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## **Idiosyncratic Volatility Puzzle: Influence of Macro-Finance Factors**

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# Idiosyncratic Volatility Puzzle: Influence of Macro-Finance Factors\*

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# Idiosyncratic Volatility Puzzle: Influence of Macro-Finance Factors

**Abstract:** In this paper, we scrutinize the cross-sectional relation between idiosyncratic volatility and stock returns. As a novelty, the idiosyncratic volatility is obtained by conditioning 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. Cleaning for macro-finance effects reverses the puzzling negative relation between returns and idiosyncratic volatility documented previously. Portfolio analysis shows that the effects from macro-finance factors are economically strong. The relation between idiosyncratic volatility and returns does not vary with the NBER business cycles. The empirical results are highly robust.

**Keywords:** Idiosyncratic volatility puzzle; Macro-finance predictors; Factor analysis; Business cycle

**JEL Classifications:** G12; G14

# 1 Introduction

An important implication of the Capital Asset Pricing Model (CAPM) is that only systematic risk is priced with idiosyncratic risk being eliminated through diversification. Yet, the 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 perfectly diversify due to market imperfections. As expected, under-diversified investors would demand return compensation for bearing idiosyncratic risk. Nonetheless, the rapidly growing empirical literature testing the idiosyncratic volatility in the cross-section of stocks often documents the so-called idiosyncratic volatility puzzle whereby stocks with high idiosyncratic volatility have low future returns, (e.g. Ang, Hodrick, Xing, and Zhang (2006), Ang, Hodrick, Xing, and Zhang (2009)). Nevertheless, the findings in Bali and Cakici (2008) challenge the robustness of the idiosyncratic volatility puzzle.

In the literature, a variety of economic mechanisms have been proposed to explain the idiosyncratic volatility puzzle. For instance, Fu (2009) argues that the one-month lagged realized idiosyncratic volatility used in Ang, Hodrick, Xing, and Zhang (2006) is a poor predictor of expected idiosyncratic volatility and, therefore, is a poor proxy for idiosyncratic risk. Estimating expected idiosyncratic volatility from an EGARCH model, Fu (2009) documents a positive risk-return trade-off relationship. This paper promotes one explanation of why the idiosyncratic volatility puzzle arises. Another explanation is offered by Huang, Liu, Rhee, and Zhang (2010) that points to an omitted variable bias when stock returns from the previous month are not explicitly controlled for in the risk-return trade-off. The authors show that by including the previous month's return the negative estimate on the lagged

realized idiosyncratic volatility is attenuated and is close to zero. 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, Nusret, and Whitelaw (2011) test for the significance of extreme positive returns and show that controlling for that the resulting idiosyncratic volatility measure is positively related to subsequent returns.

We offer a novel and attractive solution to the idiosyncratic volatility puzzle by considering the link between volatility and the macro economy. We argue that volatility may not be idiosyncratic before it has been cleaned for effects stemming from macroeconomic and financial (macro-finance hereafter) factors as well as from the traditional effects stemming from the stock market. It is now well established in the literature that there is a link between the macro economy and stock market volatility, e.g., Schwert (1989) and more recently Bloom (2009). Consequently, the macro economy could also be linked to idiosyncratic volatility as increases in macroeconomic uncertainty drives up both systematic and idiosyncratic volatility. Indeed, our results show that allowing for macro-finance factors reverses the puzzling negative relation between returns and idiosyncratic volatility.

We consider the US stock market during the sample period 1971 to 2012. We adopt a new way of obtaining idiosyncratic volatility that builds upon Boyer, Mitton, and Vorlink (2010) who estimate expected idiosyncratic skewness. The advantage of using this method is that it allows us to account for the influence of additional predictive variables compared to what is done in the previous literature. Furthermore, from a methodological point of view, we follow the recent trend in the finance literature that exploits information obtained from a large amount of macro-finance variables in predicting

asset returns, e.g., Ludvigson and Ng (2007), Goyal and Welch (2008) and Christiansen, Schmeling, and Schrimpf (2012).

Once we account for the macro-finance factors, the idiosyncratic volatility puzzle is no longer present except at the very short (1-month) horizon. Our results are concerned with volatility horizon not holding period horizon as in the previous literature. We find a strong and positive relation between returns and macro-finance related idiosyncratic volatility in the cross-section. Portfolio analysis documents that the relation between returns and idiosyncratic volatility is economically important. Further, the relation between idiosyncratic volatility and returns is not directly linked to the NBER business cycle. The findings are highly robust; to using different empirical specifications (Brandt, Brav, Graham, and Kumar (2010) and Fu (2009) extended to condition on macro-finance effects), to sub-sample analysis, to including standard cross-sectional asset pricing variables, and to including idiosyncratic skewness which is seen as a proxy for lottery preferences of investors, cf. Bali, Nusret, and Whitelaw (2011).

As long as the common set of macro-finance factors are taken into account when estimating idiosyncratic volatility, the relation between idiosyncratic volatility and returns is similar across estimation methods. This stresses the importance of accounting for macro-finance factors in financial economics.

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 followed by a number of robustness checks. Finally, we conclude. Various details are delegated to the Appendix.

## 2 Data

The idiosyncratic volatility regressions in the first step make use of daily data, while the risk-return regressions in the 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:<sup>1</sup> 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 estimate the common factors in a manner similar to Stock and Watson (2002) and Ludvigson and Ng (2007). Let  $X_t$  denote a large vector ( $N \times 1$ ) of macro-finance variables. These variables, are related to the unobserved common factors according to

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<sup>1</sup>The Fama and French (1993) are freely available from Kenneth French' web page

$$X_t = \Lambda F_t + e_t \tag{1}$$

where  $\Lambda$  is an  $N \times r$  matrix of factor loadings and  $F_t$  describes the  $r$  dimensional vector of unobserved common factors, where  $r \ll N$ . The  $N \times 1$  vector  $e_t$  denotes the purely idiosyncratic errors that are allowed to be serially correlated and weakly correlated across macro-finance variables.<sup>2</sup> The above equation reflects the fact that the elements of  $F_t$  represent pervasive forces that drive the common dynamics of  $X_t$ .

We use  $N = 174$  macro-finance variables similar to Ludvigson and Ng (2007), for further details consult Table 1A in the Appendix.<sup>3</sup> The macro-finance variables fall into the following broad groups: Employment and hours; exchange rates and oil prices; housing; interest rates, money and credit; output; prices and inflation; stock market. The number of factors is determined by the information criteria developed in Bai and Ng (2002). The criteria indicates that the factor structure is well described by six common factors, i.e.  $r = 6$ . Taken together, these six factors account for 85% of the variation of the 174 monthly macro-finance variables. Moreover, to capture any nonlinear effects we also make use of the squares of the factors.

Figure 1A in the Appendix displays the  $R$ -squared values of the regressions of the 174 individual macro-finance variables against each of the six common factors. We caution that any labeling of the factors is not perfect, because each factor to some degree is influenced by all the variables in the data set and the orthogonalization means that none of them will correspond exactly to a precise economic concept like output or prices, which are nat-

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<sup>2</sup>This cross-correlation must vanish as  $N$  goes to infinity. See Stock and Watson (2002) for a formal discussion of the required restrictions on the cross-correlation of the idiosyncratic errors.

<sup>3</sup>Note however that Ludvigson and Ng (2007) use quarterly data while our analysis is based on monthly data.



urally correlated. Broadly speaking, the first factor is mostly related to the federal funds rate and various employment variables; the second factor loads primarily on money supply; the third on prices; the fourth on employment indicators; the fifth on housing and prices and inflation. Finally, the sixth factor is most strongly related to output.

### 3 Econometric Methodology

The econometric analysis consists of two steps which are described here.

#### 3.1 Step 1: Idiosyncratic Volatility

The first step of our modelling procedure is to pin down the idiosyncratic volatility based on the standard and the macro-finance variables. In principle, we would prefer to account for both standard and macro-finance factors at the same time, but this is infeasible due to the fact the standard variables are available at the daily frequency whereas the macro-finance factors are only available at the monthly frequency.

First, we estimate a standard measure of idiosyncratic volatility following Ang, Hodrick, Xing, and Zhang (2006) and Fu (2009).  $\tau$  accounts for the daily observations,  $t$  accounts for monthly observations, and  $i$  keeps track of the company. There is one regression per stock per month. In particular, in every month  $t$ , the daily excess return of stock  $i$ ,  $(R_{i\tau} - r_\tau)$ , is regressed on the daily Fama and French (1993) and Fama and French (1996) factors: the market portfolio ( $MKT_\tau$ ), the small minus big portfolio ( $SMB_\tau$ ), and the high minus low portfolio ( $HML_\tau$ ):

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

The standard idiosyncratic volatility for stock  $i$  in month  $t$ ,  $IV_{it}$ , is the standard deviation of the regression residuals in eq. (2) multiplied by the square root of the number of trading days in that month. The results are robust to using the market model with only two estimated coefficients in place of the Fama and French (1993) specification, more follows at the end of the paper.

Next, we obtain the idiosyncratic volatility based on the macro-finance factors by adopting the analysis in Boyer, Mitton, and Vorlink (2010).<sup>4</sup> For stock  $i$  at time  $t$  over horizon  $T$ , we regress the idiosyncratic volatility on the macro-finance factors and the squared macro-finance factors lagged  $t - T$  periods, also accounting for the lagged value of the idiosyncratic volatility:

$$IV_{i,t} = \beta_{0t} + \beta'_{1t}F_{t-T} + \beta'_{2t}F_{t-T}^2 + \beta_{3t}IV_{i,t-T} + u_{it} \quad (3)$$

Then we use the prediction from this regression as the estimate of the macro-finance cleaned idiosyncratic volatility:

$$\widehat{IV}_{i,t,t+T} = \widehat{\beta}_{0t} + \widehat{\beta}'_{1t}F_t + \widehat{\beta}'_{2t}F_t^2 + \widehat{\beta}_{3t}IV_{i,t} \quad (4)$$

Furthermore, to show convincingly that our results are driven by the macro-finance factors and not by other sources we also obtain the idiosyncratic volatility without the macro-finance factors, i.e. where  $\beta_{1t} = \beta_{2t} = 0$  in the above regressions.

We consider short (1-month) and intermediate horizons of 6 to 12 months,  $T = \{1, 6, 12\}$  in detail. Later on we analyze all horizons up to 12 months on a general level.

In Table 1, we report the average coefficient estimates, average standard

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<sup>4</sup>Boyer, Mitton, and Vorlink (2010) estimate the expected idiosyncratic skewness using other types of independent variables than macro-finance factors.

errors, average  $t$ -statistics, and average adjusted  $R$ -squared values from estimating eq (3) with and without macro-finance factors. The results show that across different horizons there is a substantial increase in model fit induced by including macro-finance factors. Thus, the model fit is not driven by autoregressive behavior. Factor 1, Factor 3, Factor 5, and Factor 6 as well as Factor 5 squared and Factor 6 squared are statistically significant. Furthermore, the distribution of the coefficient estimates, standard errors and  $R$ -squared values suggest that the results are not driven by specific firms or outliers (results not shown).

[Insert Table 1]

### 3.2 Step 2: Idiosyncratic Volatility and Stock Returns

The second step consists of cross-sectional regressions of individual stocks, similar in spirit to Fama and MacBeth (1973) regressions. Here we use the idiosyncratic volatility based on the macro-finance factors for a given stock to predict its return. In addition, we control for other relevant variables. Specifically, for each month  $t$  we run the following cross-sectional regression:

$$R_{i,t} = \gamma_{0t} + \gamma_{1t} \widehat{IV}_{i,t,t+T} + \gamma'_{2t} Z_{i,t} + \varepsilon_{i,t} \quad (5)$$

where  $i = 1, \dots, N_t$  keeps track of the stock identity,  $N_t$  denotes the total number of stocks in month  $t$ , and  $T$  is the volatility horizon.  $R_{i,t}$  is the realized return on stock  $i$  in month  $t$ .  $Z_{i,t}$  is a vector of various firm characteristics that are known to explain cross-sectional returns such as the estimate of stock  $i$ 's beta in month  $t$ ,  $Beta_{i,t}$ , 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 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 coefficient of variation of the previous 36 months' turnover,  $\ln(CVTURN)_{i,t}$ , stock  $i$ 's compound gross return from month  $t - 7$  to  $t - 2$ ,  $Ret(-2, -7)$ , as a proxy for momentum. We do not explicitly include a proxy for reversals, say  $Ret(-1)$ , in our regressors list as in Huang, Liu, Rhee, and Zhang (2010), because the two measures  $Ret(-2, -7)$  and  $Ret(-1)$  are supposedly highly correlated.<sup>5</sup>

From eq. (5) we obtain coefficient estimates for each month,  $\hat{\gamma}_{jt}$  for  $j = 0, 1, 2$ . Then, the final coefficient estimates,  $\hat{\gamma}_j$  are the averages across month-specific estimates, respectively with standard errors based on Newey and West (1987). The under-diversification hypothesis and the idiosyncratic volatility puzzle are tested as alternatives to the null hypothesis regarding the gamma coefficient  $H_0 : \gamma_1 = 0$ . That is, the null hypothesis is that the idiosyncratic volatility is irrelevant and hence not priced.

$$H_0 : \gamma_1 = 0 \text{ (irrelevance)} \tag{6}$$

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

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

When  $\gamma_1$  is positive, the investor is compensated for bearing idiosyncratic risk. On the other hand, a negative  $\gamma_1$  is in accordance with the idiosyncratic volatility puzzle from the previous literature.

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<sup>5</sup>There is one such correlation coefficient per company per month.

## 4 Results: Idiosyncratic Volatility and Returns

In this section, we show the main results. Table 2 holds the regression results for various specifications for  $T = 1, 6, 12$ .

[Insert Table 2]

Panel *A* summarizes the results with various firm characteristics included, but without the idiosyncratic volatility. Note that the sign of the coefficient estimates from the various firm characteristics does not change in any of the subsequent models. Thus, these firm characteristics are truly control variables. These signs are generally consistent with previous studies in the literature.

Panel *B* shows the results when the idiosyncratic volatility is estimated conditioning on the macro-finance factors. Note, by using the idiosyncratic volatility based on the short (1-month) horizon, the relation is negative and significant, thus in accordance with the idiosyncratic volatility puzzle. More importantly, the results at the intermediate horizon (6 and 12 months) show that the risk-return trade-off turns positive and significant at the 1% level, a result which supports the under-diversification hypothesis. The average gamma coefficient of around 0.14 is close to the estimates in Fu (2009), which lends further support to our findings.

To show that our results are driven by the macro-finance factors and not by other sources we consider the case without conditioning upon macro-finance factors. Panel *C* holds the results. Here, the relation between idiosyncratic volatility and returns is strongly negative implying that investors are not compensated for taking on additional risk, rather the opposite is true,

i.e. the idiosyncratic volatility puzzle. The findings without macro-finance factors are consistent with the findings in Ang, Hodrick, Xing, and Zhang (2006) and Ang, Hodrick, Xing, and Zhang (2009).

We investigate if the results are robust to including firm specific control variables in addition to the macro-finance factors when estimating the idiosyncratic volatility in eq (3). For this we use the firm specific variables that are also used in eq (5). The cross-sectional regressions from eq. (5) are qualitatively similar (not tabulated). Specifically, with macro-finance factors the gamma coefficient is significantly positive while without macro-finance factors it is significantly negative.

We investigate further variations across all volatility horizons,  $T = 1, ..12$  (not tabulated). The results for horizons of 2-months and up are all similar, namely that the gamma coefficients are all significantly positive and of about the same size. Only for the 1-month horizon is the gamma coefficient significantly negative. It is worth noting that whereas the current paper considers volatility horizons, the previous literature considers holding period returns, so the results are not directly comparable. More specifically, at the aggregate market level of conditional volatility and conditional return, Harrison and Zhang (1999), Lundblad (2007), and Bandi and Perron (2008) uncover a significantly positive risk-return trade-off only at very long holding period horizons, which is nonexistent at short holding periods such as one month.

## 5 Business Cycle Variations

In this section we document that the positive relation between idiosyncratic volatility and returns when taking macro-finance factors into account is truly caused by conditioning appropriately upon the macro-finance factors and

not by other excluded economic variables. For this purpose we introduce the NBER business cycle indicator that has previously been connected to variations in the risk-return trade-off, cf. Lustig and Verdelhan (2012) and Nyberg (2012).

We investigate the business cycle variation in the gamma coefficients from the cross-sectional regressions in eq. (5) by running time series regressions. More specifically, we consider as the dependent variable the gamma coefficients  $\gamma_{1t}$  from eq. (5) for the models with and without macro-finance factors using the idiosyncratic volatility at 6 and 12 month horizons. Figure 1 shows the time series of these gamma coefficients at the 6 month horizon. The independent variables are the NBER business cycle indicator, and the six macro-finance factors and their squares.<sup>6</sup>

[Insert Figure 1]

[Insert Table 3]

Table 3 holds the results. When conditioning upon macro-finance factors, the gamma coefficients are related to the macro-finance factors. The NBER business cycle indicator is always insignificant, so the business cycle indicator is not in itself important. This is also evident from Figure 1. Without macro-finance factors there is little evidence of systematic time-variation across the business cycles. This is also strongly evident from Figure 1.

Thus, the fact that it is important to account for macro-finance factors when estimating idiosyncratic volatility is not caused by ignoring variations across the business cycle. This may be in contrast to the findings regarding the aggregate market conditional volatility and conditional returns in Lustig

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<sup>6</sup>The results are robust to including the Economic Policy Uncertainty Index of Baker, Bloom, and Davis (2013) as it is insignificant. The index is freely available at [www.policyuncertainty.com](http://www.policyuncertainty.com).

and Verdelhan (2012) and Nyberg (2012) who show that Sharpe ratios are higher in recessions than in expansions. Nevertheless, it is still 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.

## 6 Portfolios Sorted on Idiosyncratic Volatility

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

[Insert Table 4]

In Table 4, we report equal-weighted average monthly returns of quintile portfolios and differences between the extreme portfolios. In constructing these portfolio returns we cross-sectionally sort each stock into five equal-sized groups based on the idiosyncratic volatility,  $\widehat{IV}_{i,t,t+T}$ . Panel *A* reports portfolio returns for the idiosyncratic volatility estimated over 6 months (the portfolio formation month is  $t+6$ ), while Panel *B* reports results for the idiosyncratic volatility estimated over 12 months (the portfolio formation month is  $t+12$ ). Further, we compute the risk adjusted (equally-weighted) average return over the next 6 months (holding period is up to 6 months). We also report portfolio hedge returns as the difference in the average portfolio returns between the extreme quintiles (High minus Low volatility). Test statistics are reported based on time series variation in these portfolio hedge



returns. This approach assumes monthly rebalancing and ignores the impact of transaction costs. For robustness we also report the spreads in the alphas of the hedged portfolio (regressed on Fama and French (1993) factors) along with the corresponding Newey and West (1987)  $t$ -statistics.<sup>7</sup>

Across these alternative volatility measures, there is an economically significant predictive association between expected volatility and average future returns. Average returns increase monotonically from the first quintile to the fifth quintile. The largest increase in average returns occurs between fourth and fifth quintiles. For example, the 0.40% monthly portfolio hedge differential between the High and Low portfolios (quintiles) sorted on idiosyncratic volatility over the next 6 months for explaining simultaneous returns (RET0) amounts to an annualized 4.9% return differential. This is both statistically and economically significant. The Fama and MacBeth (1973) (FM) test statistic of 2.38 is equivalent to a monthly Sharpe ratio of 0.11; cf. Lewellen (2010) for a mapping of FM  $t$ -statistics to Sharpe ratios. Across both volatility measures with hedge portfolio returns estimated for 0-6 months ahead (RET0 - RET6) in Panels *A* and *B*, the monthly Sharpe ratio ranges from 0.06 to 0.11. These are economically significant, cf. Lewellen (2010). All in all, the average risk-adjusted return differences between the extreme portfolios are positive and significant with very few exceptions.

To get a clearer picture of the role of the macro-finance factors, Panels *C* and *D* report the corresponding results when idiosyncratic volatility is obtained without appropriately conditioning the macro-finance factors. In this sorting, the average return on the highest idiosyncratic volatility portfolio is lower than the average return on the other four portfolios, though the difference is not statistically significant. These analyses provide convincing

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<sup>7</sup>The results are even stronger if we use the Carhart (1997) 4-factor model in place of the Fama and French (1993) model.

evidence that only when expected idiosyncratic volatility is estimated using the macro-finance factors there is a significant positive relation between expected idiosyncratic volatility and portfolio returns.

## 7 Robustness Analysis

Here we show that our results are highly robust to a number of alternative specifications. The robustness confirms the usefulness of our specification. The clear conclusion is that by conditioning upon macro-finance factors when estimating the idiosyncratic volatility we are able to offer a new solution to the idiosyncratic volatility puzzle. The standard idiosyncratic volatility used in previous research seems to be inadequate because it does not account for effects from macro-finance factors.

### 7.1 Sub-Sample Analysis

We conduct sub-sample analysis because Campbell, Lettau, Malkiel, and Xu (2001) document a positive trend in idiosyncratic volatility during their sample period (1962–1997). This could imply that there is time variation in the relation between idiosyncratic volatility and future returns. To check this, we investigate the 1971-1989 period and the 1990-2012 period thereby using 1990 as the splitting point. Table 5 holds the sub-sample cross-sectional regressions from eq. (5). The relation between idiosyncratic volatility and stock returns appears identical across the two sub-samples and the results for the two sub-periods are similar to those for the entire sample period contained in Table 2. Thus, 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

We add the idiosyncratic skewness as a proxy for lottery preferences of investors to the regressions in eq. (5) where the idiosyncratic skewness is estimated as in Boyer, Mitton, and Vorlink (2010). The lottery preferences interpretation stems from Bali, Nusret, and Whitelaw (2011). The results are tabulated in Table 6 for both the entire sample and the sub-samples. The idiosyncratic skewness is significant in all specifications. There is a negative relation such that the larger the idiosyncratic skewness is, the smaller is the expected return. This is similar to the findings to Boyer, Mitton, and Vorlink (2010) and Bali, Nusret, and Whitelaw (2011).

Even though, the idiosyncratic skewness enters significantly into the relation between idiosyncratic volatility and future returns it does not qualitatively change the impact of the other variables including the idiosyncratic volatility. Thus, the relation is invariant to including idiosyncratic skewness.

[Insert Table 6]

## 7.3 Alternative Idiosyncratic Volatility Measures

We investigate if the results are robust to variations in the way we estimate the idiosyncratic volatility. We now try the Brandt, Brav, Graham, and Kumar (2010) method extended to condition upon macro-finance factors into account. This implies using the market model to estimate the idiosyncratic volatility, that is the same as above but setting  $\alpha_2 = \alpha_3 = 0$  in eq. (2). In Table 7 we show the cross-section regressions. The results across horizons are qualitatively similar to the results in Table 2.

[Insert Table 7]

We also use the EGARCH specification of Fu (2009) extended to account for the macro-finance factors. Again, the cross-sectional results shown in Table 8 do not differ qualitatively from those in Table 2. Note that the Brandt, Brav, Graham, and Kumar (2010) and Fu (2009) idiosyncratic volatility estimates are strongly correlated (correlation coefficient of 99%), so it is not surprising that the two sets of results are similar.

Overall, the results here show that as long as we take the common set of macro-finance factors into account when estimating the idiosyncratic volatility we find similar results. Thus, the specific estimation procedure for the idiosyncratic volatility is not overly important, as long as, the effects from macro-finance factors are taken into account. This underscores the importance of allowing for macro-finance factors when estimating the idiosyncratic volatility for the stock market.

## 8 Conclusion

In this paper, we offer a novel and attractive solution to the idiosyncratic volatility puzzle by considering the link between idiosyncratic volatility and the macro economy. We provide a new measure of the idiosyncratic volatility that conditions upon macro-finance factors as well as upon the standard asset pricing variables. The macro-finance factors are constructed from a large pool of macroeconomic and financial variables. Once we account for the macro-finance effects in the idiosyncratic volatility we find that the idiosyncratic volatility puzzle disappears and that the relation between idiosyncratic volatility and stock returns is significantly and strongly positive. Portfolio analysis documents that the positive relation is also economically important. We uncover only few variations across the volatility horizon, except that the

idiosyncratic volatility puzzle remains only at the short very horizon. We document that the relation between idiosyncratic volatility and returns is not related to the NBER business cycles. The empirical results are robust to different measures of the idiosyncratic volatility, to different sub-samples, and to the inclusion of standard asset pricing variables and the idiosyncratic skewness. In summary, our results show that it is essential to condition on macro-finance factors when estimating idiosyncratic volatility, but that it is not overly important how this is done.

In future research it would be of interest to investigate further if accounting for macro-finance factors is able to solve the idiosyncratic volatility puzzle at other financial markets besides the US stock market such as European stock markets.

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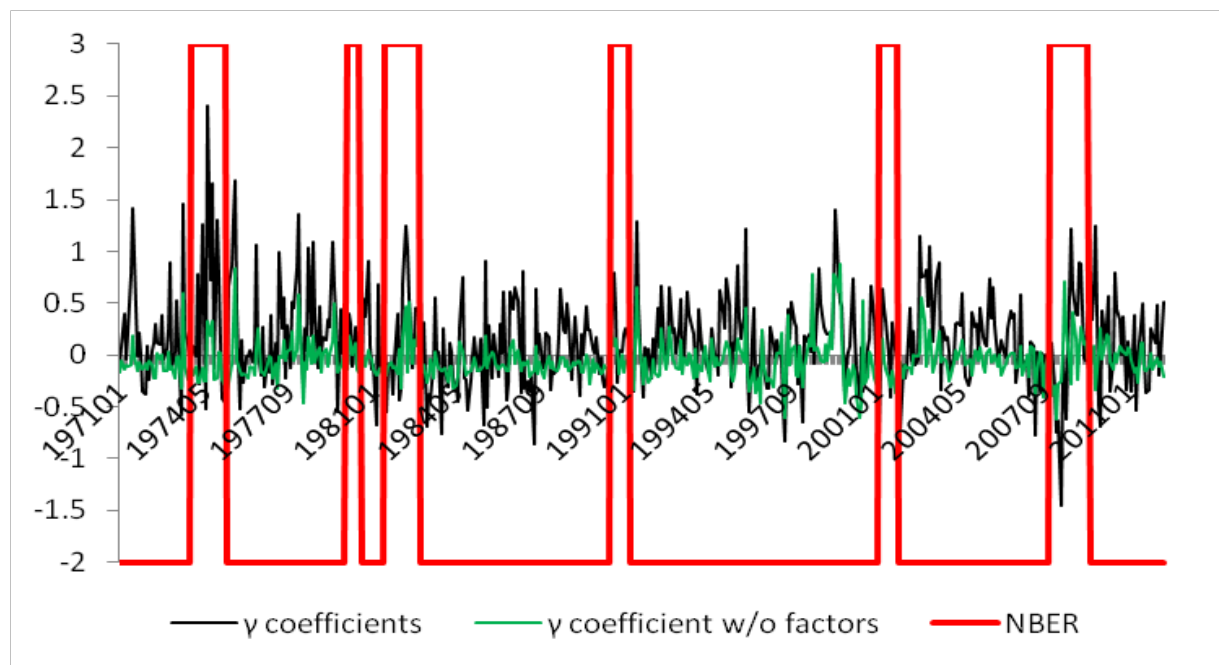
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**Figure 1:** Time Series of Gamma Coefficients for T=6



Notes: The figure shows the estimated gamma coefficients for horizon T=6 for the idiosyncratic volatility that is conditioned on the macro-finance factors (black line) and that is not (green line). The red line symbolizes NBER recessions (different scaling).

**Table 1: Idiosyncratic Volatility Regressions**

Panel A: With Macro-Finance Factors

T		cons	f1	f2	f3	f4	f5	f6	f1 <sup>2</sup>	f2 <sup>2</sup>	f3 <sup>2</sup>	f4 <sup>2</sup>	f5 <sup>2</sup>	f6 <sup>2</sup>	IV <sub>t-T</sub>	Adj R <sup>2</sup>
1	Av. Coef.	15.36	-0.18	0.13	0.01	0.00	0.04	0.07	0.05	0.02	0.01	0.01	-0.01	0.01	0.27	57.7%
	Stdev	10.18	0.03	0.09	0.00	0.00	0.01	0.03	0.06	0.01	0.01	0.01	0.00	0.00	0.08	
	t-statistic	1.51	-6.39	1.44	3.62	0.01	3.08	2.15	0.76	1.25	1.29	1.18	-3.11	2.15	3.56	
6	Av. Coef.	15.37	-0.17	0.13	0.02	0.00	0.04	0.06	0.05	0.02	0.01	0.01	-0.01	0.01	0.13	52.3%
	Stdev	10.08	0.03	0.09	0.00	0.00	0.01	0.03	0.06	0.01	0.01	0.01	0.00	0.00	0.04	
	t-statistic	1.53	-5.98	1.43	3.90	-0.58	2.99	2.22	0.76	1.25	1.29	1.17	-3.28	2.14	3.15	
12	Av. Coef.	15.36	-0.17	0.13	0.02	0.00	0.04	0.06	0.05	0.02	0.01	0.01	-0.01	0.01	0.11	54.2%
	Stdev	9.96	0.03	0.09	0.01	0.00	0.01	0.03	0.06	0.01	0.01	0.01	0.00	0.00	0.04	
	t-statistic	1.54	-5.95	1.43	3.81	-0.78	2.97	2.25	0.76	1.24	1.30	1.16	-3.34	2.14	3.04	

Panel B: No Macro-Finance Factors

T		cons	IV <sub>t-T</sub>	Adj R <sup>2</sup>
1	Av. Coef.	9.30	0.38	42.0%
	Stdev	5.97	0.10	
	t-statistic	1.56	3.84	
6	Av. Coef.	11.68	0.22	39.7%
	Stdev	7.16	0.07	
	t-statistic	1.63	3.34	
12	Av. Coef.	12.40	0.15	36.7%
	Stdev	7.35	0.05	
	t-statistic	1.69	3.16	

Notes: The table shows the average coefficients, average standard deviations, average t-statistics, and average adjusted R-squared values from estimating eq. (3).

**Table 2:** Cross-Sectional Risk-Return Regressions

## Panel A: No Idiosyncratic Volatility

	cons	beta	ln(ME)	ln(b/m)	Ret(-2,-7)	Ln(TURN)	Ln(CVTURN)	IV(T)	Adj R <sup>2</sup>
	1.47	0.09	-0.19	0.10	0.44	-0.15	-0.51		4.2%
	( 4.16)***	( 0.91)	(-4.63)***	( 2.55)**	( 1.72)*	(-2.09)**	(-7.)***		

## Panel B: With Macro-Finance Factors

T	cons	beta	ln(ME)	ln(b/m)	Ret(-2,-7)	Ln(TURN)	Ln(CVTURN)	IV(T)	Adj R <sup>2</sup>
1	2.62	0.16	-0.30	0.07	0.34	-0.07	-0.47	-5.13	4.9%
	( 8.38)***	( 2.04)**	(-8.36)***	( 2.03)**	( 1.34)	(-1.15)	(-7.02)***	(-5.19)***	
6	1.12	0.05	-0.16	0.10	0.52	-0.19	-0.53	0.15	4.7%
	( 3.58)***	( 0.57)	(-4.1)***	( 2.84)***	( 2.12)**	(-2.86)***	(-7.35)***	( 6.06)***	
12	1.12	0.05	-0.16	0.10	0.52	-0.19	-0.53	0.14	4.7%
	( 3.58)***	( 0.58)	(-4.11)***	( 2.85)***	( 2.12)**	(-2.84)***	(-7.35)***	( 5.99)***	

## Panel C: No Macro-Finance Factors

T	cons	beta	ln(ME)	ln(b/m)	Ret(-2,-7)	Ln(TURN)	Ln(CVTURN)	IV(T)	Adj R <sup>2</sup>
1	2.77	0.18	-0.31	0.07	0.32	-0.06	-0.47	-5.76	4.9%
	( 9.1)***	( 2.2)**	(-8.77)***	( 1.91)*	( 1.27)	(-1.)	(-6.9)***	(-5.97)***	
6	2.71	0.18	-0.30	0.07	0.32	-0.07	-0.46	-5.48	5.0%
	( 8.85)***	( 2.3)**	(-8.81)***	( 1.96)**	( 1.31)	(-1.08)	(-6.95)***	(-5.23)***	
12	2.73	0.18	-0.30	0.06	0.32	-0.07	-0.46	-5.75	5.0%
	( 9.01)***	( 2.24)**	(-8.84)***	( 1.86)*	( 1.28)	(-1.09)	(-6.87)***	(-5.29)***	

Notes: The table reports the average coefficients and average t-statistics from the cross-sectional regressions in eq. (5). IV(T) is the T-month-ahead idiosyncratic volatility from eq. (4), beta is estimated using the two-step procedure described by Fama and French (1992), ln(ME) is the log of market capitalization, b/m is the log of book-to-market ratio, ln(TURN) is the average share turnover in the past 36 months, ln(CVTURN) is the coefficient of variation of the previous 36 months' turnover, and Ret(-2,-7) is the compound gross return from month t-7 to t-2. \*/\*\*/\*\* indicates that the parameter is significant at the 10%/5%/1% level.

**Table 3:** Time-Variation in Gamma Coefficients

## Panel A: With Macro-Finance Factors

T	const	NBER	f <sub>1</sub>	f <sub>2</sub>	f <sub>3</sub>	f <sub>4</sub>	f <sub>5</sub>	f <sub>6</sub>	f <sub>1</sub> <sup>2</sup>	f <sub>2</sub> <sup>2</sup>	f <sub>3</sub> <sup>2</sup>	f <sub>4</sub> <sup>2</sup>	f <sub>5</sub> <sup>2</sup>	f <sub>6</sub> <sup>2</sup>	Adj R <sup>2</sup>
6	0.1 ***	0.1													0.0%
6	0.1 ***	-0.1	1.4 ***	1.3 ***	0.1	0.4	-1.2 **	0.5	-2.7	3.6	1.8	1.6	11.6 **	-3.6 *	6.0%
12	0.1 ***	0.1													0.0%
12	0.1 ***	-0.1	1.3 ***	1.3 **	0.0	0.4	-1.2 ***	0.5	-2.1	3.7	2.5	0.5	11.4 ***	-4.3	6.0%

## Panel B: No Macro-Finance Factors

T	const	NBER	f <sub>1</sub>	f <sub>2</sub>	f <sub>3</sub>	f <sub>4</sub>	f <sub>5</sub>	f <sub>6</sub>	f <sub>1</sub> <sup>2</sup>	f <sub>2</sub> <sup>2</sup>	f <sub>3</sub> <sup>2</sup>	f <sub>4</sub> <sup>2</sup>	f <sub>5</sub> <sup>2</sup>	f <sub>6</sub> <sup>2</sup>	Adj R <sup>2</sup>
6	-5.7 ***	1.7													0.0%
6	-3.8 ***	-1.8	22.2	53.9 *	22.7	-21.2	6.5	-8.1	-12.9	87.9	-338	-30.5	154	-523 *	3.0%
12	-6.0 ***	1.9													0.0%
12	-5.0 ***	-3.7	22.5	54.9 *	22.9	-9.9	5.5	-15.5	-15.5	329	-169	-19.8	207	-391	3.0%

Notes: The tables shows the estimated coefficients from regressing the gamma parameters on the NBER recession indicator, and macro-finance factors and their squared values. \*/\*\*/\*\* indicates that the parameter is significant at the 10%/5%/1% level.

**Table 4:** Portfolios Formed on Idiosyncratic Volatility

Panel A: With Macro-Finance Factors, T=6

	RET0	RET1	RET2	RET3	RET4	RET5	RET6
Bottom	1.17	1.20	1.24	1.27	1.24	1.27	1.25
2	1.25	1.28	1.25	1.26	1.29	1.28	1.29
3	1.27	1.29	1.28	1.30	1.30	1.35	1.28
4	1.25	1.35	1.33	1.33	1.37	1.34	1.36
Top	1.56	1.53	1.52	1.51	1.54	1.59	1.58
Hedge (top-bottom)	0.40	0.34	0.28	0.23	0.30	0.33	0.32
FM t-stat	2.38	2.00	1.68	1.42	1.81	1.94	1.96
Sharpe	0.11	0.09	0.08	0.06	0.08	0.09	0.09
Alpha-hedge	0.16	0.29	0.31	0.33	0.34	0.38	0.43
N-W tstat (Alpha-hedge)	1.36	1.65	1.60	1.67	1.70	1.90	2.29

Panel B: With Macro-Finance Factors, T=12

	RET0	RET1	RET2	RET3	RET4	RET5	RET6
Bottom	1.19	1.22	1.21	1.24	1.28	1.31	1.26
2	1.25	1.24	1.25	1.24	1.30	1.29	1.30
3	1.25	1.32	1.28	1.31	1.28	1.31	1.28
4	1.25	1.35	1.36	1.34	1.34	1.31	1.33
Top	1.56	1.52	1.51	1.52	1.55	1.61	1.59
Hedge (top-bottom)	0.38	0.32	0.31	0.28	0.27	0.31	0.33
FM t-stat	2.32	1.89	1.85	1.70	1.61	1.90	2.00
Sharpe	0.10	0.09	0.08	0.08	0.07	0.09	0.09
Alpha-hedge	0.14	0.24	0.34	0.37	0.30	0.37	0.43
N-W tstat (Alpha-hedge)	1.21	1.41	1.74	1.91	1.55	1.94	2.30

Panel C: No Macro-Finance Factors, T=6

	RET0	RET1	RET2	RET3	RET4	RET5	RET6
Bottom	1.26	1.30	1.31	1.31	1.33	1.32	1.29
2	1.37	1.40	1.40	1.43	1.42	1.43	1.40
3	1.45	1.50	1.49	1.47	1.48	1.52	1.51
4	1.37	1.38	1.37	1.39	1.42	1.43	1.44
Top	0.96	0.98	0.96	0.97	0.99	1.04	1.02
Hedge (top-bottom)	-0.32	-0.34	-0.37	-0.36	-0.36	-0.30	-0.28
FM t-stat	-1.28	-1.39	-1.48	-1.45	-1.44	-1.19	-1.14
Sharpe	-0.06	-0.06	-0.07	-0.07	-0.07	-0.05	-0.05
Alpha-hedge	-0.51	-0.46	-0.34	-0.18	-0.24	-0.23	-0.17
N-W tstat (Alpha-hedge)	-2.52	-1.96	-1.23	-0.65	-0.82	-0.79	-0.60

Panel D: No Macro-Finance Factors, T=12

	RET0	RET1	RET2	RET3	RET4	RET5	RET6
Bottom	1.27	1.29	1.30	1.31	1.33	1.32	1.31
2	1.35	1.40	1.40	1.41	1.43	1.44	1.42
3	1.49	1.48	1.49	1.48	1.49	1.52	1.51
4	1.35	1.40	1.38	1.40	1.43	1.42	1.42
Top	0.96	0.97	0.95	0.97	0.97	1.04	1.00
Hedge (top-bottom)	-0.33	-0.34	-0.37	-0.35	-0.37	-0.30	-0.32
FM t-stat	-1.33	-1.38	-1.52	-1.44	-1.52	-1.23	-1.33
Sharpe	-0.06	-0.06	-0.07	-0.07	-0.07	-0.06	-0.06
Alpha-hedge	-0.49	-0.43	-0.34	-0.17	-0.25	-0.23	-0.22
N-W tstat (Alpha-hedge)	-2.40	-1.75	-1.22	-0.61	-0.86	-0.79	-0.77

Notes: The table shows the results from forming quintile portfolios sorted after idiosyncratic volatility. In Panels A and B conditioning on macro-finance factors and in Panels C and D not.

**Table 5: Sub-Sample Cross-Sectional Regressions**

## Panel A: 1971-1989 With Macro-Finance Factors

T	const	beta	ln(ME)	b/m	Ret(-2,-7)	Ln(TURN)	Ln(CVTURN)	IV(T)	Adj R2
1	2.31 ( 5.86)	0.06 ( .61)	-0.22 -( 5.06)	0.17 ( 2.8)	0.59 ( 1.9)	-0.14 -( 1.73)	-0.31 -( 4.14)	-6.27 -( 4.7)	5.5%
6	0.82 ( 1.75)*	-0.08 (-0.76)	-0.08 (-1.54)	0.21 ( 3.3)***	0.84 ( 2.72)***	-0.24 (-2.88)***	-0.32 (-4.21)***	0.17 ( 4.48)***	5.2%
12	0.82 ( 1.73)*	-0.08 (-0.76)	-0.08 (-1.54)	0.21 ( 3.31)***	0.84 ( 2.72)***	-0.24 (-2.88)***	-0.33 (-4.23)***	0.17 ( 4.52)***	5.2%

## Panel B: 1971-1989 No Macro-Finance Factors

T	const	beta	ln(ME)	b/m	Ret(-2,-7)	Ln(TURN)	Ln(CVTURN)	IV(T)	Adj R2
1	2.40 ( 6.05)	0.07 ( .72)	-0.23 -( 5.29)	0.17 ( 2.75)	0.57 ( 1.84)	-0.14 -( 1.67)	-0.31 -( 4.15)	-6.79 -( 5.45)	5.5%
6	2.36 ( 5.76)***	0.06 ( 0.63)	-0.23 (-5.12)***	0.17 ( 2.79)***	0.57 ( 1.85)*	-0.14 (-1.67)*	-0.31 (-4.06)***	-6.55 (-5.38)***	5.6%
12	2.40 ( 5.72)***	0.07 ( 0.69)	-0.23 (-4.99)***	0.16 ( 2.76)***	0.59 ( 1.9)*	-0.14 (-1.67)*	-0.30 (-4.07)***	-7.22 (-5.83)***	5.6%

## Panel C: 1990-2012 With Macro-Finance Factors

T	const	beta	ln(ME)	b/m	Ret(-2,-7)	Ln(TURN)	Ln(CVTURN)	IV(T)	Adj R2
1	2.89 ( 6.16)	0.25 ( 2.08)	-0.36 -( 6.9)	-0.01 -( .35)	0.12 ( .33)	-0.02 -( .17)	-0.61 -( 5.96)	-4.16 -( 2.93)	5.3%
6	1.35 ( 3.22)***	0.15 ( 1.15)	-0.22 (-4.13)***	0.01 ( 0.2)	0.25 ( 0.66)	-0.14 (-1.39)	-0.71 (-6.43)***	0.13 ( 4.1)***	5.0%
12	1.36 ( 3.25)***	0.15 ( 1.15)	-0.23 (-4.16)***	0.01 ( 0.2)	0.24 ( 0.66)	-0.14 (-1.38)	-0.71 (-6.41)***	0.13 ( 3.96)***	5.0%

Panel D: 1990-2012 No Macro-Finance Factors

T	const	beta	ln(ME)	b/m	Ret(-2,-7)	Ln(TURN)	Ln(CVTURN)	IV(T)	Adj R2
1	3.09 ( 6.92)	0.26 ( 2.19)	-0.37 -( 7.27)	-0.02 -( .5)	0.10 ( .28)	0.00 -( .04)	-0.60 -( 5.79)	-4.90 -( 3.44)	5.3%
6	3.00 ( 6.79)***	0.28 ( 2.42)**	-0.37 (-7.46)***	-0.02 (-0.51)	0.11 ( 0.3)	-0.01 (-0.11)	-0.60 (-5.91)***	-4.58 (-2.82)***	5.3%
12	3.01 ( 7.02)***	0.27 ( 2.31)**	-0.37 (-7.63)***	-0.02 (-0.62)	0.10 ( 0.25)	-0.01 (-0.12)	-0.60 (-5.82)***	-4.50 (-2.67)***	5.3%

Notes: The table shows the results from the regression in eq. (5) for two sub-samples and two volatility horizons. \*/\*\*/\*\* indicates that the parameter is significant at the 10%/5%/1% level.



**Table 6: Idiosyncratic Skewness Effects**

## Panel A: With Macro-Finance Factors

T	cosnt	beta	ln(ME)	b/m	Ret(-2,-7)	Ln(TURN)	Ln(CVTURN)	IV(T)	Iskewness	Adj R2
6	1.18 ( 3.71)***	0.05 ( 0.53)	-0.16 (-4.13)***	0.10 ( 2.67)***	0.49 ( 1.97)**	-0.18 (-2.68)***	-0.52 (-7.09)***	0.15 ( 6.06)***	-0.22 (-7.06)***	4.8%
12	1.18 ( 3.71)***	0.05 ( 0.54)	-0.16 (-4.14)***	0.10 ( 2.67)***	0.49 ( 1.97)**	-0.18 (-2.67)***	-0.52 (-7.09)***	0.14 ( 5.97)***	-0.22 (-7.05)***	4.8%

## Panel B: No Macro-Finance Factors

T	cosnt	beta	ln(ME)	b/m	Ret(-2,-7)	Ln(TURN)	Ln(CVTURN)	IV(T)	Iskewness	Adj R2
6	2.77 ( 8.96)***	0.19 ( 2.35)**	-0.31 (-8.83)***	0.07 ( 1.99)**	0.30 ( 1.19)	-0.06 (-0.99)	-0.45 (-6.67)***	-5.46 (-5.21)***	-0.21 (-7.08)***	5.1%
12	2.79 ( 9.12)***	0.18 ( 2.3)**	-0.31 (-8.86)***	0.07 ( 1.89)*	0.29 ( 1.17)	-0.06 (-01.)	-0.45 (-6.59)***	-5.74 (-5.29)***	-0.21 (-7.15)***	5.1%

Notes: The table shows the results from estimating the regression in eq. (5) extended with the idiosyncratic skewness. \*/\*\*/\*\* indicates that the parameter is significant at the 10%/5%/1% level.

**Table 7:** Alternative Volatility Specifications With Macro-Finance Factors

## Panel A: BBGK Model

T	cons	beta	ln(ME)	b/m	Ret(-2,-7)	Ln(TURN)	Ln(CVTURN)	IV(T)	Adj R2
1	1.80 ( 5.47)***	0.11 ( 1.23)	-0.23 (-6.1)***	0.09 ( 2.35)**	0.41 ( 1.63)	-0.13 (-1.89)*	-0.47 (-6.68)***	-4.10 (-4.94)***	4.8%
6	1.05 ( 3.38)***	0.04 ( 0.48)	-0.16 (-4.01)***	0.10 ( 2.78)***	0.53 ( 2.12)**	-0.19 (-2.88)***	-0.54 (-7.36)***	0.15 ( 6.05)***	4.7%
12	1.03 ( 3.3)***	0.04 ( 0.47)	-0.15 (-3.99)***	0.10 ( 2.78)***	0.53 ( 2.14)**	-0.19 (-2.92)***	-0.54 (-7.41)***	0.15 ( 6.19)***	4.7%

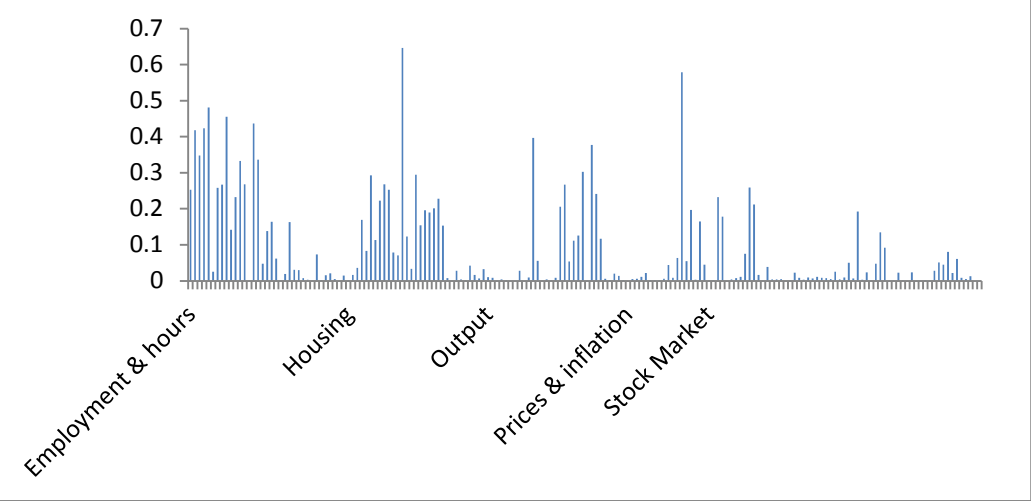
## Panel B: EGARCH Model

	cons	beta	ln(ME)	b/m	Ret(-2,-7)	Ln(TURN)	Ln(CVTURN)	IV	Adj R2
	1.13 ( 3.59)***	0.05 ( 0.56)	-0.16 (-4.09)***	0.10 ( 2.85)***	0.52 ( 2.12)**	-0.19 (-2.85)***	-0.53 (-7.35)***	0.15 ( 6.07)***	4.7%

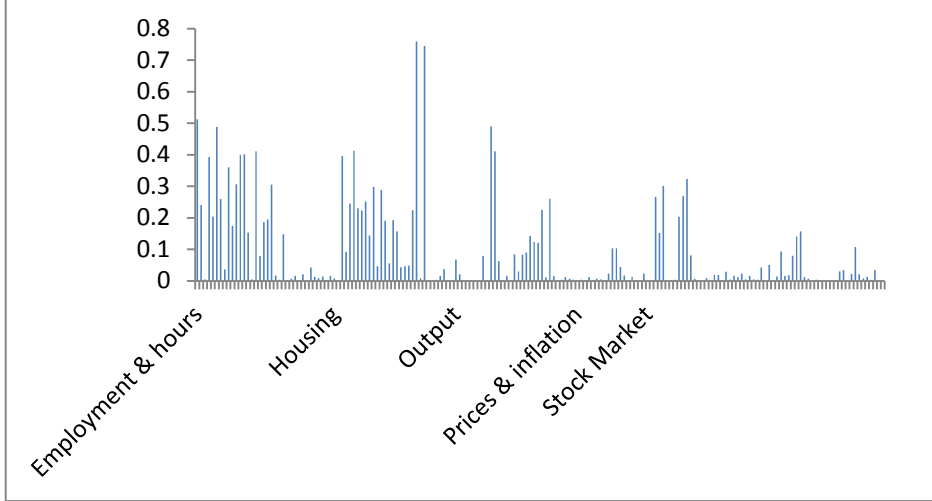
Notes: The table shows the results from the regression in eq. (5). In Panel A we use the Brandt, Brav, Graham, and Kumar (2010) specification in place of eq. (2) and in Panel B we use the EGARCH specification in place of eq. (2). \*/\*\*/\*\* indicates that the parameter is significant at the 10%/5%/1% level.

Figure 1A: R-Squared Values for Factors

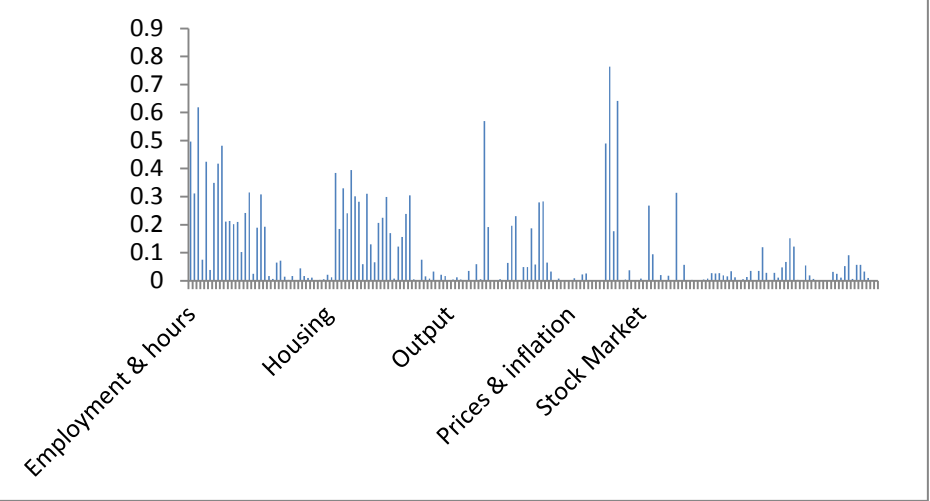
Factor 1



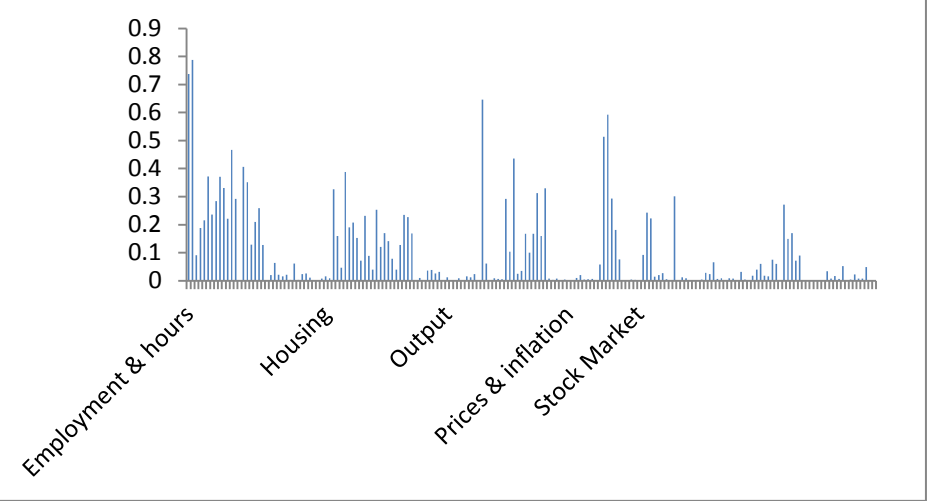
Factor 2



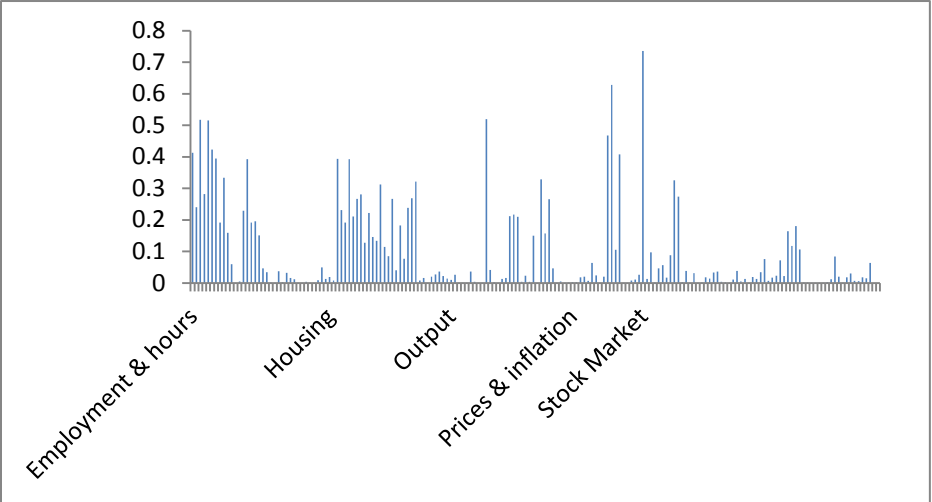
Factor 3



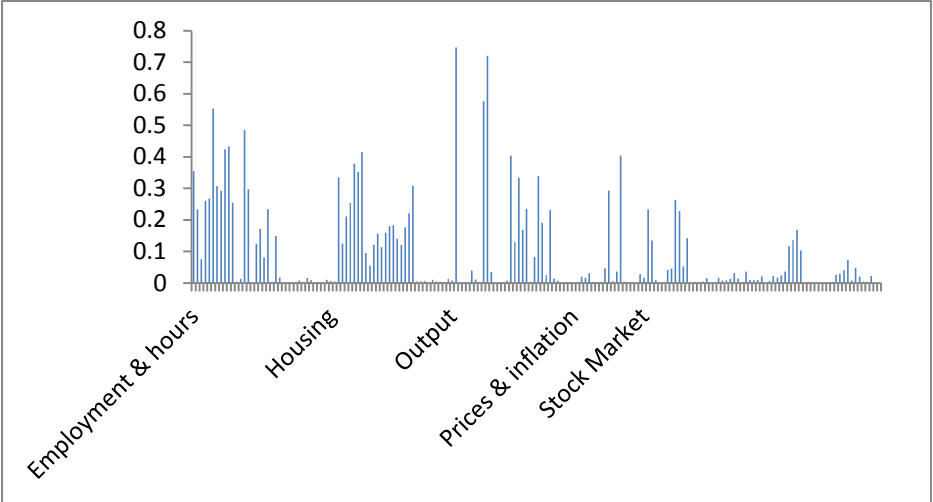
Factor 4



Factor 5



Factor 6



**Table 1A: Macro-Finance Variables**

<b>Category</b>	<b>Variable</b>
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 ₤ 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 SADI
Prices & inflation	US PRODUCER PRICE INDEX - FINISHED CONSUMER GOODS SADI
Prices & inflation	US PRODUCER PRICE INDEX - INTERMEDIATE MATERIALS SADI
Prices & inflation	US PRODUCER PRICE INDEX - CRUDE MATERIALS SADI
Prices & inflation	US CPI - COMMODITIES SADI
Prices & inflation	US CPI - APPAREL SADI
Prices & inflation	US CPI - ALL URBAN: ALL ITEMS SADI
Prices & inflation	US CPI - TRANSPORTATION SADI
Prices & inflation	US CPI - MEDICAL CARE SADI
Prices & inflation	US CPI - DURABLES SADI
Prices & inflation	US CPI - SERVICES SADI
Prices & inflation	US CPI - ALL ITEMS LESS FOOD SADI
Prices & inflation	US CPI - ALL ITEMS LESS SHELTER SADI
Prices & inflation	US CPI - ALL ITEMS LESS MEDICAL CARE SADI
Prices & inflation	US CHAIN-TYPE PRICE INDEX FOR PCE - DURABLES SADI
Prices & inflation	US CHAIN-TYPE PRICE INDEX FOR PCE - NONDURABLE GOODS SADI
Prices & inflation	US CHAIN-TYPE PRICE INDEX FOR PCE - SERVICES SADI
Prices & inflation	US CHAIN-TYPE PRICE INDEX FOR PERSONAL CONSMPTN.EXPENDITURE SADI
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

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