L'Institut bénéficie du soutien financier de l'Autorité des marchés financiers ainsi que du ministère des Finances du Québec

Note technique

NT 14-01

Forecasting and Hedging Systematic Risk

Janvier 2014

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Key Words:
Beta, Systematic Risk, Forecast, Hedge, Asset Pricing

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Executive Summary

Failure of widely applied models to accurately predict systematic risk has shown to carry detrimental impact for portfolios' returns. It is due to this misestimated systematic risk beta that portfolio managers have difficulty in constructing market-neutral portfolios. Even the so-called market neutral portfolios turned out to have considerable market risk during the last financial crisis. Forecasting and hedging market risk to construct market neutral portfolios has been a challenge for portfolio managers throughout the years.

In this technical note, we review state-of-the-art methods to model and forecast systematic risk and to implement these forecasts to hedge systematic risk using derivatives. To this end, we first present the theoretical foundations behind what is called realized betas to measure systematic risk. We discuss how one can use realized betas to model and forecast this type of risk. We then show how to use these forecasts to hedge systematic risk using derivative products. We present some results suggesting that using forecasts based on some macroeconomic and financial variables improves the hedging performance.

I Introduction

Achieving a market-neutral portfolio has been the absorbing aim of portfolio managers over years. The main interest behind such portfolios lies in their ability to provide consistent returns independent of market fluctuations, while being exposed to low levels of risk. In practice, building a market-neutral portfolio is usually done through a beta-neutral portfolio, dollar-neutral portfolio or a weighted portfolio between these two.

Hedge funds are commonly perceived as market-neutral portfolios, but there exists evidence that under different circumstances this has not been the case. To illustrate, during the most recent financial crisis, in August 2007 various so-called "market-neutral" hedge funds performed poorly with extremely large losses during four consecutive days (from Monday, August 6th, until Thursday, August 9th). Different studies (Asness, Krail, and Liew (2001), Patton (2009), and Bali, Brown, and Caglayan (2011)) indicate that hedge fund returns are exposed to market risk. Bali, Brown, and Caglayan (2012) even after taking into account a rich variety of control variables still find robust results indicating a significantly positive relation between the hedge fund returns and systematic risk.

Considering beta a measure of systematic risk, beta forecasts affect managers' decisions on how to combine long and short positions in order to maintain an overall market neutral portfolio. To see this, consider an investor who wants to hedge the systematic risk of a long position by taking a short position in the S&P 500 index futures. Beta plays a key role in determining the number of contracts required to neutralize the possible variations in the value of the portfolio. Together with the value of the portfolio to be hedged and the value of the relevant futures contract, beta is used to determine the futures hedge ratio, which compares the value of the futures to the value of the hedged portfolio. Thus, failing to predict beta accurately results in hedging positions that do not match the risk extent that needs to be mitigated. In this study we try to hedge the risk exposure for different beta forecasts and try to determine the best beta forecasts that yield lower variance of the hedged returns.

In addition, beta estimates find a wide applicability both in theory and in practice in stock valuation, cost of equity estimation and portfolio management. Ghysels (1998) and Wang (2003) show the effect of different beta forecasts on asset pricing and portfolio optimization. Since beta is a major determinant of the cost of equity, it also plays a significant role in the cost of capital computation. Under the assumption that everything is equal, the higher the beta of a company is, the higher will be its cost of capital used as discount/hurdle rate, implying lower present value of the future cash flows of the company. This fact clearly shows the key effect of beta on company valuation.

This note is organized as follows. Part II continues with theoretical foundations of realized betas. Part III consists of data description. Part IV presents the two cornerstone models of this study used to forecast systematic risk and their testing results. The last part (V) shows the results of futures hedging application and our main suggestion.

II Theoretical Foundations of Realized Betas

Realized beta indicates the extent to which the return of a risky asset covaries with the return on the market portfolio. Therefore, the covariability of the rate of return of the risky asset with the rate of return on the market portfolio determines the expected rate of return on the risky asset. Realized beta is defined as the ratio of realized individual equities' covariance with the market to the realized market variance. Our beta forecasts in this study depend on calculated realized betas. In compliance with the work of Andersen, Bollerslev, Diebold and Wu (2006), we suppose that p_t, which denotes the logarithmic Nx1 vector price process, follows multivariate continuous-time stochastic volatility diffusion,

$$dp_t = \mu_t dt + \Omega_t dW_t \tag{1}$$

where W_t represents a standard N-dimensional Brownian motion. Ω_t and μ_t are strictly stationary and jointly independent of W_t. Depending on Ω_t and μ_t, the continuously compounded return for h-periods has the following distribution:

$$r_{t+h,h} |\, \sigma\{\mu_{t+\tau}, \Omega_{t+\tau}\}_{\tau=0}^{h} \sim N\left(\int_0^h \mu_{t+\tau}\, d\tau, \int_0^h \Omega_{t+\tau} d\tau\right) \tag{2}$$

For $\Delta \to 0$ (for sampling frequency approaching infinity), the theory of quadratic variation under weak regularity conditions implies the following result:

$$\sum_{j=1,\ldots,[h/\Delta]} r_{t+j\cdot\Delta,\Delta} \cdot r'_{t+j\cdot\Delta,\Delta} - \int_0^h \Omega_{t+\tau} d\tau \to 0 \tag{3}$$

Defining the realized market volatility as:

$$\hat{v}^2_{M,t,t+h} = \sum_{j=1,\ldots,[h/\Delta]} r^2_{(N),t+j\cdot\Delta,\Delta} \tag{4}$$

and the realized covariance of individual security i with the market M as:

$$\hat{v}_{iM,t,t+h} = \sum_{j=1,\ldots,[h/\Delta]} r_{(i),t+j\cdot\Delta,\Delta} \cdot r_{(N),t+j\cdot\Delta,\Delta} \tag{5}$$

the ratio of stock covariance with the market to the market variance used to define beta of stock i can be denoted as:

$$\hat{\beta}_{i,t,t+h} = \frac{\hat{v}_{iM,t,t+h}}{\hat{v}^2_{M,t,t+h}} \rightarrow \beta_{i,t,t+h} = \frac{\int_0^h \Omega_{(iN),t+\tau} d\tau}{\int_0^h \Omega_{(NN),t+\tau} d\tau} \qquad (6)$$

Thus, under the assumption of high sampling frequency ($\Delta \rightarrow 0$) we can obtain consistent beta estimates.

Different forecasting models are used extensively throughout literature to predict beta. A very common one is that of Fama and MacBeth (1973), which uses a rolling window of monthly observations over the past five years to forecast betas. In this approach beta is the slope coefficient estimated from the regression of monthly stock returns on market returns. Papageorgiou, Reeves and Xie (2012) refer to the Fama MacBeth approach as "an historical accident" based on the fact that there does not exist a plausible explanation to use monthly stock returns while daily returns are available. Andersen, Bollerslev, Diebold and Wu (2006) provide another approach where quarterly realized betas are computed using daily observations. Hooper, Ng and Reeves (2008) fit the beta time series to the autoregressive model (AR1) to predict a quarter ahead by using quarterly realized betas estimated from daily stocks and index returns over a five-year period. Reeves & Wu (2013) approach utilizes high frequency return data. A very recent approach has been that of Gonzalez, Nave and Rubio (2012) studying the cross-sectional variation of expected returns for a large cross section of industry and size/book-to-market portfolios. This approach implements mixed data sampling (MIDAS) to estimate a portfolio's conditional beta. MIDAS (Ghysels, Santa-Clara, and Valkanov (2003)) renders possible the use of data obtained from unequally spaced intervals. Carrying their own strengths and weaknesses, various models are broadly used to attain beta estimates.

Ghysels and Jacquier (2006) state that the two main empirical approaches to model the dynamics of betas are either by using data driven filters such as the rolling sample estimates in Fama and MacBeth (1973) or by establishing parametric relationships between betas and macroeconomic indicators, as in Shanken (1990) and Ferson and Harvey (1991, 1993, 1999). Following Ghysels and Jacquier (2006) (from now on GJ (2006)), this note combines both approaches to estimate betas. It shows that betas can be predicted by a set of different variables. We also take into account the mean and median across the variables as two separate variables in order to observe whether the aggregate factors are more explanatory compared to individual variables. As mentioned in GJ (2006), using approximately 22 daily returns per month results in highly variable betas that lead to imprecise estimation. This issue can be corrected by the use of intra-daily returns (Andersen, Bollerslev, Diebold and Wu (2005)). However, intra-daily returns are available for relatively short data spans. Like GJ (2006) including all the proxy variables in the model, we use all firm specific and macroeconomic variables in a single framework.

III Data Description

Data used to estimate betas are the daily value-weighted returns on 25 Portfolios formed on Size and Book-to-Market and the excess market returns. We also run our model for the 30 Industry value-weighted portfolio returns. Returns for both types of portfolios are obtained from Kenneth R. French's website for three sample periods: 1927-2010, 1927-1964 and 1965-2010.

Kenneth French[1] data is obtained from CRSP database. Portfolios are constructed on a yearly basis at the end of June and they are intersections of five portfolios formed on book to market ratio (BE/ME) and five portfolios formed on size (market equity, ME). The size breakpoints for a specific year are the NYSE market equity quintiles at the end of June of that year. BE/ME for June in the current year is the book equity for the last fiscal year end in previous year divided by ME for December of the previous year. The BE/ME breakpoints are also NYSE quintiles.

The portfolios for July of a specific year (t) to June of the following year (t+1) include all AMEX, NYSE, and NASDAQ stocks for which there is available market equity data for December of the previous year (t-1) and June of the current year (t), and positive book equity data for (t-1). The risk-free rate and the market return are also downloaded from Kenneth French's website available under the "Fama-French factors" section.

We implement all firm specific and macroeconomic variables in a single framework. The categorized independent variables are presented in Table 1.

Table 1.
Table one lists the explanatory variables implemented to predict the realized betas. Each predictor variable is classified into one of the aggregate categories: Financial Ratios, Bond Yield Measures, Corporate Variables, Macroeconomic Variables and Risk Factors.

Classification of Predicting Variables				
Aggregate Ratios	**Aggregate Bond Yield Measures**	**Corporate Variables**	**Macroeconomic Variables**	**Risk factors**
Dividend Price Ratio	Long Term Yield	Dividend Payout Ratio	Consumption, Wealth, Income Ratio	Excess Market Return
Dividend Yield	Term Spread	Net Equity Expansion	Investment to Capital Ratio	Small Minus Big
Earnings Price Ratio	Default Yield Spread		Employment growth rate	High Minus Low
Book-to-Market Ratio	Default Return Spread		Unemployment growth rate	Momentum
10-year m.a[2] of earnings per price	Inflation		Production Index	Stock Variance
	Treasury bills			Long Term Rate of Return

[1] All data available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[2] Moving-average.

In the last section of this study we implement full-size S&P 500 Index Futures to hedge the systematic risk. We receive futures data from the Quandlbeta web page[3]. Under the "Historical Contracts" section we observe the data availability starting from the second quarter of year 1982. The listed contracts exist for the months of March (H), June (M), September (U) and December (Z). The full-size S&P 500 Index Futures contract is cash-settled relying on the S&P 500 Index and they are traded on the Chicago Mercantile Exchange (CME). Each contract is worth $250 times full-size S&P 500 Index. Prices are quoted in Index points.

IV Forecasting Systematic Risk

In-Sample Estimation

Given the quarterly data on predictor variables, we need to obtain the quarterly estimates of beta for our three samples. These quarterly betas are obtained from the linear regression of excess daily portfolio returns on the excess daily market returns.

We extract the risk-free rate from the portfolios' returns to obtain portfolio excess returns and go on with estimating the CAPM regression. Given that all the inputs of this regression are in daily terms, the linear regression equation is constructed in such a way that it accounts for the number of days per quarter. Hence, running a regression by using the data for each business day of the three-months period corresponding to every quarter of our sample, we achieve quarterly forecasts of beta. When computing the number of trading days per month we can clearly observe the number of quarterly observations. For example, the last sample period (1965-2010) consists of 552 months, therefore 184 quarters. From now on, throughout the paper we keep illustrating our model by considering as main sample the period 1965-2010.

Out-of-Sample Estimation

We use two distinct models for the out-of-sample estimations. The first one is the classic AR (1) model:

$$\beta_{i,t} = b_{i,0} + b_{i,1}\beta_{i,t-1} + u_{i,t} \qquad (7)$$

and our predictive factors' model, which in addition to (7) includes the lagged values of predictive variables:

$$\beta_{i,t} = b_{i,j,0} + b_{i,j,1}\beta_{i,t-1} + b_{i,j,2}x_{j,t-1} + u_{i,j,t} \qquad (8)$$

where i indicates the portfolio, j the predicting variable and t the corresponding quarter.

We refer to model (7) as the benchmark model, where betas are predicted based solely on their lagged values (AR (1)). The set of explanatory variables in Model (8) is inclusive of the three Fama-French factors.

[3] http://www.quandl.com/futures/full-size-s-and-p-500-index-futures.

Even if there are no clear-cut rules on the choice of sampling frequency and the number of lags, current literature still uses the rolling windows of 60 monthly returns as Fama and MacBeth (1973). We obtain beta forecasts by estimating the models based on overlapping windows of 60 quarters of observations for the out-of-sample period between the 1st quarter of 1980 and the last quarter of 2010. To illustrate, for the first quarter in the out-of-sample period 1980Q1, the model is estimated using 15 years of quarterly data between 1965Q1 and 1979Q4.

$$\hat{\beta}^{f}_{i,1980Q1} = \hat{b}_{i,0} + \hat{b}_{i,1} \cdot \beta_{i,1979Q4} \qquad (7a)$$

$$\hat{\beta}^{f}_{i,j,1980Q1} = \hat{b}_{i,j,0} + \hat{b}_{i,j,1} \cdot \beta_{i,1979Q4} + \hat{b}_{i,j,2} \cdot x_{j,1979Q4} \qquad (8a)$$

$\hat{b}_{i,0}, \hat{b}_{i,1}, \hat{b}_{i,j,0}, \hat{b}_{i,j,1}, \hat{b}_{i,j,2}$ are estimated using the data from the period starting 1965Q1 until 1979Q4.

Being aware that the set of independent variables includes estimates of beta, we are suspicious of error-in-variables problem, and as a consequence of endogeneity too. This issue might generate inconsistent OLS estimates. Therefore, as in GJ (2006) we run each model using both IV and OLS estimates and compare accordingly. Correlation of the explanatory variable with the error term is indicated as follows (GJ (2006)):

$$\beta_{i,t} = b_{i,j,0} + b_{i,j,1}\left(\beta_{i,t-1} + \varepsilon_{t-1}\right) + b_{i,j,2}x_{j,t-1} + \left(u_{i,j,t} + \varepsilon_{i,j,t-1} - \varepsilon_{i,j,t}\right) \qquad (9)$$

The valid instrument should not be correlated to the measurement error in $\beta_{i,t-1}$ and highly correlated with $\beta_{i,t-1}$. Following GJ (2006), the valid instrument of $\beta_{i,t-1}$ is specified as follows:

$$\hat{\beta}_{i,t-1} = b_{i,j,0} + b_{i,j,1}\beta_{i,t-2} + \text{residual} \qquad (10)$$

$\hat{\beta}_{i,t-1}$ replaces $\beta_{i,t-1}$ in (7) and (8).

To test the out-of-sample results from the 15 years rolling window, three commonly used tests are implemented: The Diebold Mariano test, Mincer-Zarnowitz regression and the Root Mean Square Forecast Error (RMSFE).

To check for the superiority of one model over the other and for the robustness of the results, we implement Diebold Mariano (1995) test and Mincer-Zarnowitz (1969) regression. The DM test tests the null of equality of forecast accuracy of the two forecasts under general assumptions. The statistic is calculated based on the loss differential. The test assumes that the loss differential process is stationary. DM also corrects for the autocorrelation that multi-period forecast errors usually exhibit. An efficient h-period forecast has forecast errors following MA (h-1) processes. Diebold-Mariano uses a Newey-West type estimator for sample variance of the loss differential to overcome this issue.

The Mincer-Zarnowitz regression is used to test whether predictions from forecasting models are

unbiased and efficient.

$$\beta_{t+h} = \alpha + \beta \cdot \hat{\beta}_{t+h|t} + e_{t+h|h} \qquad (11)$$

t here indicates the current time period and the forecast is made for h-steps ahead. In our context h equals one.

After estimating the parameters of this regression, we use the Wald test for the following joint hypothesis:

$$H0: \alpha = 0, \beta = 1$$

Failure to reject the null indicates unbiased (α = 0) and efficient (β = 1) forecasts.

The third test we run is the Root Mean Squared Forecasting Error test. We compute the forecasting error as shown in the formula below.

$$RMSFE_{\,i,j} = \left({}^{1}/_{T} \sum_{t=1980Q1}^{2011Q4} \left(\beta_{i,t} - \hat{\beta}_{i,j,t}^{f}\right)^{2}\right)^{1/2} \qquad (12)$$

Table 2. presents the RMSFE test results. This test is run for each of the specific predictive factors individually and the seven aggregate measures: aggregate ratios, bond yield measures, corporate variables, macroeconomic variables, risk factors and mean and medians. Thus, what we do here is obtain betas estimates by using the means of the variables categorized under each of these seven groups according to classifications provided in Table 1. Individually there are 26 variables including employment and unemployment levels, which we exclude while averaging into groups because we consider the employment growth rate and unemployment growth rate good enough representatives. We name "mean forecasts" and "median forecasts" the average and median across all the variables respectively. For both 25 Size-BM portfolios (Panel A.) and 30 Industry portfolios (Panel B.) we observe that OLS estimates dominate the benchmark AR (1) model for a greater number of portfolios compared to IV estimates. For the Size-BM portfolios aggregate bond yield measures, risk factors, mean and median forecast show to be the strongest dominants over the benchmark consistently across periods and estimates. This dominance also holds for DM and Zarnowitz test results. For the Industry portfolios, the same factors seem to outperform the benchmark but for a lower number of portfolios. For the 30 Industry portfolios the IV estimates are also not as strong as for Size-BM portfolios. Based on RMSFE individually, usually tbl, lty and ltr dominate for OLS estimates and FF3 factors for IV instruments.

Next, we go on with conducting asset-pricing tests. To improve the power of the estimates, we use Newey West estimators for asset pricing tests. The pricing error consists of the residuals emerging from the regression of portfolio returns on each of the seven aggregates estimates of beta. Having the pricing error, we estimate the root mean squared error in a similar way with (12). As shown in Table 3., based on this test as well, model (8) outperforms the benchmark in most of the cases for the majority of the portfolios.

Table 2.
This table shows the number of portfolios for which model (8) dominates benchmark model based on Root Mean Squared Forecast Error computed as in (12). The variable X of model (8) in this case consists of the seven aggregate measures. Results are reported for 25 Size – Book to Market Portfolios (**Panel A.**) and 30 Industry Portfolios (**Panel B**.), which are constructed as given in Kenneth French website. Columns of the table indicate the ordinary least squares and instrumental variables estimates computed under each sample period.

Panel A.

25 Size-Bm Portfolios	**1927-2010**		**1927-1964**		**1965-2010**	
	OLS	**IV**	**OLS**	**IV**	**OLS**	**IV**
Aggregate Ratios	9	3	9	5	18	7
Aggregate Bond Yield Measures	24	14	21	19	25	16
Corporate Variables	18	5	21	16	8	3
Macroeconomic Variables	23	8	11	11	22	14
Risk Factors	20	19	20	19	20	19
Mean Forecast	25	16	24	20	25	19
Median Forecast	25	19	24	19	25	18

Panel B.

30 Industry Portfolios	**1927-2010**		**1927-1964**		**1965-2010**	
	OLS	**IV**	**OLS**	**IV**	**OLS**	**IV**
Aggregate Ratios	19	3	13	4	23	9
Aggregate Bond Yield Measures	27	5	24	8	19	8
Corporate Variables	16	4	20	6	15	3
Macroeconomic Variables	21	5	4	8	24	6
Risk Factors	13	13	16	14	12	11
Mean Forecast	30	6	23	5	30	9
Median Forecast	30	12	24	11	29	10

Table 3.
Table 3. presents the number of portfolios for which the average of each of the seven groups of variables performs better than the benchmark. Values are estimated based on Root Mean Squared pricing error. Results are reported for 25 Size – Book to Market Portfolios (**Panel A.**) and 30 Industry Portfolios (**Panel B**.), which are constructed as given in Kenneth French website. Columns of the table indicate the ordinary least squares and instrumental variables estimates computed under each sample period.

Panel A.

25 Size-Bm Portfolios	1927-2010		1927-1964		1965-2010	
	OLS	IV	OLS	IV	OLS	IV
Aggregate Ratios	20	11	15	16	18	7
Aggregate Bond Yield Measures	20	12	15	12	15	13
Corporate Variables	17	14	18	17	9	11
Macroeconomic Variables	17	13	16	10	13	15
Risk Factors	14	16	20	14	12	12
Mean Forecast	17	11	18	13	18	10
Median Forecast	19	14	15	16	17	17

Panel B.

30 Industry Portfolios	1927-2010		1927-1964		1965-2010	
	OLS	IV	OLS	IV	OLS	IV
Aggregate Ratios	17	15	16	17	19	17
Aggregate Bond Yield Measures	20	12	18	15	19	11
Corporate Variables	18	13	19	12	19	14
Macroeconomic Variables	19	13	12	11	19	17
Risk Factors	17	19	18	16	17	18
Mean Forecast	20	15	19	11	23	17
Median Forecast	15	18	16	15	21	17

V Hedging Systematic Risk

To compare the economic significance of our results in an out-of-sample hedging implementation, and moreover to determine the variable/group of variables that does best in terms of risk hedging, we hedge the systematic risk by (a) using market return and (b) implementing the full-size S&P 500 Index Future contracts. Considering the former, the return of the hedged position is estimated as follows:

$$\Delta_{i,j,t} = r_{i,t} - \hat{\beta}^{f}_{i,j,t} \cdot r_{M,t} \qquad (13)$$

To conduct this hedging application we short-sell $\hat{\beta}^{f}_{i,j,t|t-1}$ dollars of the market portfolio and long the portfolio return. We try to find out the factors that reduce volatility more when hedging

occurs. Knowing that perfect hedge should yield a zero hedging return (hence, zero hedging error) and zero volatility, the obtained volatility estimates (not reported here)[*4] show that on average long-term rate of return (ltr), treasury bill (tbl), excess market return (mktrf), high minus low (hml) and e/p ratio reduce volatility more than the other factors and more than the benchmark.

In Table 4. we present the number of portfolios for which the average of the variables classified under each of Aggregate Ratios, Aggregate Bond Yield Measures, Corporate Variables, Macroeconomic Variables, Risk Factors, Mean and Median Forecast categories outperforms the benchmark. The dominance is measured based on the volatility of the hedged returns ($\Delta_{i,j,t}$) in (13). $\hat{\beta}^{f}_{i,j,t}$ corresponds to the average beta estimates across the group of variables listed under each category. As in previous sections, to check the strength of our results, the estimates are conducted for both ordinary least square and instrumental variable estimators. From Panel A. of Table 4. we can clearly observe that OLS results are mainly stronger compared to IV results for the 25 Size-Book to market portfolios. Aggregate bond yield measures, corporate variables, risk factors and mean across all the variables seem to yield less volatile hedging returns. Considering not only the number of portfolios for which it outperforms the benchmark, but also the consistency across three sample periods, aggregate bond yield measures show to be the strongest category in this hedging framework. Panel B. of Table 4. clearly implies that 30 Industry portfolios context is not as strong as the 25 Size-BM one in terms of showing that model (8) carries a higher economic significance than the benchmark model.

[4] Available upon request.

Table 4.
This table provides the number of portfolios for which the average of each of the seven groups of variables outperforms the benchmark. Values are estimated based on the volatility of the hedged returns. Volatility of the hedged returns is computed as in (13), in which portfolio returns are hedged using market return. Results are reported for 25 Size – Book to Market Portfolios (**Panel A.**) and 30 Industry Portfolios (**Panel B**.), which are constructed as given in Kenneth French website. Columns of the table indicate the ordinary least squares and instrumental variables estimates computed under each sample period.

Panel A.

25 Size-Bm Portfolios	**1927-2010**		**1927-1964**		**1965-2010**	
	OLS	**IV**	**OLS**	**IV**	**OLS**	**IV**
Aggregate Ratios	3	5	8	9	11	15
Aggregate Bond Yield Measures	17	13	18	17	18	21
Corporate Variables	14	7	21	19	12	7
Macroeconomic Variables	10	8	6	5	6	9
Risk Factors	8	8	20	18	13	12
Mean Forecast	12	9	17	15	13	15
Median Forecast	6	7	10	15	13	14

Panel B.

30 Industry Portfolios	**1927-2010**		**1927-1964**		**1965-2010**	
	OLS	**IV**	**OLS**	**IV**	**OLS**	**IV**
Aggregate Ratios	12	4	10	6	16	13
Aggregate Bond Yield Measures	19	10	12	11	15	9
Corporate Variables	20	8	16	13	19	9
Macroeconomic Variables	16	8	14	11	18	11
Risk Factors	11	15	10	14	17	14
Mean Forecast	16	7	14	11	20	13
Median Forecast	14	16	14	15	19	18

To show a concrete picture of the volatility measure obtained from the hedging practice with the market return, in Table 5. we present the median hedged return volatility measures of our previously described seven aggregates and the benchmark. In Panel A. we provide the medians across the 25 Size-BM portfolios and in Panel B. the median measures across the 30 Industry portfolios. The median volatility measures are denoted in percentage terms. Results indicate that 30 Industry Portfolios exhibit a higher volatility.

Table 5.
This table presents median of the volatility of the hedged portfolio returns (13) for the benchmark and each aggregate measure. Panel A. shows medians computed across the 25 Size – Book to Market Portfolios and Panel B. medians across 30 Industry Portfolios. Both 25 Size-Bm and 30 Industry Portfolios are built as described in Kenneth French website. Columns of the table indicate the ordinary least squares and instrumental variables estimates computed under each sample period. Values are expressed in percentages.

Panel A.

25 Size-Bm Portfolios	1927-2010		1927-1964		1965-2010	
	OLS	IV	OLS	IV	OLS	IV
Benchmark	5.440	5.464	4.423	4.457	5.711	5.736
Aggregate Ratios	5.428	5.462	4.454	4.475	5.700	5.712
Aggregate Bond Yield Measures	5.395	5.422	4.446	4.468	5.663	5.703
Corporate Variables	5.428	5.463	4.409	4.435	5.611	5.671
Macroeconomic Variables	5.418	5.838	4.440	4.466	5.646	5.826
Risk Factors	5.437	5.461	4.413	4.444	5.708	5.766
Mean Forecast	5.419	5.452	4.432	4.457	5.686	5.701
Median Forecast	5.426	5.458	4.428	4.455	5.704	5.729

Panel B.

30 Industry Portfolios	1927-2010		1927-1964		1965-2010	
	OLS	IV	OLS	IV	OLS	IV
Benchmark	6.141	7.289	5.391	5.756	6.228	6.424
Aggregate Ratios	6.155	7.294	5.382	5.976	6.218	6.562
Aggregate Bond Yield Measures	6.108	7.028	5.402	5.918	6.181	6.881
Corporate Variables	6.131	6.994	5.409	5.757	6.203	6.474
Macroeconomic Variables	6.129	7.173	5.388	5.783	6.235	6.448
Risk Factors	6.163	6.670	5.391	5.936	6.204	6.426
Mean Forecast	6.134	7.033	5.397	5.854	6.210	6.847
Median Forecast	6.139	6.449	5.394	5.721	6.217	6.454

In the same way with the preceding hedging application, now we continue with hedging using full-size S&P 500 Index Future contracts. As stated in the Data Description section, the futures data is limited to the period starting 1982Q2. In our hedging application we use the future contracts' data starting from the beginning of year 1983 and ending the last quarter of 2010. Table 6 provides the number of portfolios that outperform the AR (1) benchmark model. This dominance is measured in terms of standard deviations of the hedged returns. Similarly to (13), instead of market return, we use futures' returns calculated from given price data as follows:

$$\delta_{i,j,t} = r_{i,t} - \hat{\beta}^{f}_{i,j,t} \cdot r_{f,t} \qquad (14)$$

Tables 6. Reports the results for both types of portfolios (Panel A. and Panel B.). As in the

previous hedging application, aggregate bond yield measures keep being the leader in terms of outperforming the benchmark for the 25 Size-BM portfolios. It is followed by aggregate ratios, overall mean and median forecasts, which show to be significantly dominating the benchmark. For the 30 Industry portfolios, aggregate ratios together with general mean and median forecasts outperform the benchmark at a higher extent compared to other aggregate categorizations. Even if not the leading dominant here, aggregate bond yield measures still outperform the benchmark significantly.

Table 6.
Table 6. shows the number of portfolios for which the average of each of the seven groups of variables dominates the benchmark. Values are estimated based on the volatility of the hedged returns. Volatility of the hedged returns is estimated as in (14) where portfolio returns are hedged using full-size S&P 500 Index Future returns. Results are reported for 25 Size – Book to Market Portfolios (**Panel A.**) and 30 Industry Portfolios (**Panel B**.), which are constructed as given in Kenneth French website. Columns of the table indicate the ordinary least squares and instrumental variables estimates. Due to late data availability, our sample here is limited to the period between years 1983 and 2010.

Panel A.

25 Size-Bm Portfolios	**1983-2010**	
	OLS	**IV**
Aggregate Ratios	22	15
Aggregate Bond Yield Measures	24	17
Corporate Variables	13	4
Macroeconomic Variables	9	7
Risk Factors	10	6
Mean Forecast	22	13
Median Forecast	21	18

Panel B.

30 Industry Portfolios	**1983-2010**	
	OLS	**IV**
Aggregate Ratios	20	15
Aggregate Bond Yield Measures	18	12
Corporate Variables	18	13
Macroeconomic Variables	17	14
Risk Factors	10	15
Mean Forecast	21	16
Median Forecast	23	21

Following the same procedure as in the previous hedging application, we report in Table 7. the median hedged return volatility measures of the seven aggregate measures and the benchmark. The median volatility measures are denoted in percentage terms. Similarly to Table 5., Table 7. shows that 30 Industry portfolios exhibit a higher volatility.

Table 7.
This table presents medians of the volatilities of the hedged portfolio returns for the benchmark and each aggregate measure. Panel A. shows medians computed across the 25 Size – Book to Market Portfolios and Panel B. medians across 30 Industry Portfolios. Volatility of the hedged returns is estimated as in (14), in which portfolio returns are hedged using full-size S&P 500 Index Future returns. Both 25 Size-BM and 30 Industry Portfolios are built as described in Kenneth French website. Columns of the table indicate the ordinary least squares and instrumental variables. Due to late data availability, our sample here is constrained between years 1983 and 2010. Values are expressed in percentages.

Panel A.

25 Size-Bm Portfolios	1983-2010	
	OLS	IV
Benchmark	6.057	5.619
Aggregate Ratios	6.028	5.622
Aggregate Bond Yield Measures	5.968	5.615
Corporate Variables	5.925	5.717
Macroeconomic Variables	5.950	5.623
Risk Factors	6.071	5.659
Mean Forecast	5.995	5.624
Median Forecast	6.023	5.616

Panel B.

30 Industry Portfolios	1983-2010	
	OLS	IV
Benchmark	6.278	6.272
Aggregate Ratios	6.227	6.256
Aggregate Bond Yield Measures	6.247	6.637
Corporate Variables	6.238	6.275
Macroeconomic Variables	6.252	6.275
Risk Factors	6.265	6.260
Mean Forecast	6.242	6.530
Median Forecast	6.256	6.201

Even if not reported in this paper, it is also worth mentioning that individually, 22 predictive variables dominate the benchmark for more than ten industry portfolios. Together with the statistical tests, the hedging test indicates that there are some strong predictive variables such as lty, ltr, tms, tbl, dfr, e/p, and FF factors that beat the benchmark model strongly and consistently across different periods. The individual results for lty, dfr, tbl, tms and ltr with FF factors, which are components of aggregate bond yield and risk measures, explain the dominance of these two aggregates.

Simply put, implementing the rolling sample and moreover adding the parametric relationship as suggested in Ghysels and Jacquier (2006) leads to essential improvement not only in terms of the forecasting power of the beta, but also improvement in terms of hedging power of the systematic risk.

Overall, considering the crucial impact of the beta forecasts in portfolio optimization, there have been many attempts to provide a model that predicts beta accurately. Our study shows that the combination of rolling sample and parametric relationship models not only forecasts betas at a significant extent, but also shows superiority over the benchmark AR (1) model in both of the implemented hedging applications. Based on our results, we would suggest that using aggregate bond yield measures, risk factors and mean forecast in model (8) is highly likely to yield considerably accurate estimates of beta leading to the achievement of many researchers' and portfolio managers' common aim of efficiently hedging systematic risk.

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