Idiosyncratic Volatility Puzzle: Influence of Macro-Finance Factors*

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Abstract: We analyze the cross-sectional relation between expected idiosyncratic volatility and stock returns. The expected idiosyncratic volatility is conditioned on macro-finance factors as well as traditional asset pricing factors. The macro-finance factors are constructed from a large set of macroeconomic and financial variables. Our results show that the negative relation between expected idiosyncratic volatility and stock returns reverses to a positive one when accounting for the macro-finance effects. Portfolio analysis shows that the positive relation is economically important. The relation between expected idiosyncratic volatility and returns is not affected by business cycle variations. The empirical results are highly robust.

Keywords: Idiosyncratic volatility puzzle; Macro-finance factors; Business cycle.

JEL Classifications: G12; G14

1 Introduction

An important implication of the capital asset pricing model is that only systematic risk is priced while idiosyncratic risk is eliminated through diversification. Yet, empirical evidence suggests that investors are, in general, not well-diversified, e.g., Goetzmann and Kumar (2008). A plausible explanation for this lack of diversification is proposed by the Merton (1987) model where investors cannot diversify perfectly due to market imperfections. Therefore, under-diversified investors demand return compensation for bearing idiosyncratic risk. Nonetheless, the empirical literature documents the so-called idiosyncratic volatility puzzle whereby stocks with high idiosyncratic volatility have low future returns. The idiosyncratic volatility puzzle is initially documented by Ang, Hodrick, Xing, and Zhang (2006) and Ang, Hodrick, Xing, and Zhang (2009).

The key contribution of this paper is to offer an explanation of the idiosyncratic volatility puzzle by considering the link between idiosyncratic volatility and the macro economy. In particular, we propose a new way of calculating expected idiosyncratic volatility that builds upon Boyer, Mitton, and Vorlink (2010). Furthermore, we follow the recent trend in the financial literature that exploits information obtained from a large amount of macro-finance variables in predicting asset returns, e.g., Ludvigson and Ng (2007) and Goyal and Welch (2008). The expected idiosyncratic volatility is obtained from a regression of the traditional idiosyncratic volatility (Ang, Hodrick, Xing, and Zhang (2006)) on macro-finance factors that are obtained from a large set of macro-finance variables. Our results indicate that in the cross-section, the relation between idiosyncratic volatility and stock returns is positive conditional on macro-finance factors. Portfolio analysis shows that the positive relation between expected idiosyncratic volatility and returns is economically important. The positive relation is not linked to business cycle variations. Finally, our findings are highly robust to different measures of idiosyncratic volatility, to different sub-samples, and to the inclusion of idiosyncratic skewness.

Reviewing the literature, the findings in Bali and Cakici (2008) challenge the robustness of the idiosyncratic volatility puzzle. Fu (2009) argues that the realized idiosyncratic volatility used in Ang, Hodrick, Xing, and Zhang (2006) is a poor predictor of expected idiosyncratic volatility. Estimating expected idiosyncratic volatility from an EGARCH model, Fu (2009) documents a positive risk-return relationship. Still, Fink, Fink, and He (2012) and Guo, Kassa, and Ferguson (2014) show that the findings in Fu (2009) could be caused by a look-ahead bias in the EGARCH idiosyncratic volatility. Another explanation for the idiosyncratic volatility puzzle is offered by Huang, Liu, Rhee, and Zhang (2010) who point to an omitted variable bias because lagged stock returns are not explicitly controlled for in the risk-return trade-off. Further, Chen and Petkova (2012) find that part of the idiosyncratic volatility puzzle can be explained by adding an average variance component when estimating the idiosyncratic volatility. On the other hand, Bali, Cakici, and Whitelaw (2011) show that when controlling for extreme positive returns, the resulting idiosyncratic volatility measure is positively related to subsequent returns. According to Stambaugh, Yu, and Yuan (2015), short sale restrictions and stronger effects at overpriced than under-priced stocks explain the idiosyncratic volatility puzzle. Herskovic, Kelly, Lustig, and Nieuwerburgh (2016) show that there is a common component in idiosyncratic volatility. Our results could indicate that the common component is related to the macro economy.

The previous literature show that stock volatility and the macro economy is strongly related, dating back to Schwert (1989). Recently, Baker, Bloom, and Davis (2016) link the cross-section of stock market volatility to the state of the macro economy as measured by the economic policy uncertainty index. Binder and Merges (2001) relate stock market volatility with economic factors such as uncertainty about the price level. Bali and Zhou (2016) show that the cross-section of stock returns depends on economic uncertainty.

The remaining part of the paper is organized as follows. First, we introduce the data. Second, we describe the econometric methodology. Third, we present the main empirical findings for the relation between expected idiosyncratic volatility and returns followed by portfolio analysis. Fourth, we discuss business cycle variations and robustness analysis. Finally, we conclude. Various details about the data are delegated to the Appendix.

2 Data

The idiosyncratic volatility regressions (first step) make use of daily data, while the risk-return regressions (second step) are based upon monthly data.

2.1 Daily Firm Data

Our sample consists of 22,528 US listed firms during the period March 1971 to December 2012 with data available in the annual Compustat/CRSP Merged Database (excluding financial and utility firms with four-digit SIC codes 4900-4999 and 6000-6999). To reduce the impact of infrequent trading on idiosyncratic volatility estimates, we require a minimum of 15 trading days in a month for which CRSP reports both a daily return and non-zero trading volume. Otherwise, the stock is excluded from the analysis of that month.

In the first step, we also use the Fama and French (1993) factors:[1] the excess return on a broad market portfolio (MKT), the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks (SMB), and the difference between the return on a portfolio of high book-to-market stocks and the return on a portfolio of low book-to-market stocks (HML).

2.2 Macro-Finance Predictors

We consider macro-finance factors as predictors in our cross-sectional regressions of stock returns. Denote the vector of factors at time t as F_t. We obtain the macro-finance predictors using 174 macro-finance variables which is similar to Ludvigson and Ng (2007).[2] The macro-finance variables fall into the following six groups: employment and hours; housing; interest rates, money, and credit; output; prices and inflation; stock market. For the identity of the 174 variables, consult Table 1A in the Appendix.[3]

We use rolling windows of 240 monthly observations to construct the macro-finance factors. For the macro-finance variables, the sample starts 240 months before the actual sample period, i.e. in 1951, in order to have macro-finance

[1] The Fama and French (1993) factors are freely available from Kenneth French' web page.

[2] Note, however, that Ludvigson and Ng (2007) use quarterly data, while our analysis is based on monthly data.

[3] The macro-finance variables are transformed to be stationary by taking logs and first differences as appropriate.

factors available for the entire analysis period.[4] In this way, we prepare *ex-ante* macro-finance factors.

For each group of macro-finance variables, we construct a macro-finance factor that is the first principal component of the variables in the group (again, based on the previous 240 observations). On average, the macro-finance factors account for between 75% and 85% of the total variation in the series in the group, cf. Table 2*A*. Thus, the factors provide strong information about the macro-finance variables.[5] By constructing the macro-finance factors this way, it is easy to interpret them as we know which part of the economy they represent, e.g. the first macro-finance factor is related to employment and hours, etc.

3 Econometric Methodology

The econometric analysis consists of two steps. In the first step, we obtain the expected idiosyncratic volatility and in the second step, we run cross-sectional regressions of stock returns on expected idiosyncratic volatility.

Throughout, we conduct a rolling-window analysis in the same manner as did when constructing the macro-finance factors. In this way, all results are *ex ante* and do not suffer from any look-ahead bias.

3.1 Step 1: Expected Idiosyncratic Volatility

The first step of our modeling procedure is to pin down the expected idiosyncratic volatility based on standard as well as macro-finance variables. To begin with, we estimate the traditional idiosyncratic volatility, and subsequently we obtain the expected idiosyncratic volatility conditional on macro-finance variables.

We estimate the traditional idiosyncratic volatility following Ang, Hodrick, Xing, and Zhang (2006) but using rolling window 1-month regressions using daily data. τ accounts for the daily observations in month t and i keeps track of the company. In every month t, the daily excess return of stock i, $(R_{it\tau} - r_{t\tau})$, is regressed on the traditional asset pricing factors: the daily market portfolio

[4] Not all macro-finance variables are available for the entire sample period, but they are included as they become available.

[5] The factors are not strongly correlated (average correlation coefficients are below 0.71), so there are not problems with multicollinearity.

($MKT_{t\tau}$), the small minus big portfolio ($SMB_{t\tau}$), and the high minus low portfolio ($HML_{t\tau}$):

$$R_{it\tau} - r_{t\tau} = \alpha_{0it} + \alpha_{1it} MKT_{t\tau} + \alpha_{2it} SMB_{t\tau} + \alpha_{3it} HML_{t\tau} + \varepsilon_{it\tau} \quad (1)$$

The traditional idiosyncratic volatility for stock i in month t, IV_{it}, is the standard deviation of the regression residuals in eq. (1) multiplied by the square root of the number of trading days in that month.[6]

Then, to obtain the expected idiosyncratic volatility for firm i in month t, we extend the methodology employed by Boyer, Mitton, and Vorlink (2010) for calculating expected skewness. For each company, we carry out 240-month rolling window regressions of the current idiosyncratic volatility on the lagged idiosyncratic volatility as well as the macro-finance factors. Therefore, the regression parameters (the β's) are time varying:

$$IV_{it} = \beta_{0t} + \beta'_{1t} F_{t-1} + \beta_{2t} IV_{i,t-1} + u_{it} \quad (2)$$

Then, the out-of-sample rolling window predictions from these regressions are defined as the expected macro-finance based idiosyncratic volatility: $\widehat{IV}_{it}$. Furthermore, we obtain the expected idiosyncratic volatility without the macro-finance factors, i.e., with $\beta_{1t} = 0$ in the above regressions.

In Table 1, we report the average coefficient estimates, average standard errors, average t-statistics, and average adjusted R-squared values from estimating eq. (2) with and without the macro-finance factors. The results show that there is a substantial increase in model fit induced by including macro-finance factors. The average adjusted R-squared goes increases from 42% to 58%. Thus, the model fit is not driven by autoregressive behavior. Furthermore, all the macro-finance factors are significant. Except for the employment and hours factor, the influence is positive for all the other macro-finance factors related to housing, interest rates, money, and credit, output, prices and inflation, and the stock market. We conclude that the idiosyncratic volatility is strongly influenced by the macro economy.

[6]Similarly, Vidal-García, Vidal, and Nguyen (2016) find the idiosyncratic volatility of mutual fund returns using the Fama and French (1993) 3-factor model.

[Insert Table 1]

3.2 Step 2: Expected Idiosyncratic Volatility and Stock Returns

The second step consists of cross-sectional regressions similar to Fama and MacBeth (1973).[7] Our analysis uses the firm-specific expected idiosyncratic volatility based on the macro-finance factors to predict its return. In addition, we control for other relevant variables. Specifically, for each month t we run the following cross-sectional regression:

$$R_{it} = \gamma_{0t} + \gamma_{1t}\widehat{IV}_{it} + \gamma'_{2t}Z_{i,t-1} + \varepsilon_{i,t} \tag{3}$$

$\widehat{IV}_{it}$ is the macro-finance based idiosyncratic volatility obtained from eq. (2), while R_{it} is the realized return on stock i in month t.

Further, we control for a vector of firm characteristics, Z_{it}, that are known to explain cross-sectional returns such as the estimate of stock i's beta in month t, $beta_{i,t}$ cf. Fama and French (1992), the log of stock i's market capitalization at the end of month t, $\ln(ME)_{i,t}$, the log of stock i's book-to-market ratio as of the end of month t based on the last fiscal year's information, $\ln(B/M)_{i,t}$, the log of stock i's average share turnover in the past 36 months, $\ln(TURN)_{i,t}$, the log of the coefficient of variation of the previous 36 months' turnover, $\ln(CVTURN)_{i,t}$, and stock i's compound gross return from month $t-7$ to $t-2$, $Ret(-2,-7)$, as a proxy for momentum.

From eq. (3) we obtain coefficient estimates for each month, $\widehat{\gamma}_{jt}$, for $j = 0, 1, 2$. Then, the final coefficient estimates, $\widehat{\gamma}_j$ are the averages across month-specific estimates. The under-diversification hypothesis and the idiosyncratic volatility puzzle are tested as alternatives to the null hypothesis regarding the coefficient γ_1. That is, the null hypothesis is that the idiosyncratic volatility is irrelevant.

[7] Cakici, Topyan, and Wang (2014) also conduct cross-sectional Fama and MacBeth (1973) regressions when investigating the Taiwanese stock market.

$$H_0 : \gamma_1 = 0 \text{ (irrelevance)} \tag{4}$$

$$H_1 : \gamma_1 > 0 \text{ (under-diversification)}$$

$$H_2 : \gamma_1 < 0 \text{ (idiosyncratic volatility puzzle)}$$

When γ_1 is positive, the investor is compensated for bearing idiosyncratic risk. On the other hand, a negative γ_1 is in accordance with the idiosyncratic volatility puzzle.

4 Results: Expected Idiosyncratic Volatility and Returns

In this section, we report the main results. Table 2 holds the cross-sectional regression results of stock returns on expected idiosyncratic volatility and firm specific characteristics.

[Insert Table 2]

First, we show the results without the expected idiosyncratic volatility. Note that the signs of the coefficients for the various firm characteristics do not change in any of the subsequent models (except for *beta* which is insignificant) . Thus, these firm characteristics are truly control variables. The signs are generally consistent with previous studies in the literature, cf. Fu (2009) and Ang, Hodrick, Xing, and Zhang (2009).

Next, we show results when the expected idiosyncratic volatility is conditioned on the macro-finance factors. We find strong evidence that the relation between stock returns and expected idiosyncratic volatility is positive and significant. This result supports the under-diversification hypothesis.

When expected idiosyncratic volatility is not conditioned on the macro-finance factors, the relation turns strongly negative, implying that investors are not compensated for taking on additional risk, rather the opposite, i.e., the idiosyncratic volatility puzzle. Note that the finding without macro-finance factors is consistent with the findings in Ang, Hodrick, Xing, and Zhang (2006) and Ang, Hodrick, Xing, and Zhang (2009).

5 Portfolios Sorted on Expected Idiosyncratic Volatility

In this section, we further examine the economic importance of the macro-finance factors by using portfolio analysis in a manner similar to Ang, Hodrick, Xing, and Zhang (2006), Ang, Hodrick, Xing, and Zhang (2009), and Fu (2009).

In the cross-section, we sort all stocks into ten equal sized groups based on the expected idiosyncratic volatility of the previous month, $\widehat{IV}_{i,t-1}$, both when it is conditioned upon macro-finance factors and when it is not. We report the equal (EW) and value (VW) weighted average monthly returns of the decile portfolios as well as the hedge portfolio (the differences between the extreme decile portfolios). We report the Fama and MacBeth (1973) t-statistics that are based on the time-series variation in the hedge portfolio returns using Newey and West (1987) standard errors. We report the risk-adjusted returns (alphas) from two different factor models, namely the three-factor model of Fama and French (1993) (FF3) and the five-factor model extended with the Carhart (1997) momentum and the Pastor and Stambaugh (2003) liquidity factor (FF5) and related t-statistics. The portfolio analysis assumes monthly rebalancing and ignores transaction costs.

[Insert Table 3]

The portfolio results in Table 3 are qualitatively similar for EW and VW portfolios. Consistent with the results in the previous section, we find that the average returns increase (more or less monotonically) from the low to the high decile portfolio when accounting for macro-finance factors in the expected idiosyncratic volatility. Consistent with prior studies, when the expected idiosyncratic volatility does not take macro-finance factors into account, the average returns decrease.

The average returns on the hedge portfolios are highly significant based on both expected idiosyncratic volatility measures. For the expected idiosyncratic volatility based on macro-finance factors, the returns on the hedge portfolios are significantly positive and economically important (1.05 and 1.23 percentage per month). For the expected idiosyncratic volatility without macro-finance factors, the average returns on the hedge portfolios are negative. Similarly, the alphas on the FF3 and FF5 are significantly positive and negative in the same manner.

6 Business Cycle Variations

In this section, we investigate whether the positive relation between expected idiosyncratic volatility and returns, when conditioning upon the macro-finance factors, holds across business cycle variations. To this end, we differentiate between expansions and recessions by using the NBER business cycle indicator.

[Insert Table 4]

In Table 4, we show the average parameter estimates from the cross-sectional regressions of stock returns on expected idiosyncratic volatility separately for recessions and for expansions. Conditioning on the macro-finance factors, the relation between stock returns and expected idiosyncratic volatility is significantly positive in both recessions and expansions. Thus, the under-diversification documented when conditioning upon macro-finance factors is not due to business cycle variations.

In contrast, when we do not account for the macro-finance factors, the relation turns negative in recessions and expansions (as for the entire sample period), though it is insignificant in recessions.

Figure 1 shows the time series of the gamma coefficients with and without the macro-finance factors. There is no discernible relation between the gamma coefficients and the business cycle.

[Insert Figure 1]

Overall, the fact that it is important to account for macro-finance factors when estimating expected idiosyncratic volatility is not caused by ignoring variations across the business cycle. This is in contrast to the findings regarding the aggregate market conditional volatility and conditional returns in Lustig and Verdelhan (2012) and Nyberg (2012), who show that Sharpe ratios are higher in recessions than in expansions. Nevertheless, it is in accordance with the findings of Ghysels, Plazzi, and Valkanov (2013) regarding the aggregate market conditional volatility, who show that the Sharpe ratios are related to flight-to-safety variation.

7 Robustness Analysis

Here, we show that our results are highly robust to a number of alternative specifications.

7.1 Sub-Sample Analysis

Campbell, Lettau, Malkiel, and Xu (2001) document a positive trend in idiosyncratic volatility during 1962–1997. Similar to Campbell, Lettau, Malkiel, and Xu (2001) we conduct sub-sample analysis to investigate whether there is time variation in the relation between idiosyncratic volatility and future returns. To this end, we treat the 1971-1989 and 1990-2012 periods, separately. Table 5 reports the sub-sample cross-sectional regressions from eq. (3). Our main results hold across the two sub-samples with the expected idiosyncratic volatility coefficient for the entire sample period (Table 2) being roughly the average of the those of the two sub-samples. Thus, we conclude our results are not caused by sub-sample variations or choice of an updated or unusual sample period.

[Insert Table 5]

7.2 Skewness Results

Next, we add idiosyncratic skewness to the regressions in eq. (2) with the idiosyncratic skewness being estimated as in Boyer, Mitton, and Vorlink (2010).[8] The results are tabulated in Table 6. We find a negative relation such that the larger the idiosyncratic skewness is, the smaller is the expected return. This applies to all three specifications, and corroborates other papers in the literature (Boyer, Mitton, and Vorlink (2010) and Bali, Cakici, and Whitelaw (2011)). Note the effect of the idiosyncratic skewness does not change the impact of the

[8] Bali, Cakici, and Whitelaw (2011) interpret idiosyncratic skewness as lottery preferences. Hur and Luma (2017) also control for idiosyncratic skewness.

other variables, including the expected idiosyncratic volatility. Thus, the results are invariant to including idiosyncratic skewness.

[Insert Table 6]

7.3 Alternative Idiosyncratic Volatility Measures

Finally, we investigate whether the results are robust to variations in how we estimate the idiosyncratic volatility. In Table 7, we show the cross-section regressions.

[Insert Table 7]

We use the EGARCH specification of Fu (2009) to estimate the idiosyncratic volatility. We note the cross-sectional results do not differ qualitatively from those in Table 2.

Fink, Fink, and He (2012) and Guo, Kassa, and Ferguson (2014) extend the analysis in Fu (2009) to avoid potential look ahead bias in the expected idiosyncratic volatility estimated from the EGARCH model. They do so by relying only on up to time $t-1$ returns (rather than time t) for estimating time t idiosyncratic volatility parameters. The empirical results hardly change compared to Table 2. Thus, the positive relation between stock returns and expected idiosyncratic volatility conditional on macro-finance factors, is not caused by look ahead bias.

We follow the Brandt, Brav, Graham, and Kumar (2010) and use the market model to estimate the idiosyncratic volatility, i.e. setting $\alpha_2 = \alpha_3 = 0$ in eq. (1). The expected idiosyncratic volatility turns insignificant. Thus, it is important to account for all three Fama and French (1993) factors when estimating the idiosyncratic volatility.

8 Conclusion

In this paper, we offer an alternative explanation of the idiosyncratic volatility puzzle by considering the link between expected idiosyncratic volatility and the macro economy. We provide a new measure of the expected idiosyncratic volatility that conditions upon macro-finance factors as well as upon traditional asset pricing factors. The macro-finance factors are constructed from a large pool of macroeconomic and financial variables. Controlling for macro-finance effects in the idiosyncratic volatility eliminates the well-known idiosyncratic volatility puzzle. In fact, the relation between expected idiosyncratic volatility and stock returns turns positive. Portfolio analysis shows that the positive relation is economically important. Further, we document that the relation between expected idiosyncratic volatility and returns is not related to the business cycle. The empirical results are robust to different measures of the idiosyncratic volatility, to different sub-samples, and to inclusion of idiosyncratic skewness.

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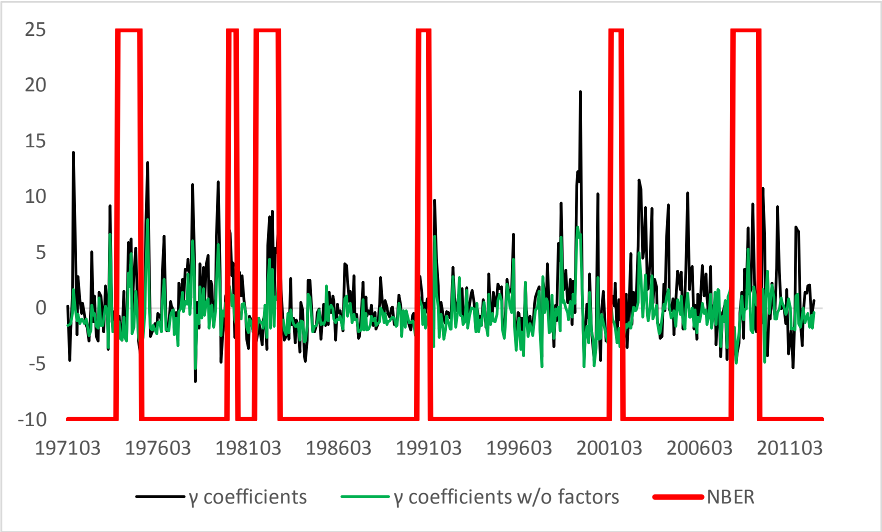
Fig. 1: Time Series of Gamma Coefficients



Notes: The figure shows the estimated gamma coefficients (γ1) from eq. (3) when the idiosyncratic volatility is conditioned on the macro-finance factors (black line) and when it is not (green line). The red line symbolizes NBER recessions (different scaling)

Table 1: Idiosyncratic Volatility Regressions

Panel A: With Macro-Finance Factors

	constant	employment, hours	housing	interest rates, money, credit	output	prices, inflation	stock market	IV_{t-1}	Adj R^2
Av. Coef.	10.68	-0.11	0.14	0.03	0.03	0.02	0.08	0.30	57.53%
Stdev	7.31	0.02	0.01	0.01	0.01	0.01	0.01	0.02	
t-statistic	-1.46	-7.07	14.33	2.73	5.45	2.14	9.12	13.73	

Panel B: Without Macro-Finance Factors

	constant	IV_{t-1}	Adj R^2
Av. Coef.	9.30	0.38	41.57%
Stdev	5.97	0.02	
t-statistic	1.56	18.35	

Notes: The table shows the average coefficients, average standard deviations, average t-statistics, and average adjusted R-squared values from estimating eq. (2).

Table 2: Cross-Sectional Risk-Return Regressions

	cons	beta	ln(ME)	ln(B/M)	Ret(-2,-7)	ln(TURN)	ln(CVTURN)	E(IV)	R^2
No Idiosyncratic Volatility	1.47	0.08	-0.19	0.09	0.44	-0.16	-0.47		4.47%
t-statistic	4.14***	0.88	-4.53***	2.43**	1.71*	-2.25**	-6.65***		
With Macro-Finance Factors	0.17	-0.03	-0.07	0.10	0.59	-0.23	-0.56	6.32	5.63%
t-statistic	0.54	-0.48	-2.18**	2.76***	2.56***	-4.11***	-8.25***	3.33***	
Without Macro-Finance Factors	2.71	0.17	-0.30	0.07	0.34	-0.07	-0.42	-5.62	4.91%
t-statistic	8.85***	2.18**	-8.38***	2.05**	1.35	-1.15	-6.16***	-5.75***	

Notes: The table reports the average coefficients and Newey and West (1987) t-statistics from the cross-sectional regressions in eq. (3) of stock returns on various variables: beta is estimated using the two-step procedure described by Fama and French (1992), ln(ME) is the log of market capitalization, ln(B/M) is the log of book-to-market ratio, ln(TURN) is the log of the average share turnover in the past 36 months, ln(CVTURN) is the log of the coefficient of variation of the previous 36 months' turnover, Ret(-2,-7) is the compound gross return from month t-7 to t-2, and E(IV) is the expected idiosyncratic volatility. */**/*** indicates that the parameter is significant at the 10%/5%/1% level.

Table 3: Portfolios Sorted on Expected Idiosyncratic Volatility

	With Macro-Finance Factors		Without Macro-Finance Factors	
	EW	VW	EW	VW
Low	1.03	1.14	1.21	1.07
2	1.11	1.24	1.32	1.06
3	1.20	1.32	1.35	1.01
4	1.25	1.52	1.43	0.96
5	1.29	1.61	1.50	1.09
6	1.30	1.63	1.51	0.87
7	1.23	1.43	1.51	0.69
8	1.18	1.36	1.33	0.37
9	1.20	1.55	1.17	0.15
High	2.08	2.37	0.78	-0.67
Hedge (High-Low)	1.05	1.23	-0.45	-1.78
t-statistic	2.30	1.84	-1.52	-5.78
Alpha (FF3) Hedged	0.72	1.11	-0.57	-1.76
t-statistic	2.00	3.05	-1.69	-5.21
Alpha (FF5) Hedged	0.68	1.05	-0.56	-1.61
t-statistic	1.87	2.89	-1.65	-4.76

Notes: The table shows the average monthly returns of the decile portfolios sorted by expected idiosyncratic volatility and the hedge portfolio (high minus low). EW and VW are equal and value weighted portfolios. The t-statistics are based on Newey and West (1987) standard errors. The table shows the risk-adjusted returns (alphas) from two different factor models; FF3 of Fama and French (1993) and FF5 of Carhart (1997) and Pastor and Stambaugh (2003).

Table 4: Business Cycle Cross-Sectional Regressions

Panel A: NBER Expansions

	cons	beta	ln(ME)	ln(B/M)	Ret(-2,-7)	ln(TURN)	ln(CVTURN)	E(IV)	R^2
With Macro-Finance Factors	0.11	-0.10	-0.04	0.11	0.68	-0.23	-0.54	4.14	5.56%
t-statistic	0.33	-1.46	-1.22	2.67***	2.65***	-3.97***	-7.17***	2.13**	
Without Macro-Finance Factors	2.30	0.07	-0.24	0.08	0.44	-0.09	-0.42	-6.13	4.92%
t-statistic	7.29***	0.96	-6.66***	2.07**	1.58	-1.38	-5.49***	-6.03***	

Panel B: NBER Recessions

	cons	beta	ln(ME)	ln(B/M)	Ret(-2,-7)	ln(TURN)	ln(CVTURN)	E(IV)	R^2
With Macro-Finance Factors	0.47	0.33	-0.22	0.06	0.11	-0.26	-0.70	17.56	5.99%
t-statistic	0.58	1.65*	-2.58***	0.78	0.33	-1.50	-4.04***	3.40***	
Without Macro-Finance Factors	4.81	0.70	-0.59	0.02	-0.22	0.02	-0.41	-2.97	4.87%
t-statistic	6.27***	2.71***	-6.90***	0.31	-0.57	0.14	-2.63***	-1.04	

Notes: The table reports the average coefficients and Newey and West (1987) t-statistics from the cross-sectional regressions in eq. (3) of stock returns on various variables separately for expansions (Panel A) and recessions (Panel B). beta is estimated using the two-step procedure described by Fama and French (1992), ln(ME) is the log of market capitalization, ln(B/M) is the log of book-to-market ratio, ln(TURN) is the log of the average share turnover in the past 36 months, ln(CVTURN) is the log of the coefficient of variation of the previous 36 months' turnover, Ret(-2,-7) is the compound gross return from month t-7 to t-2, and E(IV) is the expected idiosyncratic volatility. */**/*** indicates that the parameter is significant at the 10%/5%/1% level.

Table 5: Sub-Sample Cross-Sectional Regressions

Panel A: 1971-1989

	cons	beta	ln(ME)	ln(B/M)	Ret(-2,-7)	ln(TURN)	ln(CVTURN)	E(IV)	R^2
No Idiosyncratic Volatility	1.14	-0.07	-0.11	0.20	0.75	-0.23	-0.27		5.04%
t-statistic	2.23**	-0.60	-1.97**	3.15***	2.35**	-2.66***	-3.53***		
With Macro-Finance Factors	0.61	-0.11	-0.07	0.19	0.83	-0.24	-0.31	3.67	6.01%
t-statistic	1.70**	-1.20	-1.67*	2.98***	2.87***	-3.01***	-4.21***	1.99**	
Without Macro-Finance Factors	2.33	0.06	-0.22	0.17	0.60	-0.14	-0.23	-6.53	5.53%
t-statistic	5.86***	0.59	-4.92***	2.75***	1.95*	-1.75*	-3.09***	-5.16***	

Panel B: 1990-2012

	cons	beta	ln(ME)	ln(B/M)	Ret(-2,-7)	ln(TURN)	ln(CVTURN)	E(IV)	R^2
No Idiosyncratic Volatility	1.75	0.21	-0.26	0.00	0.18	-0.10	-0.65		4.78%
t-statistic	3.58***	1.50	-4.32***	0.03	0.46	-0.94	-6.01***		
With Macro-Finance Factors	-0.21	0.03	-0.07	0.03	0.38	-0.23	-0.77	8.56	5.74%
t-statistic	-0.43	0.30	-1.49	0.73	1.11	-2.82***	-7.90***	3.11***	
Without Macro-Finance Factors	3.02	0.27	-0.36	-0.01	0.11	-0.01	-0.58	-4.85	5.26%
t-statistic	6.75***	2.27**	-7.07***	-0.29	0.30	-0.15	-5.66***	-3.37***	

Notes: The table shows the results from the regression in eq. (3) of stock returns on varios variables for two sub-samples. beta is estimated using the two-step procedure described by Fama and French (1992), ln(ME) is the log of market capitalization, ln(B/M) is the log of book-to-market ratio, ln(TURN) is the log of the average share turnover in the past 36 months, ln(CVTURN) is the log of the coefficient of variation of the previous 36 months' turnover, Ret(-2,-7) is the compound gross return from month t-7 to t-2, and E(IV) is the expected idiosyncratic volatility. */**/*** indicates that the parameter is significant at the 10%/5%/1% level.

Table 6: Idiosyncratic Skewness Effects

	cons	beta	ln(ME)	ln(B/M)	Ret(-2,-7)	ln(TURN)	ln(CVTURN)	E(IV)	Skewness	R^2
No E(IV)	1.52	0.09	-0.19	0.10	0.42	-0.15	-0.45		-0.22	4.56%
t-statistic	4.30***	0.99	-4.46***	2.65***	1.63	-2.09**	-6.15***		-7.18***	
With Macro-Finance Factors	0.23	-0.03	-0.07	0.11	0.56	-0.23	-0.55	6.38	-0.25	5.75%
t-statistic	0.74	-0.39	-2.26**	2.77***	2.43**	-3.98***	-7.99***	3.35***	-7.98***	
Without Macro-Finance Factors	2.77	0.18	-0.30	0.07	0.31	-0.07	-0.40	-5.60	-0.21	5.03%
t-statistic	8.97***	2.25**	-8.42***	2.07**	1.23	-1.07	-5.92***	-5.75***	-7.18***	

Notes: The table shows the results from estimating the regression in eq. (3) of stock returns on various variables extended with the idiosyncratic skewness. beta is estimated using the two-step procedure described by Fama and French (1992), ln(ME) is the log of market capitalization, ln(B/M) is the log of book-to-market ratio, ln(TURN) is the log of the average share turnover in the past 36 months, ln(CVTURN) is the log of the coefficient of variation of the previous 36 months' turnover, Ret(-2,-7) is the compound gross return from month t-7 to t-2, and E(IV) is the expected idiosyncratic volatility. */**/*** indicates that the parameter is significant at the 10%/5%/1% level.

Table 7: Alternative Volatility Specifications With Macro-Finance Factors

	cons	beta	ln(ME)	ln(B/M)	Ret(-2,-7)	ln(TURN)	ln(CVTURN)	E(IV)	R^2
EGARCH	1.20	0.05	-0.17	0.10	0.51	-0.18	-0.53	0.12	4.66%
t-statistic	3.81***	0.58	-4.24***	2.66***	2.05**	-2.73***	-7.21***	5.20***	
FFH and GKF	-4.82	-0.41	0.41	0.16	1.87	-0.48	-0.84	0.31	9.53%
t-statistic	-14.45***	-5.46***	12.10***	4.12***	8.81***	-7.86***	-10.45***	14.08***	
BBGK	1.47	0.07	-0.20	0.13	0.45	-0.18	-0.44	0.00	5.04%
t-statistic	3.69***	0.69	-3.96***	2.87***	1.61	-2.29**	-4.88***	-0.44	

Notes: The table shows the results from the regression in eq. (3). We use the EGARCH specification in place of eq. (2), the Brandt, Brav, Graham, and Kumar (2010) (BBGK) specification in place of eq. (2), and Fink, Fink, and He (2012) and Guo, Kassa, and Ferguson (2014), (FFH and GKF) in place of eq. (2). */**/*** indicates that the parameter is significant at the 10%/5%/1% level.

Table 1A: Macro-Finance Variables

Category	Variable
Employment & hours	US TOTAL CIVILIAN EMPLOYMENT VOLA
Employment & hours	US UNEMPLOYMENT RATE SADJ
Employment & hours	US AVERAGE DURATION OF UNEMPLOYMENT (WEEKS) VOLA
Employment & hours	US UNEMPLOYED DISTRIBUTION - LESS THAN 5 WEEKS SADJ
Employment & hours	US UNEMPLOYED DISTRIBUTION - 5 TO 14 WEEKS SADJ
Employment & hours	US UNEMPLOYED FOR 15 WEEKS OR MORE VOLA
Employment & hours	US UNEMPLOYED FOR 15 TO 26 WEEKS VOLA
Employment & hours	US UNEMPLOYED DISTRIBUTION - 27 WEEKS & OVER SADJ
Employment & hours	US AVERAGE WEEKLY INITIAL CLAIMS - UNEMPLOYMENT INSURANCE CURA
Employment & hours	US EMPLOYED - TOTAL PRIVATE VOLA
Employment & hours	US EMPLOYED - GOODS-PRODUCING VOLA
Employment & hours	US EMPLOYED - MINING VOLA
Employment & hours	US EMPLOYED - CONSTRUCTION VOLA
Employment & hours	US EMPLOYED - MANUFACTURING VOLN
Employment & hours	US EMPLOYED - DURABLE GOODS VOLA
Employment & hours	US EMPLOYED - NONDURABLE GOODS VOLA
Employment & hours	US EMPLOYED - SERVICE-PROVIDING VOLN
Employment & hours	US EMPLOYED - TRADE, TRANSPORTATION, & UTILITIES VOLA
Employment & hours	US EMPLOYED - WHOLESALE TRADE VOLA
Employment & hours	US EMPLOYED - RETAIL TRADE VOLA
Employment & hours	US EMPLOYED - FINANCIAL ACTIVITIES VOLN
Employment & hours	US EMPLOYED - GOVERNMENT VOLN
Employment & hours	US AVG WKLY HOURS - TOTAL PRIVATE NONFARM VOLA
Employment & hours	US AVG WKLY HOURS - MANUFACTURING VOLA
Employment & hours	US AVG OVERTIME HOURS - MANUFACTURING VOLA
Employment & hours	US CHICAGO PURCHASING MANAGER DIFFUSION INDEX - EMPLOYMENT NADJ
Employment & hours	US AVG HOURLY REAL EARNINGS - CONSTRUCTION CONA
Employment & hours	US AVG HOURLY REAL EARNINGS - GOODS-PRODUCING CONA
Employment & hours	US AVG HOURLY REAL EARNINGS - MANUFACTURING CONA
Employment & hours	US SWISS FRANCS TO US $
Employment & hours	US JAPANESE YEN TO US $

Employment & hours	US UK Θ TO US $
Employment & hours	US CANADIAN $ TO US $
Employment & hours	EM U.S. $ TO 1 EURO (ECU PRIOR TO 1999)
Employment & hours	US WTI CRUDE OIL SPOT PRICE
Housing	US NEW PRIVATE HOUSING UNITS STARTED (AR) VOLA
Housing	US HOUSING STARTED - NORTHEAST (AR) VOLA
Housing	US HOUSING STARTED - MIDWEST (AR) VOLA
Housing	US HOUSING STARTED - SOUTH (AR) VOLA
Housing	US HOUSING STARTED - WEST (AR) VOLA
Housing	US NEW PRIVATE HOUSING UNITS AUTHORIZED BY BLDG.PERMIT (AR) VOLA
Housing	US HOUSING PERMITS AUTHORIZED - NORTHEAST (AR) VOLA
Housing	US HOUSING PERMITS AUTHORIZED - MIDWEST (AR) VOLA
Housing	US HOUSING PERMITS AUTHORIZED - SOUTH (AR) VOLA
Housing	US HOUSING PERMITS AUTHORIZED - WEST (AR) VOLA
Interest rates, money & credit	US TREASURY BILL SECONDARY MARKET RATE ON DISCOUNT BASIS-3 MONTH
Interest rates, money & credit	US TREASURY BILL SECONDARY MARKET RATE ON DISCOUNT BASIS-6 MONTH
Interest rates, money & credit	US FEDERAL FUNDS RATE (AVG.)
Interest rates, money & credit	US PRIME RATE CHARGED BY BANKS
Interest rates, money & credit	US TREASURY CONST MAT 1 YEAR (D) - MIDDLE RATE
Interest rates, money & credit	US TREASURY CONST MAT 5 YEAR (D) - MIDDLE RATE
Interest rates, money & credit	US TREASURY CONST MAT 10 YEAR (W) - MIDDLE RATE
Interest rates, money & credit	US CORPORATE BOND YIELD - MOODY'S AAA, SEASONED ISSUES
Interest rates, money & credit	US CORPORATE BOND YIELD - MOODY'S BAA, SEASONED ISSUES
Interest rates, money & credit	US INTEREST RATE SPREAD-10 YEAR TREASURY BONDS LESS FEDERAL FUND
Interest rates, money & credit	US MONEY STOCK - CURRENCY IN CIRCULATION CURA
Interest rates, money & credit	US MONEY STOCK - SAVINGS DEPOSITS CURA
Interest rates, money & credit	US MONEY STOCK - SMALL TIME DEPOSITS AT COMMERCIAL BANKS CURA
Interest rates, money & credit	US MONEY SUPPLY M2 CURA
Interest rates, money & credit	US MONETARY BASE CURA
Interest rates, money & credit	US REQUIRED RESERVES OF DEPOSITORY INSTITUTIONS CURA
Interest rates, money & credit	US NONBORROWED RESERVES OF DEPOSITORY INSTITUTIONS CURA
Interest rates, money & credit	US COMMERCIAL & INDUSTRIAL LOANS OUTSTANDING CONA
Interest rates, money & credit	US COMMERCIAL & INDL LOANS, NET CHANGE (AR) (BCI 112) CURA
Interest rates, money & credit	US CONSUMER CREDIT OUTSTANDING CURA

Interest rates, money & credit	US CONSUMER INSTALLMENT CREDIT TO PERSONAL INCOME (RATIO) SADJ
Output	US UNIV OF MICHIGAN CONSUMER SENTIMENT - EXPECTATIONS VOLN
Output	US INDUSTRIAL PRODUCTION - TOTAL INDEX VOLA
Output	US INDUSTRIAL PRODUCTION - FINAL PRODUCTS VOLN
Output	US INDL PROD - FINAL PRODUCTS, TOTAL VOLA
Output	US INDL PROD - CONSUMER GOODS VOLA
Output	US INDL PROD - DURABLE CONSUMER GOODS VOLA
Output	US INDL PROD - NONDURABLE CONSUMER GOODS VOLA
Output	US INDUSTRIAL PRODUCTION - BUSINESS EQUIPMENT SADJ
Output	US INDL PROD - MATERIALS VOLN
Output	US INDL PROD - DURABLE GOODS MATERIALS VOLN
Output	US INDL PROD - NONDURB GOODS MATERIALS VOLA
Output	US INDUSTRIAL PRODUCTION - MANUFACTURING (SIC) VOLA
Output	US INDL PROD - RESIDENTIAL UTILITIES VOLA
Output	US INDL PROD - FUELS VOLA
Output	US CHICAGO PURCHASING MANAGER DIFFUSION INDEX-PRODN. (SA) SADJ
Output	US CAPACITY UTILIZATION - MANUFACTURING VOLA
Output	US ISM PURCHASING MANAGERS INDEX (MFG SURVEY) SADJ
Output	US CHICAGO PURCHASING MANAGER DIFFUSION INDEX-NEW ORDERS(SA)
Output	US CHICAGO PURCHASING MANAGER DIFFUSION INDEX-DELIVERIES(SA)
Output	US CHICAGO PURCHASING MANAGER DIFFUSION INDEX-INVENTORIES(SA)
Output	US MANUFACTURERS NEW ORDERS FOR NONDEFENSE CAPITAL GOODS(BCI 27)
Output	US MANUFACTURERS NEW ORDERS - CONSUMER GOODS & MATERIALS CURA
Output	US MANUFACTURERS NEW ORDERS, DURABLE GOODS CONA
Output	US MANUFACTURERS UNFILLED ORDERS - DURABLE GOODS INDUS. CONA
Output	US MANUFACTURING & TRADE INVENTORIES CONA
Output	US RATIO OF MFG. & TRADE INVENTORIES TO SALES CONA
Output	US PERSONAL INCOME (MONTHLY SERIES) (AR) CURA
Output	US PERSONAL INCOME LESS TRANSFER PAYMENTS CONA
Output	US SERVICES, PERSONAL CONSUMPTION EXPENDITURES SADJ
Output	US MANUFACTURING & TRADE SALES CONA
Output	US SALES OF RETAIL STORES CONA
Prices & inflation	US PPI - FINISHED GOODS SADJ
Prices & inflation	US PRODUCER PRICE INDEX - FINISHED CONSUMER GOODS SADJ

Prices & inflation	US PRODUCER PRICE INDEX - INTERMEDIATE MATERIALS SADJ
Prices & inflation	US PRODUCER PRICE INDEX - CRUDE MATERIALS SADJ
Prices & inflation	US CPI - COMMODITIES SADJ
Prices & inflation	US CPI - APPAREL SADJ
Prices & inflation	US CPI - ALL URBAN: ALL ITEMS SADJ
Prices & inflation	US CPI - TRANSPORTATION SADJ
Prices & inflation	US CPI - MEDICAL CARE SADJ
Prices & inflation	US CPI - DURABLES SADJ
Prices & inflation	US CPI - SERVICES SADJ
Prices & inflation	US CPI - ALL ITEMS LESS FOOD SADJ
Prices & inflation	US CPI - ALL ITEMS LESS SHELTER SADJ
Prices & inflation	US CPI - ALL ITEMS LESS MEDICAL CARE SADJ
Prices & inflation	US CHAIN-TYPE PRICE INDEX FOR PCE - DURABLES SADJ
Prices & inflation	US CHAIN-TYPE PRICE INDEX FOR PCE - NONDURABLE GOODS SADJ
Prices & inflation	US CHAIN-TYPE PRICE INDEX FOR PCE - SERVICES SADJ
Prices & inflation	US CHAIN-TYPE PRICE INDEX FOR PERSONAL CONSMPTN.EXPENDITURE SADJ
Stock Market	S&P 500 COMPOSITE - PRICE INDEX
Stock Market	S&P INDUSTRIAL - PRICE INDEX
Stock Market	S&P500 METALS & MINING - PRICE INDEX
Stock Market	S&P500 MOVIES & ENTERTAINMENT - PRICE INDEX
Stock Market	S&P500 MULTI-LINE INSURANCE - PRICE INDEX
Stock Market	S&P500 OIL & GAS EXPLOR & PROD - PRICE INDEX
Stock Market	S&P500 PACKAGED FOODS - PRICE INDEX
Stock Market	S&P500 PERSONAL PRODUCTS SI - PRICE INDEX
Stock Market	S&P500 PROPERTY & CASUALTY INSUR - PRICE INDEX
Stock Market	S&P500 RAILROADS - PRICE INDEX
Stock Market	S&P500 RESTAURANTS - PRICE INDEX
Stock Market	S&P500 SOFT DRINKS - PRICE INDEX
Stock Market	S&P500 SPECIALTY STORES - PRICE INDEX
Stock Market	S&P500 STEEL - PRICE INDEX
Stock Market	S&P500 TOBACCO SI - PRICE INDEX
Stock Market	S&P500 TRUCKING - PRICE INDEX
Stock Market	S&P 500 EW CONSUMER STAPLES - PRICE INDEX
Stock Market	S&P 500 EW ENERGY - PRICE INDEX

Stock Market	S&P 500 EW FINANCIALS - PRICE INDEX
Stock Market	S&P 500 EW HEALTH CARE - PRICE INDEX
Stock Market	S&P 500 EW I&T - PRICE INDEX
Stock Market	S&P 500 EW MATERIALS - PRICE INDEX
Stock Market	S&P 500 EW T/COMM - PRICE INDEX
Stock Market	S&P 500 EW UTILITIES - PRICE INDEX
Stock Market	S&P 500 EW UTILITIES T/COMM - PRICE INDEX
Stock Market	S&P 500 TELECOM & IT - PRICE INDEX
Stock Market	S&P500 AIR FREIGHT & COURIERS SI - PRICE INDEX
Stock Market	S&P500 AIRLINES - PRICE INDEX
Stock Market	S&P500 ALUMINIUM - PRICE INDEX
Stock Market	S&P500 APPAREL & ACCESSORIES - PRICE INDEX
Stock Market	S&P500 APPAREL RETAIL - PRICE INDEX
Stock Market	S&P500 AUTO PARTS & EQUIP - PRICE INDEX
Stock Market	S&P500 AUTOMOBILE MANUFACTURERS - PRICE INDEX
Stock Market	S&P500 BANKS - PRICE INDEX
Stock Market	S&P500 BCAST - PRICE INDEX
Stock Market	S&P500 COMM. EQUIPMENT - PRICE INDEX
Stock Market	S&P500 COMMERCIAL PRINTING - PRICE INDEX
Stock Market	S&P500 COMPUTER HWARE - PRICE INDEX
Stock Market	S&P500 CONSTRUCTION & ENGINEER SI - PRICE INDEX
Stock Market	S&P500 DEPARTMENT STORES - PRICE INDEX
Stock Market	S&P500 DIVERSIFIED FINANCIALS - PRICE INDEX
Stock Market	S&P500 DIVERSIFIED METALS & MINING - PRICE INDEX
Stock Market	S&P500 DRUG RETAIL - PRICE INDEX
Stock Market	S&P500 ELECTRIC UTILITIES SI - PRICE INDEX
Stock Market	S&P500 ENVR & FA CILITIES SERV - PRICE INDEX
Stock Market	S&P500 FOOD RETAIL - PRICE INDEX
Stock Market	S&P500 FOOTWEAR - PRICE INDEX
Stock Market	S&P500 GENERAL MERCH STORES - PRICE INDEX
Stock Market	S&P500 GOLD - PRICE INDEX
Stock Market	S&P500 HEALTH CARE EQUIP - PRICE INDEX
Stock Market	S&P500 HEALTH CARE FACILITIES - PRICE INDEX
Stock Market	S&P500 HOME IMPROVE RETAIL - PRICE INDEX

Stock Market	S&P500 HOMEBUILDING - PRICE INDEX
Stock Market	S&P500 HOTELS - PRICE INDEX
Stock Market	S&P500 HOUSEHOLD PRODUCTS SI - PRICE INDEX
Stock Market	S&P500 HOUSEWARES & SPECIALTIES - PRICE INDEX
Stock Market	S&P500 INDUSTRIAL CONGLOMERATE SI - PRICE INDEX
Stock Market	S&P500 INTEGRATED OIL & GAS - PRICE INDEX
Stock Market	S&P500 LIFE & HEALTH INS - PRICE INDEX

Notes: The 174 macro-finance variables are divided into the following categories: Employment and hours; housing; interest rates, money and credit; output; prices and inflation; stock market. Sources: DataStream and Global Financial Data.

Table 2A: Descriptive Statistics for Macro-Finance Factors

	Average variation explained	Average correlation coefficient
Employment, hours	75.40%	0.50
Housing	75.30%	0.53
Interest rates, money, credit	78.40%	0.56
Output	81.70%	0.61
Prices, inflation	84.70%	0.71
Stock market	78.60%	0.55

Notes: The table shows the average proportion of variation in the underlying macro-finance variables that is explained by the factor (column 1) and the average correlation coeffient of the factor with the other factors (column 2).