-time versus revised macroeconomic data varies across bank-based and market-oriented financial systems. In this respect, it would also be interesting to study whether banking regulation matters for the estimates of the risk premium using real-time and revised macroeconomic data.

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