PORTFOLIO MODELING

The US Equity Risk Model

We describe the new US Equity Risk Model that is employed in POINT, the Barclays Capital portfolio analytics and modeling platform. It is a multi-factor model that incorporates industry, fundamental, and technical factors. It was developed without legacy issues to provide a more precise risk perspective and the basis for improved portfolio construction. It incorporates important innovations compared to standard equity factor models: proprietary factors that capture default risk and earnings manipulation, new methodologies for the estimation of industry betas and fundamental factor exposures, and a new class of highly responsive models to predict both systematic and idiosyncratic risk. The performance of the model is robust across different market environments, including during 2008.

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1. Executive Summary[1]

Superior investment performance requires prudent risk management practices. A key element in the management of risk is the risk model used to assess the uncertainty in the portfolio returns. Risk models allow portfolio managers to quantify different sources of risk inherent in their portfolios. A valuable risk model should be both economically intuitive and statistically powerful. The US Equity Model is built to capture the major investment themes followed by portfolio managers in the US financial markets and to accurately forecast future volatility of equity portfolios.

The model has very distinctive features:

1. It is a brand new model with no legacy issues. We started with a clean sheet and were able to take a critical approach to current practices in equity risk modeling. This flexibility gave us the ability to consider all possible alternatives at each stage of the process and to utilize state of the art research.

2. It employs a new set of methodologies that are not common practice in the industry. These include:

   – Estimation of monthly exposures to the industry factors (betas) through a proprietary model that incorporates daily data. The methodology renders sensitivities that are robust and yet very dynamic. We call them POINT Mixed-Frequency Betas (PMBs).

   – Construction of new proprietary risk factors such as (i) a financial distress factor based on default probabilities rather than the typical (and stale) leverage information and (ii) an earnings management factor that checks earnings against cash flows information.

[1]We would like to thank Anthony Lazanas, Matthew Rothman, Michael Lee, and Jesus Ruiz-Mata, for their valuable comments and suggestions. Gary Wang, Jerome Hauser, and Chandra Koppella contributed to the development and implementation of the risk model in POINT.

- Non-linear transformation of the loadings for some fundamental factors. This non-linear transformation is employed only when there is overwhelming statistical and economic evidence for improved volatility estimates.
- Proprietary mixed frequency models to estimate monthly systematic and idiosyncratic volatilities using daily data. The use of this data makes the model both robust and very responsive to changing market conditions.

Our empirical analysis was undertaken with a critical mindset and a strong preference for robustness and interpretability of the results. This was especially apparent in the factor selection procedures we employed to select the most powerful drivers of risk from an exhaustive list of candidate factors. Moreover, risk models lately have been the focus of attention in terms of their (lack of) ability to quickly respond to changing market conditions. One of the objectives in developing this new model was to balance the trade-off between creating a dynamic model and producing reasonably stable risk estimates. The new US Equity Model is built to be a monthly model, but in many instances, we utilize higher frequency data (daily). There are many benefits to using daily data in such cases. For a given data period, its use delivers many more data points, allowing us to create more precise and robust estimates[1]. Also, it is possible to produce estimates that react more quickly to changes in the market conditions. We use the information in higher frequency data to provide (i) improved estimates of sensitivities to industry factors (betas) and (ii) volatility estimates that have more predictive power for both systematic and idiosyncratic risk. What makes this approach feasible is the fact that US stocks are typically liquid, even at the daily level. We talk more about the use of daily data in the following sections of the paper.

The new US Equity Risk Model is implemented in POINT – Barclays Capital portfolio analytics and modeling platform – as a part of the Global Risk Model (GRM), see Joneja/Dynkin *et al.* (2005). The new model replaces the current ERA Global Model (see Lai (2005)) in POINT for US stocks. Increased presence of multi-strategy managers augments the need to correctly account for correlations between different asset classes. In this regard, POINT exclusively positions itself as a true multi-asset-class portfolio analysis platform. It combines a comprehensive set of fixed income and equity models within a single tool. In addition to being a multi-asset-class platform, POINT is also a multi-functionality tool with which users can connect the risk model with the optimizer, perform scenario analysis, and run a return attribution analysis.

Our research capitalizes on the equity and fixed income knowledge at Barclays Capital. The use of POINT Corporate Default Probability as a factor in the new US Equity Model is an example of the interaction between the credit and the equity expertise within POINT. In the development phase of the model, we have interacted extensively with equity research, trading, and strategy groups, utilizing their knowledge and experience. One consequence of such interaction is the use of the "Change in Discretionary Accruals" factor in our model that was originally implemented in the ROQS model (see Rothman, Lee, and Wei (2007)) developed by the Quantitative Equity Strategies Group at Barclays Capital.

Model Snapshot

The US Equity Model consists of a set of industry, fundamental, and technical factors. It is a cross-sectional model in which factor loadings are known and factor realizations are estimated via cross-sectional regressions. The estimation universe is the set of largest 2000

[1] The use of higher frequency data requires careful consideration of aggregation issues. The techniques we use explicitly account for them.

stocks in the US (defined at the end of June of every year). We use a three-step procedure to estimate the model. In the first step, we estimate the industry factors on a univariate basis. Each stock loads with its beta onto a single industry where we use a widely followed classification scheme – GICS level 2 with 24 industries – to define the industry classification. In the second step, we estimate the fundamental and technical factor realizations through a multivariate regression. In the last step, we estimate the residual market volatility factor, the intercept of the model, which captures all the residual systematic movements in stock returns and ensures that the idiosyncratic returns are mean zero.

We can maintain a clean interpretation of the industry risk by estimating these factors and betas on a univariate basis in the first step of the calibration process. As a result, the estimated industry factors, which form the major part of the model, are statistically very close to the actual GICS level 2 value weighted industry indices. To compute betas, the sensitivities to the industry factors, we employ a novel methodology that employs daily data. Rather than estimating the beta from historical monthly returns, we compute the realized betas within each month and then combine these historical intra-month betas into a forecast by means of an optimal weighting scheme. The use of daily data provides us with a much larger number of data points that lets us produce more robust estimates of the betas. The use of well known industry factors with univariate beta exposures allows for a straightforward interpretation and simplifies hedging systematic industry and market risk.

We performed a thorough factor selection methodology to choose the fundamental/ technical factors used in the model. We first identified a large set of factors to be tested through a survey of both industry and academic practice. After eliminating most of the candidate factors using univariate testing, we performed multivariate analysis with a smaller set of factors to select the final set of fundamental and technical factors in our model. The analysis was based on statistical procedures, but guided by economic intuition. The following is a list of fundamental/technical variables used in our model:

1. Market Value (SIZE)
2. Book to Price (BP)
3. Earnings to Price (EP)
4. POINT Corporate Default Probability (CDP)
5. Share Turnover (TURN)
6. Momentum (MOM)
7. Change in Discretionary Accruals (ACC)
8. Total Yield (YLD)
9. Residualized Realized Volatility (RVOL)
10. Residualized Forward E/P (FEP)

Even though the fundamental/technical factor realizations are estimated jointly and only in the second step, these factors keep their clean univariate interpretation to a large degree. To check this statement, we estimate each fundamental/technical factor separately on a univariate basis and observe that they are highly correlated with their multivariate version (see Section 2.4 Fundamental and Technical Factors for details).

The inputs to the second step of the estimation process are stock returns (net of industry) and fundamental/technical factor loadings. Our research shows strong evidence of non-linear relationships between stock returns and factor loadings for certain fundamental/technical factors. For instance, a difference in market capitalization of fifty million dollars between two relatively small companies has very different implications for risk and returns than the same difference for relatively large companies. To capture this we perform non-linear transformations to the loadings of some selected factors. This approach removes systematic biases in volatility estimation inherent in linear factor models. It also reduces the misspecification error that potentially gets passed on to the estimation of the other factors. In the end, we decided to be extremely conservative, using these non-linear transformations only for factors in which there are significant improvements in the risk forecast. We found this to be the case for the Market Value, Earnings to Price and the POINT Corporate Default Probability risk factors.

After performing the non-linear transformations, we standardize the loadings of all fundamental/technical factors such that the market portfolio (the value weighted portfolio of stocks in the core estimation universe) has zero loading to all of these fundamental/technical factors. Standardization de-means the loadings and implies a relative view on their values. As the fundamental/technical variables aim to explain cross-sectional variations across stocks above and beyond the influence of industry exposure, what is more relevant for a stock in the estimation of risk is the relative value of its loading with respect to the loadings of other stocks in the market at a given point in time, not the absolute value of its loading.

As the major goal of the risk models is to predict future volatility of individual securities and portfolios, it is critical to have a high-quality volatility estimation model on top of a strong factor model. To estimate the volatility of systematic factors in the US Equity Risk Model, we developed a proprietary mixed frequency, two-factor volatility estimation model that employs daily data. Instead of using monthly factor realizations to predict the volatility, our model performs the prediction based on the intra-month movements of the factors. This makes the prediction very dynamic and the estimates much more responsive to changing market conditions.

Another part of the model in which we employ daily data is the estimation of the idiosyncratic risk. As the nature of individual securities can change quickly, the use of daily data becomes even more relevant in the idiosyncratic risk model. Due to its use, we do not need a long return history for a stock in order to calculate its idiosyncratic risk. We employ actual firm-specific residual stock returns coming out of a daily model to compute our idiosyncratic risk estimate. We then fine-tune these forecasts with information regarding the firm's specific characteristics, such as size, to capture mean-reverting properties of its idiosyncratic risk.

In Section 2 of our paper, we define the US Equity Risk Model in detail. Some major discussion points include the estimation process used to calibrate the model, the proprietary methodology we have developed to compute exposures to the industry factors, and the selection methodology used to pick the fundamental and technical factors. Section 3 describes the mixed frequency two-factor model we have developed to estimate the systematic factor volatilities. Section 4 describes the major features of the idiosyncratic risk model. Section 5 demonstrates how well the model performs in a backtesting out-of-sample framework. Section 6 illustrates the links between our credit and equity risk models. Section 7 shows the level of detail in the POINT risk reports. Finally, Section 8 summarizes our discussion of the US Equity Risk Model.

2. The US Equity Risk Model

In this section, we describe the US Equity Risk Model in detail. First, we discuss our data sources and how we process the data. We then introduce the major aspects of the factor model for US equities and describe the estimation process in detail. We continue our discussion by introducing the industry factors and the proprietary methodology we have developed to estimate the industry exposures – PMBs. After illustrating some of the univariate and multivariate analyses we have performed to select the fundamental/technical factors, we describe the selected factors and the transformations applied to their loadings. We then introduce the residual market volatility factor of the third step of the regression and conclude with a discussion on the premise of macro factors in equity risk models.

2.1. Data

Clean and accurate data is a prerequisite for building a valuable model. We pay special attention to all types of data issues, such as eliminating outliers, adjusting the data for corporate actions, merging different databases, and avoiding possible biases. We employ the most prominent data sources available in the market and run extensive pre-processing before using any type of data.

We have employed the following databases in the model building process:

1. *Compustat Point in Time (CPIT) Database* is the source of all fundamental data. CPIT provides non-restated data, which is the information that was available at that time in the history. This feature allows us to run a much more realistic model building process free of look-ahead bias.

2. *CRSP* daily and monthly databases are used for price, return, and other technical data such as volume and shares outstanding. CRSP is a well-recognized database in the US for its precision in tracking the history of stock issues. In particular, this database tracks corporate events remarkably well.

3. *IBES Consensus* is the data source for historical analyst estimates such as earnings estimates and the growth projections for companies. Earnings estimate data go back to 1976.

4. *GICS* is a widely recognized classification system employed by portfolio managers around the globe. For industry classification in the risk model, we use GICS level 2, which is available as early as 1985 and groups firms into 24 industries. We remain attentive to future changes in industry definitions and classifications.

While constructing the model, we examined the possibility of using option-related data. Unfortunately, the use of this data in this context has some problems, namely that (i) implied volatilities include a hard-to-measure risk premium we would like to exclude from the analysis, and (ii) liquid option data is available only for a relatively small set of stocks. In the end, we decided not to use this dataset, as the perceived advantages seemed relatively small.

We are very careful connecting these datasets, improving, when possible, over commercially available solutions. We also employed comprehensive data cleaning procedures. All data was thoroughly cleaned and all input variables, such as stock returns, industry betas, and fundamental ratios, are winsorized. We have identified sensible cut-off points for all these variables by looking carefully into their distributions. This brings robustness to the estimation process in the sense that we do not allow the factor realizations to be affected by a few extreme values.

We use a 20 year data period (1987-2007) to select our factors and to calibrate our model. In most of the analysis, we test our conclusions on several sub-samples, selected by time periods, industries, volatility regimes, etc. This allows us to be confident that our model performs consistently well across different market conditions.

2.2. Model Description

In this section, we introduce the structure of the new US equity risk model. The model covers all US stocks and consists of a set of industry, fundamental, and technical factors. To define the 24 industries in the model, we use the Global Industry Classification Standard (GICS), a widely followed industry classification scheme among US portfolio managers. To select the fundamental and technical factors, we explored variables that represent the major investment themes of US portfolio managers. A good risk factor has a solid economic rationale and is statistically powerful; it explains cross-sectional variation in stock returns, and it improves the ability of the model to predict future volatilities of securities and portfolios.

We aimed to be parsimonious in the factor selection process as a model with too many factors can very well be misspecified. The use of more factors increases the explanatory power of the model in-sample, but a model with too many factors can produce very unstable parameter estimates and perform poorly out-of-sample. Therefore, we complement our analysis by performing a significant number of out-of-sample tests in the factor selection process (see Section 5 for more details).

The US Equity Risk Model is defined as follows[2]:

$$r_i^t = \beta_i^{t-1} I^t + \sum_{j=1}^{n} \ell_{ij}^{t-1} F_j^t + R^t + \varepsilon_i^t$$

where r_i^t is the rate of return for stock i at time period t

I^t is the industry factor corresponding to stock i

β_i^{t-1} is the beta of the stock to the industry factor, calculated at $t-1$

F is the set of fundamental and technical factors

ℓ_{ij}^{t-1} is the loading of stock i to factor F_j calculated at $t-1$

R^t is the residual market volatility factor

ε_i^t is the residual return for stock i at time t

All factors in the model are implicit; factor exposures are explicit (observable) and factor realizations are estimated via cross-sectional regressions. The only exception to this statement is the industry factor exposures, which are first estimated on a univariate basis and then used as exposures in a cross-sectional regression to estimate the industry factor realizations. Cross-sectional models are generally considered to be more robust than time-series models as the number of parameters estimated in each month is small compared to the size of the cross-section of stock returns available. Proponents of the time series models like to point out that factors in such models are given, so their interpretation is

[2] As the main use of the model is to predict future volatilities of portfolios, all factor loadings are lagged by one time period with respect to the stock returns while performing the cross-sectional regressions in all steps. If a stock is missing any of its fundamental/technical variable loadings, we assign a loading of 0, and if the beta is missing, we assign a beta of 1.

straightforward. In a cross-sectional model, with estimated risk factors, interpretation of the factors can be harder. This argument is one of our major reasons to propose a step-wise regression in our cross-section model. With this methodology, we are able to preserve a very clean interpretation of the industry risk factors, as documented below. In a one-step cross-sectional model, this is not the case.

As mentioned in Section 1, the estimation process consists of three steps:

STEP 1:

$$r_i^t = \beta_i^{t-1} I^t + v_i^t$$

In the first step, we first estimate the industry exposures – PMBs – via the aforementioned methodology and then regress the total stock returns to betas to estimate the industry factors. Each stock is assigned to a single industry, as motivated below. Estimating the betas and the industry factors in the first step of the process on a univariate basis allows us to keep a clean interpretation for them: our industry risk factors are very close to actual industry indices (correlations are about 95% and volatilities are also similar). To be able to produce sensible factor estimates, we make sure that all industries are well populated.

STEP 2:

$$v_i^t = \sum_{j=1}^{n} \ell_{ij}^{t-1} F_j^t + \gamma_i^t$$

In the second step, we regress the residuals from the first step to the set of fundamental/technical factor loadings to estimate their factor realizations in a multivariate setting. The dependent variable of this regression is stock returns net of industry and thus the factors can be interpreted as the systematic movements in stock returns with regard to the fundamentals and technicals that can not be explained by the industry factors. We tested several specifications for the model, but the evidence (both in- and out-of-sample) shows overwhelmingly that industry is the most robust indicator of forward-looking volatility for a diverse set of portfolios. We therefore decided to estimate the industry factors in the first step (keeping their interpretation) and the fundamental/technical factors in the second step.

STEP 3:

$$\gamma_i^t = R^t + \varepsilon_i^t$$

In the third step, we regress the residuals from the second step to a unit loading, which is basically a regression with only an intercept. This factor captures all the residual systematic movements in stock returns and ensures that the final residuals are mean zero. By having an intercept in the last step of the process, it does not dilute the interpretation of other factors in the model. For instance, if we had an intercept in the first step, its interpretation would be a “market factor.” Its presence would also change the interpretation of the industry factors into more of an “industry-net-of-market” factor, taking us away from our goal. Moreover, by pulling this factor to the third step, we significantly decrease its importance, as all co-movements are first assigned to factors estimated in the first two steps. The third step intercept has only a 0.26% average monthly volatility, whereas a first step intercept would have about 3%. So this factor goes from being a “market” factor to being a residual and pervasive systematic factor.

As we mentioned above, each stock loads onto only one of the 24 available industry factors – the industry that corresponds to its GICS level 2 classification. However, stocks load on to all fundamental and technical factors. The loading of a stock to these factors is a function of the value of the corresponding fundamental/technical variables for that stock (loading of a stock to the EP factor is a function of the EP ratio of the stock). All stocks also load on to the residual market volatility factor with a unit loading. But it is important to note that even though there are a total of 35 factors in the model, each stock loads on to only 12 of these 35 factors as each stock loads onto only one industry factor.

For a stock that is missing any of its loadings, we use sensible default values to extend coverage. Extended coverage allows the model to capture a significant part of the systematic risk, even for securities with missing loadings. For instance, if a security does not have an industry beta, we assume a beta of 1. Hence, the security can still load on to the relevant industry factor, which is the major risk factor in the model. Furthermore, if a security does not have any industry information at all, it loads on to what we call the core factor. The core factor is a weighted average of all stock returns in our estimation universe and can be interpreted as a common market factor for all US equities. If a stock is missing any of its fundamental/technical factor loadings, we assign a loading of 0 to that factor. One can think of this as an average market loading as we standardize all fundamental/technical factor loadings such that the market portfolio (portfolio of all stocks in our estimation universe) has a loading of 0 to all these factors. See Section 2.4 for a detailed description of the standardization process.

Simple regression methods, such as Ordinary Least Squares, assume homoskedasticity in stock-specific volatilities. However, there is a substantial degree of cross-sectional variation in stock-specific volatilities. Therefore, to estimate the factor realizations, we perform a weighted least squares regression in which weights are a decreasing function of the realized volatility of daily residual returns. Hence, more weight is assigned to companies with smaller residual risk, which tend to be relatively large and mature. As a result, they have a larger contribution to the factor estimates, which contributes to the robustness of the estimation process.

The estimation universe consists of the largest 2000 stocks in the US with respect to their market capitalizations. This sample covers large, mid, and small-cap sections of the market. We do not include any ADRs, ETFs, or close-end funds in our estimation universe. 2000 is large enough to cover all market-cap sections of the market, except the micro-cap stocks that could add unintended noise to the estimation process. We set the estimation universe as the largest 2000 stocks at the end of every June and use that universe throughout the next one-year period. Preventing changes in the estimation universe within the year diminishes the survivorship bias that would be significant if we reselected the largest 2000 every month.

We describe in detail the factors of the US Equity Model in the remainder of this section. First, we introduce the industry factors and explain the methodology used to estimate the betas using daily data. Then we illustrate the univariate and multivariate test procedures used to select the fundamental/technical variables, discuss each variable in detail, and explain the transformations applied to the loadings of these variables. We also describe the residual market volatility factor, which captures any residual systematic exposure in the model. Finally, we discuss the evidence regarding macroeconomic factors in our model.

2.3. Industry Factors

Industry factors comprise the main part of the US Equity Risk Model in terms of risk for diversified portfolios. We use GICS level 2 as our industry classification, which has 24 industry groups and assigns every stock to a single industry. We do not make multiple industry assignments for companies with multiple business lines. Our choice comes from the fact that (i) our industries are relatively broadly defined, and (ii) we know of no robust way to generically identify several lines of business for a specific company. In our implementation, though, we reserve the right to re-classify firms to one or several industries, based on sound econometric or institutional knowledge.

There are several reasons we choose to go with GICS level 2. First, more granular definitions (e.g., GICS level 3) would render industries with relatively few firms, making the separation between systematic and idiosyncratic risk less clear. Second, the use of specific betas to each company gives us more flexibility in defining our industries at the granularity we feel ideal – our estimated betas map returns into whatever set of industries we use. Third, our study of the credit markets (see Rosten and Silva (2007)) suggests a similar number of industries. This simplifies the integration across these two models. Fourth, our backtesting suggests that (i) a much larger set of industries makes it harder to compute robust correlations across industry factors, while (ii) a smaller set of industries (e.g., GICS level 1) generally underestimates the diversification across industries some portfolios may have. Finally, Section 5 shows that GICS 2 captures well the risk of many different portfolios, namely those constructed around the GICS level 1 or GICS level 3 classifications.

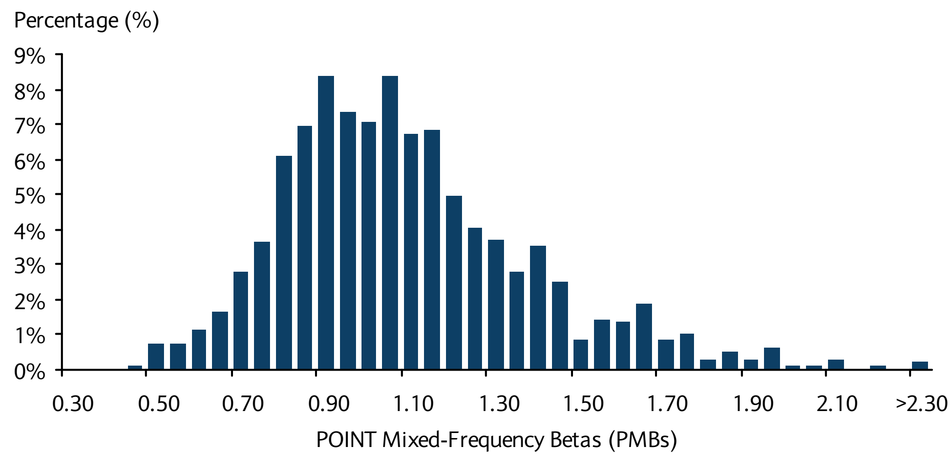
Beta Estimation

We use a proprietary methodology to estimate the POINT Mixed-Frequency Beta (PMB), a firm's exposure to the relevant industry factor. The question of how to measure, predict, and use equity factor betas has been of extensive concern in both industry and academia over the past several decades. While there is largely a consensus about the view that betas of both individual stocks and portfolios can hardly be expected to be constant throughout time, there is little or no consensus as to the dynamic nature of time-varying betas, and more importantly, how this should be taken into account in an empirical setting.

Statistical estimation of time-varying beta is typically performed by using rolling windows of data to find the beta by simple regression (possibly time-weighted). These windows usually consist of monthly observations of up to five years of data. This approach gives accurate estimates of beta only under very specific assumptions on the dynamic properties of stock returns and factor realizations. Moreover, no attempt is usually made to use past data to predict the future beta, it is simply assumed that the sample estimate is the best predictor of the future beta realization; i.e., the ex-post historical beta is the best predictor of future beta. As betas are a function of variances and co-variances, the whole standard approach is analogous to calculating the sample standard deviation over the past five years and using this as a forecast of volatility over the next month; clearly a suboptimal practice.

Most risk models either use a beta of 1 to the industry factors or estimate the betas using monthly return observations. The use of predetermined unit betas bypasses the estimation process of betas and as such does not introduce estimation error into the model. The cost of this approach is that these constant betas are biased for most stocks, most of the time. As an illustration, Figure 1 shows the distribution of the industry PMBs for all stocks in the Russell 1000 at the end of January 2009. We can see that for a large number of stocks, we estimate betas to be significantly different than 1. In this example, 20% of the stocks have PMBs above 1.3 and 7% have them below 0.7. Although the (misspecification) bias might average out for large, well-diversified portfolios, it may lead to significant misrepresentation of risk and expected returns in smaller portfolios, or portfolios that are tilted toward high or low betas.

Figure 1: Distribution of POINT Mixed-Frequency Betas (PMBs) for the Russell 1000 index as of January 31, 2009



Source: Barclays Capital Portfolio Modeling

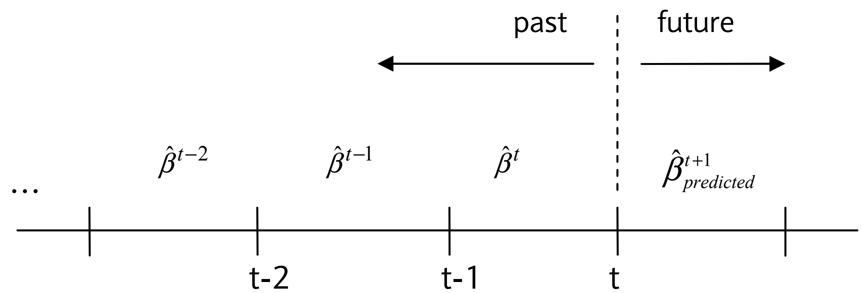
Estimating betas from monthly returns has the potential to reduce the bias that comes with the use of unit betas, but suffers from severe estimation error in many cases. We employ a novel approach that uses daily data to reduce the estimation error in the beta estimation process, while providing locally unbiased beta estimates.

Instead of estimating the beta from past monthly returns, we compute the monthly realized betas using daily observations and then combine them into a forecast through an optimized weighting scheme. In more detail, we compute realized betas $\hat{\beta}_i^t$ for every stock *i* in every month *t* and use them to construct a predicted beta $\hat{\beta}_{i,predicted}^{t+1}$ as:

$$\hat{\beta}_{i,predicted}^{t+1} = \sum_{l=1}^{L} w_i^{t-1} \hat{\beta}_i^{t-l+1}$$

where weights *w* are determined by a flexible, low-dimensional parametric function. This parameter is found in an optimization problem that maximizes the predictive power of our betas. In other words, the forecasted beta is a weighted average of historically realized monthly betas, where the weights are determined to capture the time-series properties of the time-varying beta process. The optimization approach allows us to combine information in the realized betas (which are based on higher-frequency data) with information in monthly returns to arrive at beta forecasts that incorporate information at different frequencies efficiently.

Figure 2: Conceptual Timeline of the Estimation of Beta



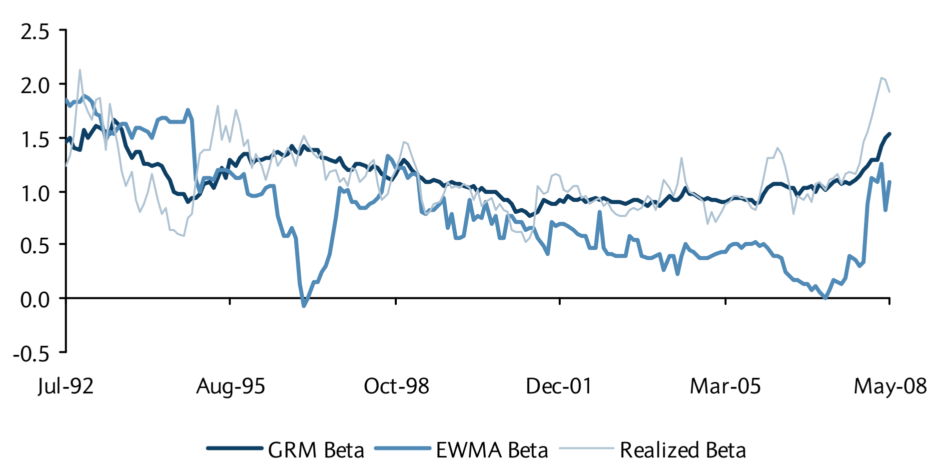
Source: Barclays Capital Portfolio Modeling

Figure 2 illustrates the conceptual timeline: we compute historical realized intra-month betas using daily return observations on industry portfolios and individual stocks. We then predict next month's beta for every stock through a time-series model of these historical monthly betas.

Our methodology does significantly better than existing procedures in predicting the nature of future returns. It provides truly dynamic estimates of the realized beta over the relevant investment horizon that can adjust to changes in the market conditions much faster. Our robust estimation methodology, coupled with the relatively broad industry definitions, greatly enhances our ability to predict the industry exposures accurately. Therefore, we do not have to assume a beta of 1, which would significantly under/overestimate risk in many cases.

Figure 3 illustrates our beta approach by plotting the realized and estimated betas for Washington Mutual from July 1992 to May 2008 (later acquired by JPM Chase). The exponentially weighted beta (EWMA) estimate based on monthly data is seemingly subject to a large degree of estimation error, as evidenced in the sudden drop in beta in the first half of 1996. Our betas (PMBs) provide stable, unbiased sensitivities that respond accurately to changing firm and market conditions. During this period, our beta oscillated between 1 and 1.5. Setting the beta to one could result in significant biases for a prolonged amount of time. For instance, from January to May 2008, the realized beta for Washington Mutual was consistently at about 2.

Figure 3: Realized and Forecasted Industry Betas for Washington Mutual



Source: Barclays Capital Portfolio Modeling

We tested our betas in several dimensions. The first is the predictive power for future realized beta. We use Mincer-Zarnowitz (see Mincer, J. and V. Zarnowitz (1969)) type regressions to assess the predictive power of beta estimates for future realized betas.

$$\hat{\beta}^t_{realized} = \alpha + \gamma \hat{\beta}^t_{forecast} + \varepsilon^t$$

Figure 4 shows the R-squared of the regression of predicted beta on realized beta for the individual stocks in our estimation universe for all the months in the past 18 years. Our proprietary beta has by far the most power in explaining future realized beta.

Figure 4: R-squared for Different Beta Methodologies

POINT Mixed-Freq Betas (PMBs)	0.19
EWMA Beta	0.03
Constant Beta	0.00

Source: Barclays Capital Portfolio Modeling

To look at beta performance from a different perspective, we consider out-of-sample hedging performance of the predicted beta. This strategy is implemented by selling short the respective industry index by a dollar amount equal to the forecasted betas for each dollar invested in the stock. For instance, if the stock has a beta of 1.2, we would go long $1 of the stock, and short $1.2 of the industry index the stock belongs to. If we then regress the realized return of this hedged portfolio on the industry portfolio, we should find no significant exposure to the industry period-by-period (and therefore, on average). Figure 5 compares the average out-of-sample ex-post exposure for the individual stocks in our estimation universe for all months over the past 18 years. These numbers illustrate our findings that estimated betas significantly improve upon constant betas, and that our proprietary beta methodology significantly outperforms established methodologies. The results tend to be more dramatic for portfolios biased toward high or low betas.

Figure 5: Out-of-Sample Tests for Betas

	Absolute Ex-Post Monthly Beta	Absolute Reduction in Exposure from Constant Beta
POINT Mixed-Freq Betas (PMBs)	0.05	63%
EWMA Betas	0.11	27%
Constant Beta	0.15	0%

Source: Barclays Capital Portfolio Modeling

2.4. Fundamental and Technical Factors

In this section, we first illustrate the selection methodology used for fundamental/technical factors. Then we define each of these factors and talk about their major attributes. Finally, we describe the transformations applied to the loadings of fundamental/technical factors, namely standardization and non-linear transformation. Before we go into the details of the discussion, Figure 6 gives a brief description of each fundamental/technical factor in the model.

Figure 6: Definitions of Fundamental/Technical Factors in the Model

Factor	Type	Definition
Industry	Sector	GICS level 2 industries
Market Value	Size	Log of market capitalization
Book to Price	Valuation	Book value over current market capitalization
Earnings to Price	Valuation	Last 4Q earnings over current market capitalization
POINT Corporate Default Probability	Leverage	Next one-year corporate default probability from the proprietary Barclays Capital model
Change in Discretionary Accruals	Earnings Management	Measures the degree of earnings management
Total Yield	Dividend	Last year's dividends plus stock repurchases minus resales divided by market capitalization
Residualized Forward E/P	Valuation	Next 4Q earnings forecast over current market capitalization - residualized
Share Turnover	Liquidity	Daily volume traded over common shares outstanding averaged the over the past month
Momentum	Momentum	Cumulative stock return in the period from month t=-10 to t=-1
Residualized Realized Volatility	Technical Variability	Realized volatility of daily returns over the past three months – residualized

Source: Barclays Capital Portfolio Modeling

In order to select these fundamental and technical factors, we performed a rigorous multi-step analysis. In the first step, we identified a comprehensive superset of potential factors[3]. In the second step, we analyzed each factor on a univariate basis, by which we eliminated the majority and ended up with a small subset of factors. The idea behind the univariate testing in the second step is that if a factor does not perform well even on a univariate basis, it is not interesting on a multivariate framework. Finally, in the last step, we performed factor selection analysis in a multivariate setting via the cross-sectional regressions to define the final set of factors to be included into the model.

The key objective of the univariate analysis is to find factors that can be employed in a multi-factor framework to distinguish high from low volatility stocks. A simple but very intuitive analysis in the univariate testing is the quantile analysis. Here we partition the estimation universe into quantiles along a specific variable of interest and analyze differences across them[4]. At a given month t, all stocks in the estimation universe are ranked with respect to the value of the variable of interest. Stocks with the smallest values constitute the first quintile portfolio (Q1) and the largest values constitute the last quintile portfolio (Q5). Then we compute the portfolio returns for these quintiles for the next one-month period (t+1). We compute the time-series volatility of these portfolio returns for each quintile and aim to unravel existing patterns across these quintile portfolio volatilities.

Figure 7 illustrates three different patterns for quintile volatilities. As we can see, quintile volatilities for the Market Value (SIZE) factor have a monotonically decreasing pattern with smaller stocks exhibiting higher volatility. The Momentum (MOM) factor exhibits a U-shaped pattern in volatilities with extreme movers (on both sides) having higher volatility. On the other hand, the CDP factor exhibits a different pattern than the other two, where the volatility does not vary among low to medium CDP stocks, but it increases exponentially as we move from medium CDP to high CDP stocks. These different patterns have material impact on the loading-setting strategy we define later.

[3] A list of all variables used in the univariate test is available upon request.
[4] See, for instance, Chan, Karceski, and Lakonishok (1998).

Figure 7: Univariate Analysis of Market Value, Momentum, and POINT Corporate Default Probability Factors

	SIZE	MOM	CDP
Q1 -low	3.16%	1.88%	0.88%
Q2	2.54%	1.01%	0.88%
Q3	1.94%	0.80%	0.94%
Q4	1.24%	0.94%	1.40%
Q5 -high	0.68%	1.47%	2.10%

Source: Barclays Capital Portfolio Modeling

We repeat this analysis using different data samples, to identify whether the observed pattern is robust across different market conditions and different sectors. For instance, Figure 8 illustrates that the Market Value variable exhibits a consistent pattern in quintile volatilities across high/low volatility environments and for the first/second half of the data period[5].

Figure 8: Performance of the Market Value Variable in Different Market Environments

	Low Vol	High Vol	First Half	Second Half
Q1 -low	2.70%	4.45%	2.71%	3.56%
Q2	2.24%	3.41%	2.41%	2.67%
Q3	1.70%	2.65%	1.81%	2.07%
Q4	1.06%	1.76%	1.01%	1.43%
Q5 -high	0.65%	0.79%	0.75%	0.60%

Source: Barclays Capital Portfolio Modeling

These exercises are just two examples of the type of analysis done in the univariate setting. Appendix 1 shows other examples. In particular, we also analyze the history of quintile portfolios returns to get a better understanding of the differences across quintiles. We perform cross-sectional and time-series regressions on a univariate basis to gauge the explanatory power and the statistical significance of the factor. Other tests include a detailed analysis of the distribution of the variable. The output of the univariate analysis is a smaller set of variables (about 20) that we carry out for further study in the multivariate framework.

Once the univariate test is done, we start the multivariate analysis using the smaller set of variables. The idea is to test for relevance, collinearity and interpretability of the variables. Specifically, we start by running a stepwise selection procedure every month, using the cross-section of the estimation universe. In the stepwise selection we use, the procedure starts with no variable in the model and performs a multi-step process. At each step, among the variables that are not in the model, it selects the one that provides the largest contribution to the in-sample explanatory power. However, for a variable to be included in the model, it should be significant at a predetermined level (we use 5%). If this is the case, the variable is included; if not, the procedure looks for the variable with the second largest contribution, and so on. Whenever a new variable is included, each existing variable is checked whether it is still significant at a predetermined level (we use 5%) and is excluded from the model if it becomes insignificant. The procedure stops when there is no remaining variable that can be included in the model at the required significance level.

[5] High volatility regime consists of months for which the VIX index is in the top quintile of our sample period.

The goal of this analysis is to understand, from a purely statistical point of view, what variables stand out in a multivariate framework. From the stepwise procedure, we analyze several statistics of interest, such as the number of months each variable is selected, in what months/context the procedure selects more variables, and under which market conditions each variable is more likely to be selected. In addition to performing the statistical selection procedure on the entire data set, we ran it for different subsets of the data to check for the robustness of the results. Figure 9 demonstrates the performance of the final selected variables in terms of the percentage of months each variable is selected by the procedure for the whole data period, first/second half of the data period, and high/low volatility environments. As we can see in the figure, five factors consistently stand out in all cases, namely Market Value (SIZE), POINT Corporate Default Probability (CDP), Share Turnover (TURN), Momentum (MOM), and Residualized Realized Volatility (RVOL). It is interesting to see how consistent the results are.

Figure 9: Percentage of Months the Variables Are Selected

All Data		First Half		Second Half	
SIZE	69%	SIZE	62%	SIZE	58%
MOM	54%	MOM	48%	MOM	54%
TURN	53%	RVOL	44%	CDP	47%
RVOL	45%	TURN	41%	RVOL	42%
CDP	29%	CDP	31%	TURN	38%
YLD	27%	BP	28%	FEP	30%
FEP	27%	YLD	23%	EP	24%
EP	25%	EP	21%	YLD	24%
BP	23%	ACC	10%	BP	22%
ACC	20%	FEP	8%	ACC	17%

High Vol		Low Vol	
SIZE	67%	SIZE	54%
MOM	55%	MOM	49%
RVOL	52%	TURN	39%
CDP	50%	RVOL	36%
TURN	43%	CDP	31%
BP	30%	YLD	23%
FEP	29%	BP	20%
EP	27%	EP	19%
YLD	26%	FEP	15%
ACC	17%	ACC	12%

Source: Barclays Capital Portfolio Modeling

In this step, we also check for potential multi-collinearity issues. As the loadings are the independent variables in the cross-sectional regressions used to estimate the model, we ensured that the loadings in the final model do not exhibit any excess correlation. This guarantees that factors estimated from those loadings are robust. Figure 10 illustrates some statistics for the correlations between all fundamental and technical variable loadings used in the model.

Figure 10: Median Cross-Sectional Correlations between Variables in the Model

	SIZE	CDP	TURN	MOM	EP	BP	YLD	ACC	FEP
CDP	-0.28								
TURN	0.02	0.17							
MOM	0.21	-0.29	0.02						
EP	0.15	-0.29	-0.12	0.05					
BP	-0.16	0.29	-0.10	-0.28	0.03				
YLD	0.20	-0.13	-0.16	0.03	0.21	0.09			
ACC	0.08	-0.17	-0.03	0.06	0.12	-0.09	0.08		
FEP	0.02	0.07	-0.03	-0.06	0.17	0.16	0.09	-0.01	
RVOL	-0.43	0.33	0.16	-0.17	-0.32	-0.13	-0.25	-0.05	-0.13

Source: Barclays Capital Portfolio Modeling

One of the important considerations we carried through the multivariate analysis was to make sure that these factors can keep their interpretation in a multivariate setting. To check this feature, we first compute the correlations between univariate factor realizations and then check how these correlations change when we move to the multivariate setting. Correlations generally decrease in absolute value in a multivariate setting, but univariate and multivariate correlation matrices are reasonably similar. For each factor, Figure 11 illustrates the correlations between its univariate and multivariate versions. We see that the correlations are very high for all factors except for the BP factor, which still shows a reasonably high correlation. This means that the interpretation of the factors does not change significantly when we move to the multivariate setting. Appendix 2 depicts the relationship between multivariate and univariate realizations over time for all fundamental/technical factors.

Figure 11: Correlation between Univariate and Multivariate Factors

CDP	SIZE	TURN	MOM	EP	BP	YLD	ACC	FEP	RVOL
0.82	0.91	0.92	0.91	0.81	0.56	0.81	0.79	0.93	0.78

Source: Barclays Capital Portfolio Modeling

Risk Factors in Detail

Market Value (SIZE) is defined as the log of market capitalization of a company. The distribution of the market capitalization variable is highly positively skewed and the log transformation results in a better behaved distribution. We observe a monotonic relationship between Market Value and volatility where small-cap stocks tend to be more volatile than large-cap stocks.

Book to Price (BP) is a key variable in value versus growth investing. High BP stocks are generally considered to be value stocks as their low prices relative to their book values signal cheap buying opportunities. On the other hand, low BP stocks are considered to be growth stocks due to the large growth rate implied in their expensive valuations.

Earnings to Price (EP) is a very widely used valuation metric. As a variable, it behaves better than the P/E ratio as earnings can take very small values. It has an asymmetric U-shaped volatility pattern with very small EP stocks being more volatile than very high EP stocks. Like BP, EP is another key variable in value versus growth investing.

POINT Corporate Default Probability (CDP) measures the probability that the firm defaults within the next one year (a proprietary variable). Although there is not much differentiation in terms of the volatilities across low to medium CDP stocks, volatility increases exponentially as we go from medium to high CDP stocks. As a factor, it performs better than distance to default and standard measures of leverage in distinguishing low from high volatility stocks. In the case of distress events, CDP picks up very fast, whereas leverage can be very slow to change. The presence of this factor also clarifies the role of other factors, like BP and EP, by reducing their distress component. This factor is a good example of our preference toward market-driven variables. See Silva and Staal (2007) for a detailed explanation of the CDP Model.

Share Turnover (TURN) is a liquidity and technical variability measure. It also has an asymmetric U-shaped volatility pattern, with very high turnover stocks more volatile than very low ones. Very high turnover signals excess trading activity in the stock, whereas very low turnover might signal potential issues related to the lack of liquidity.

Momentum (MOM) is a variable that distinguishes recent winner and loser stocks. Stocks that have experienced large gains or losses tend to be more volatile than average performers (U-shaped profile). There is a bias toward the losers in the sense that worst performers are more volatile than best performers. In the computation of the momentum variable for each stock, we skip the last month due to potential reversal effects.

Change in Discretionary Accruals (ACC) measures the degree of earnings management by looking into the part of earnings that is directly subject to managerial discretion. It is a relative measure for each stock within its sector. It is a proprietary variable originally used in the ROQS model developed by the Quantitative Equity Strategies group at Barclays Capital.

Total Yield (YLD) is defined as the sum of dividend yield and net stock repurchases. Stocks that yield more tend to be more mature companies and less volatile. Volatility does not vary much across mid to high yield companies but rises very fast as we move from mid to low yield companies.

Residualized Realized Volatility (RVOL) proxies for the persistence of volatility. As realized volatility and share turnover are highly collinear, we regress realized volatility loadings into share turnover loadings on a cross-sectional basis and use the residual of this regression as the realized volatility loading. This loading is therefore orthogonal to the share turnover loading. We can interpret this factor as part of the realized volatility that can not be explained by share turnover.

Residualized Forward E/P (FEP) is based on the next 4Q consensus EP forecast of analysts. It is highly collinear with trailing EP and, thus, we similarly regress forward EP to the trailing EP. The loading to this factor is important especially for stocks experiencing earnings reversions. It can be interpreted as the information in analyst forecasts that is not contained in historical earnings

As we have just described, each fundamental/technical factor is identified by a single variable (except for the residualized factors, where we use two related variables). We do not combine multiple variables into a single risk factor. Combining variables not only makes the interpretation of the factors difficult but may also dilute correlations between factors, giving a false impression of diversification.

Non-linear Loadings

As we mentioned previously, the model is estimated via cross-sectional regressions. The inputs to the cross-sectional regressions are stock returns and factor loadings. Factor loadings are functions of the underlying variables for fundamental/technical factors.

Typical linear factor models with fundamental loadings use very simple transformations of the fundamental information that is used as a loading. One common transformation is a z-score transformation (i.e., de-mean and standardize the volatility of the variable), another one is the rank-ordering of the fundamental data. After transforming the fundamental data, the model is assumed to be linear.

$$r_i^t = \sum_{j=1}^{n} \ell_{ij}^{t-1} F_j^t + \varepsilon_i^t$$

These restrictive assumptions allow for a very transparent model. They also potentially lead to misleading results because of misspecification.

Connor, Hagmann, and Linton (2007) relax the standard assumption of linear factor loadings in a characteristic based factor model through a semi-parametric modeling approach. We build on their work and developed a methodology to fit smooth mappings (g_j) of standardized fundamental characteristics to factor loadings.

$$r_i^t = \sum_{j=1}^{n} \mathrm{g}_{\mathrm{j}}\left(\ell_{ij}^{t-1}\right) F_j^t + \varepsilon_i^t$$

Our research shows strong evidence of non-linear relationships between stock returns and fundamental/technical loadings for certain factors. In such cases, employing linear loadings (no transformation in loadings) might introduce significant biases in estimating the portfolio volatilities. As an example, we look at the Market Value factor. If we separate our universe into deciles based on the Market Value loading, we can compare the actual realized volatility for the extreme deciles against predictions coming from a linear and a non-linear factor model. Figure 12 illustrates how linear loadings underestimate the net-of-industry volatility for the small-cap stocks (bottom 10% market capitalization) and overestimate for large-cap stocks (top 10% market capitalization). For instance, the linear model predicts a monthly volatility of about 2% for small stock, even though the actual volatility is significantly higher (3%). Note that the non-linear transformation significantly reduces this bias.

Figure 12: Volatility for Linear vs. Non-linear Loadings for the Market Value Factor (1998-2008)

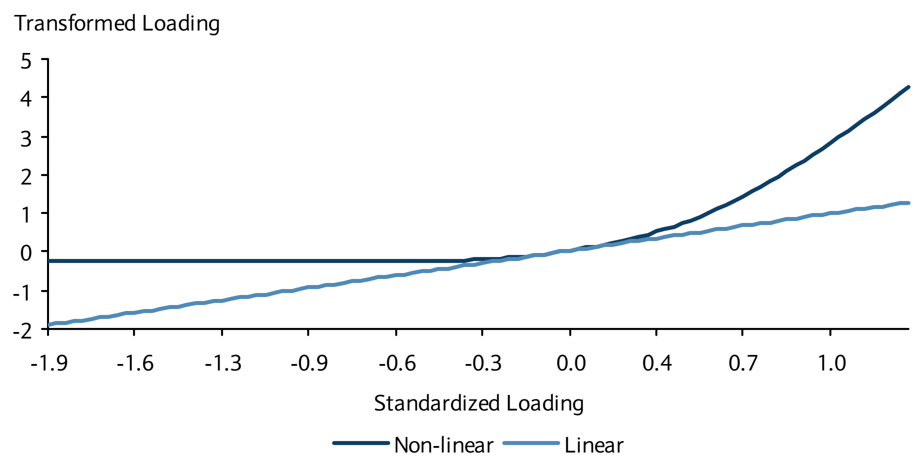
	Bottom 10%	Top 10%
Portfolio Volatility	2.97%	1.01%
Non-linear Systematic Volatility	2.75%	1.00%
Linear Systematic Volatility	1.92%	1.31%

Source: Barclays Capital Portfolio Modeling

In essence, we move beyond simple (pre-imposed) transformations of fundamental data to more flexible transformations that we can determine from the behavior of equity returns themselves. The factors and the non-linear loading transformations are jointly estimated in an iterative fashion. Our modeling approach allows for a rich set of patterns in equity returns but imposes enough structure to be economically intuitive. This approach removes systematic biases in standard linear factor models, as illustrated in Figure 12.

We analyze all our factors in this framework and use only non-linear transformations when the evidence for improved risk forecasts is overwhelming. We found this to be the case for Market Value, Earnings to Price, and Corporate Default Probability factors. We also make sure that the mapping is economically intuitive. Figure 13 depicts the non-linear transformation applied to the CDP factor. The X axis represents the standardized loading for the CDP factor and Y axis displays the corresponding transformed loading. For comparison, we present also the linear transformation (i.e., no transformation, just a 45° line). Linear transformation for the CDP factor overestimates the volatility for stocks with low CDP and underestimates for stocks with high CDP. To be able to produce more accurate volatility estimates, the non-linear transformation decreases the value of the loading (in absolute value) for low CDP stocks and increases the value of the loading for high CDP stocks. As Figure 13 illustrates, the non-linear transformation implies a view that among the stocks that have relatively low default probability, it does not matter how low the probability is for the estimation of future volatility. However, for stocks that have default probabilities higher than the average market default probability, the level of POINT CDP is important in estimating the future volatility and the estimate increases exponentially as we move to high CDP stocks.

Figure 13: Non-linear Transformation for the POINT Corporate Default Probability (POINT CDP) Variable



Source: Barclays Capital Portfolio Modeling

After we perform the non-linear transformation to Market Value, Earnings to Price, and POINT Corporate Default Probability factors, we re-standardize the loadings for all fundamental/technical variables such that the market portfolio (the estimation universe of 2000 stocks) has a loading of 0 to all these fundamental/technical factors and that a loading of 1 is one standard deviation away from the loading of the market portfolio. This implies that the market portfolio loads only on to the set of industry factors. Moreover, standardization contributes to the stationarity of the loadings, which is essential for the stationarity of the fundamental/technical factor realizations in a cross-sectional setting. As we employ cross-sectional regressions to estimate the factor realizations and then use the history of these factor realizations to estimate the volatility of portfolios, we need to make sure that the factor realizations are stationary.

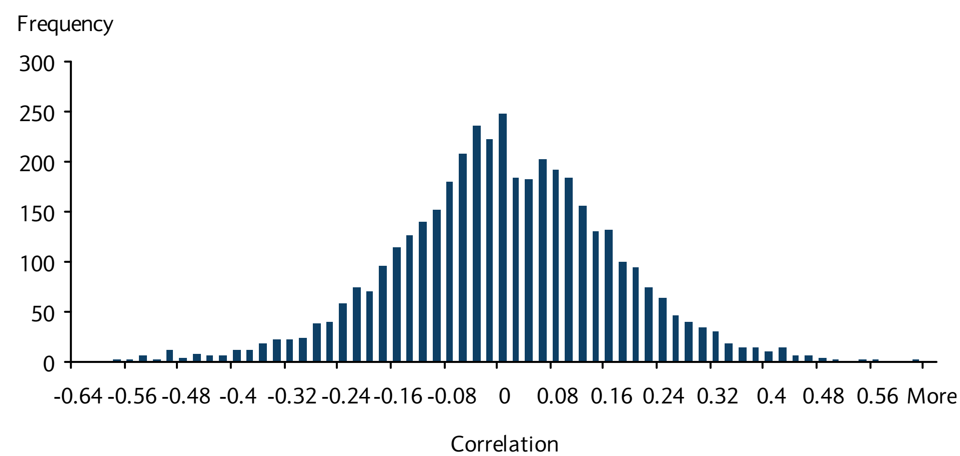
Standardization detrends variables and implies a relative view on the variable with respect to its relationship with stock volatilities. As fundamental and technical factors are used to explain cross-sectional differences across stocks, what is more relevant is the relative, not the absolute, value of the variable. A clear example of this case is the Market Value variable where market capitalizations of companies have a significant and positive time-series trend and a stock should not be assigned higher or lower risk just because the overall stock market capitalization grows. The relevant question should be how a stock stands with respect to other stocks at a given point in time (small cap vs. large cap).

2.5. Residual Market Volatility Factor

After we estimate the industry and fundamental/technical factors in the first two steps of the process, we regress the residual from the second step to a dummy variable in the third step to extract the residual market volatility factor. This third step regression with only an intercept captures residual commonality in equity returns and makes sure that final residuals from the regressions have a zero mean in the cross-section. We can think of the residual market volatility factor as a pervasive factor that captures all the residual systematic effects.

In addition to ensuring that final residuals are mean zero on a cross-sectional basis, what we eventually would like to achieve is the orthogonality, on the time series, between the idiosyncratic returns and the factor realizations. This allows for the standard decomposition of risk between systematic and idiosyncratic components. As we employ cross-sectional regressions to estimate the model and then use the time series of factors and idiosyncratic returns to estimate the risk, we need to make sure that the systematic and idiosyncratic components of the model are orthogonal in order to separate risk into systematic and idiosyncratic components (there is no theoretical framework that guarantees this result under our implementation). We performed statistical tests to ensure that this is the case. Figure 14 illustrates one such test regarding the distribution of the correlation between the idiosyncratic return of a security and its corresponding industry factor realization. As we can see in the chart, the distribution is close to normal, centered on 0, and highly symmetric, which is what we would expect in the case of the empirical distribution of two uncorrelated random variables.

Figure 14: Distribution of the Correlation between Industry Factors and Residual Returns



Source: Barclays Capital Portfolio Modeling

2.6. The Lack of Macro Factors

We thoroughly investigated the importance of macro factors in a U.S. equity factor model. We reached the conclusion that the presence of industry factors renders any tested macro variable insignificant. We have tested a wide selection of macro and financial variables including commodity factors, interest rates, rate differentials, and the CFNAI. Our analysis shows that when we add macroeconomic factors to a model with industry factors, there is no significant increase in the (in-sample) explanatory power. We expect a model with the macro variables to perform worse out-of-sample.

We do not believe that the general economic environment is irrelevant in explaining stock returns. Our intuition tells us exactly the opposite. The empirical findings suggest that most of the effect of macro conditions is captured though industry factors. Moreover, it is extremely hard to calculate with some robustness stock sensitivities to slow-moving macroeconomic variables, especially at a monthly frequency. Rather than directly modeling macroeconomic risk in our equity risk model through explicit risk factors, we believe that it is more informative to measure risk as precisely as possible and, if desired, re-project the measured risk on macro factors through the correlations between industry factors and macroeconomic variables. The inclusion of macro factors may work better for long-horizon models, e.g., models that are calibrated to annual frequencies.

3. The Volatility Model

One important dimension of portfolio and security risk is the expected and realized volatility of its returns, or alternatively, its P&L. For the new U.S. Equity Risk Model we designed a proprietary volatility model called the Mixed Frequency Volatility Model (MFVM). The premise in our model is the decomposition of the covariance matrix into correlations and volatilities. Each of these components can be modeled separately. We discuss our volatility model in some detail but leave a full description to a later publication.

As the major functionality of the risk model is to estimate the future volatility of portfolios, it is critical to have a valuable volatility estimation model in addition to a good useful factor model. For the US Equity Model, we explored new ways of estimating factor volatilities using daily data. Rigorous research of different volatility models led to the development of a proprietary mixed frequency two-factor volatility model. As in the case of our betas, we make use of daily data to predict volatilities at the lower monthly frequency. In our model the volatility of a factor is mean-reverting around a slowly changing long-term mean. The deviation from this long-term mean is determined by short-term movements in forecasted realized volatility, as measured by the appropriately scaled weighted sum of daily squared factor returns.

The factor covariance matrix Σ can be decomposed as follows:

$$\Sigma = \Lambda \Gamma \Lambda$$

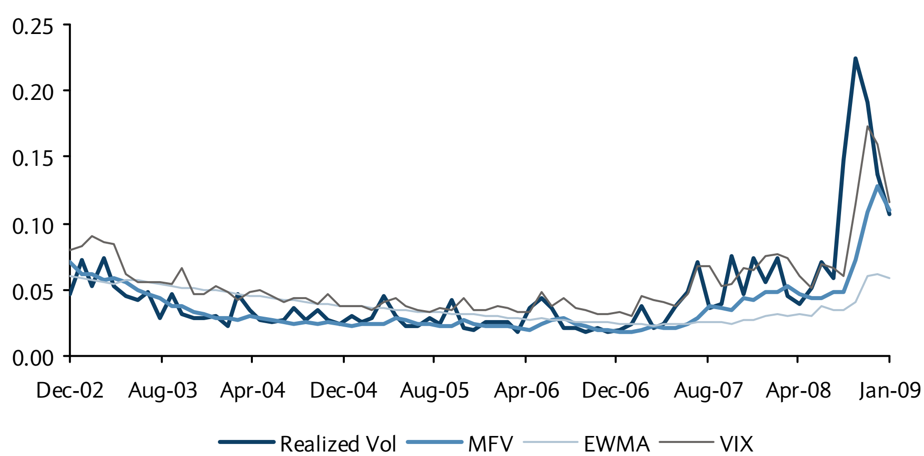
where Γ is a matrix containing correlations and Λ is a diagonal matrix containing factor volatilities. We separately model the volatilities and correlation matrix.

The MFVM models monthly factor volatilities using a mixture of flexible weighting of movements in daily returns and a slow-moving mean-reversion level of volatility. Correlations are estimated using a longer historical window of monthly returns.

The main purpose of moving beyond standard volatility models is that they do not provide forecasts that reflect current and future events adequately. A useful volatility model reacts quickly to fundamental changes in market circumstances. This can be achieved by conditioning on forward looking variables, such as implied volatilities, or by using relatively short histories of past information in constructing the volatility forecast.

When we look at the recent history, we see that there are months where there is no significant movement in the risk factors from the beginning to the end of the month but there is a large amount of factor volatility within the month. In such cases, monthly EWMA or GARCH type models are very slow in capturing the increased volatility in the market. In contrast, the use of daily data in volatility estimation makes the MFVM forecast very responsive to the changing volatility environment. To illustrate, Figure 15 plots our proprietary MFVM monthly volatility forecasts and EWMA (with one year half-life) forecasts for S&P500 made at the beginning of the month against ex-post monthly realized volatility and the appropriately scaled level of the VIX, over the period from December 2002 to January 2009. Clearly the EWMA forecasts were slow in anticipating and reacting to the turmoil in the U.S. equity markets over this time period. The EWMA model is dependent on monthly returns to extract information on volatility patterns, which means it is greatly dependent on the outcome of only a few observations to recognize changes in conditional volatility when the level of volatility abruptly changes. Our model, which makes use of daily data, recognizes and anticipates the volatility in the market based on actual intra-month volatility, not just the monthly return realization by itself. For instance, Figure 15 shows that our forecast reacted very fast to the increased volatility over the past 18 months, while the EWMA, although moving in the right direction, just took much longer to pick the new volatility scenario. From 2003 and 2006, EWMA significantly and persistently overestimates the volatility of the S&P500, while our forecast is again quite fast in adapting to the low volatility environment coming out of the 2002 recession.

Figure 15: Performance of the Volatility Forecasting Model



Source: Barclays Capital Portfolio Modeling

We can make this observation more systematic, by using statistical tests. For instance, we can use Mincer-Zarnowitz type regressions to assess the predictive power of volatility forecasts for future realized volatility.

$$\sigma^t_{realized} = \alpha + \beta\sigma^t_{forecast} + \varepsilon^t$$

In these predictive evaluation regressions our proprietary methodology delivers R^2 that are well above those found for more traditional methodologies. Figure 16 illustrates this for the S&P500 from 1990 until January 2009.

Figure 16: Out-of-sample Performance of the Volatility Forecasting Model

Forecast	R-Squared
MFVM	0.53
EWMA	0.26

Source: Barclays Capital Portfolio Modeling

In section 5, we perform other tests that corroborate this analysis. Overall, the evidence seems to support the conclusion that our model outperforms typical available volatility forecast models.

4. The Idiosyncratic Risk Model

The estimation procedure described above delivers estimated factor realizations and idiosyncratic returns (the residuals - ε_i^t - from the third step regression). In this section we detail how we use the latter to estimate idiosyncratic risk.

A typical procedure to compute idiosyncratic risk for a particular security is to use a function of the time series of its idiosyncratic returns. The function could be tilted toward more recent residual returns, if the user wants to capture faster changes in environments.

There are three generic drawbacks with this traditional approach. First, we need to have a minimum number of observations to compute the idiosyncratic volatility. For typical monthly models, this usually means at least one year of data. This precludes new securities from being explicitly modeled with this approach. The second problem is that firms may experience significant changes in their financial, operating, or competitive environment. In these cases, the history of specific returns becomes by and large meaningless. The third problem is that it takes usually too long for the estimates to react to specific firm events. Even for forecasts that more heavily weight recent observations, this is usually the case, as we always need a minimum of memory to construct a robust estimator.

Different models deal with the caveats discussed above in different ways. For instance, some models use the characteristics of the firms to impose additional structure on the forecast of idiosyncratic risk[6]. As soon as those characteristics change for a particular security, so does the idiosyncratic volatility estimate. Other models use market-wide estimates to gauge the overall level of idiosyncratic risk. Finally, there are models that try to use forward looking information – such as implied volatilities embedded in the option markets - to gauge level and changes in idiosyncratic risk.

We tested the out-of-sample performance of several different versions of idiosyncratic volatility models. We decided for a model whose major features are:

1. As with many other parts of the model, we use *daily* idiosyncratic returns to forecast monthly idiosyncratic risk. This choice delivers important advantages: we can construct a very robust estimate of the risk using relatively few months of data; therefore, the model is quite fast in picking sudden changes in idiosyncratic risk for a particular security. Note that, *as we use specific firm idiosyncratic returns directly in the construction of the idiosyncratic forecast*, the model picks these changes even if the overall level of residual risk in the economy remains constant. Moreover, because the model reacts fast, we can forfeit the use of any option data. This is important because

[6] This kind of model is widely use in our fixed income framework, where idiosyncratic risk is a function of, namely, the duration and the spread of the bond.

there are many hurdles with using these data, namely the fact that implied and realized volatility differ systematically because of risk premia, and that we have only a relatively small set of securities for which options data are liquid and reliable.

2. We complement these firm-specific residuals with information about the firm's characteristics. This allows the idiosyncratic volatility forecasts to be aligned with the forecast from other firms that share the same set of characteristics. As an example, everything else equal, for large firms high idiosyncratic volatility is relatively less persistent.

Generically, the model used can be formally described as follows. We model daily returns as:

$$r_{i,d}^{\tau} = B_i^{\tau} X^{\tau} + \varepsilon_{i,d}^{\tau}$$

Where the superscript τ stands for day τ, *X* is the set of factors deemed important for explaining daily returns, *B* is the corresponding set of loadings and $\varepsilon_{i,d}^{\tau}$ is the daily residual return from firm *i*. At the same time, we also have for each firm its monthly residual return - ε_i^t - that comes directly from step 3 of our regression procedure discussed above:

$$\gamma_i^t = R^t + \varepsilon_i^t$$

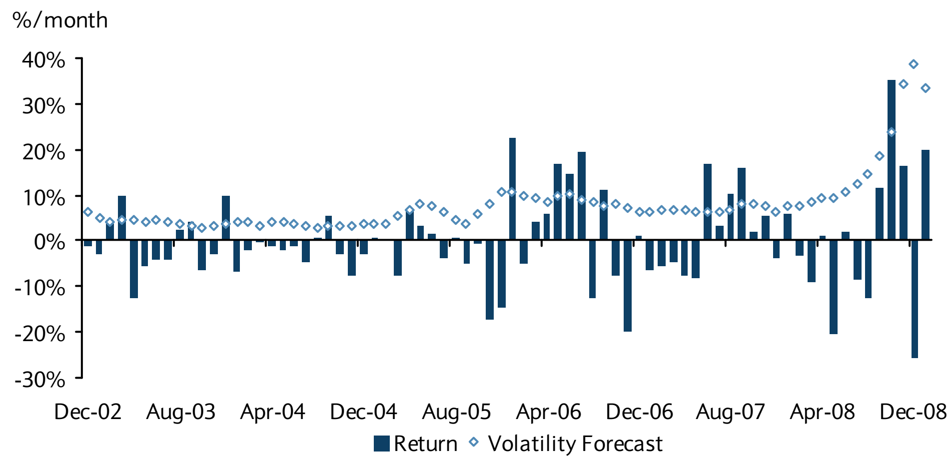
We combine the data into one single model:

$$\sigma_i^{t+1} = \phi_C^{1,t} + \phi_C^{2,t} \sum_{\tau=\tau 0}^{t} f(w^{\tau}, \varepsilon_{i,d}^{\tau})$$

Where ϕ^1, ϕ^2 are parameters, *w* a set of weights for the historical daily observations (starting at $\tau 0$) and *C* stands for characteristics: we estimate this regression separately for each subset of stocks with characteristic *C*. The parameters are estimated using prior historical relationship between daily and monthly idiosyncratic returns. Therefore, this specification allows us to account for different auto-correlation dynamics across different groups of stocks.

As an illustration of our methodology, we look at the members of the Dow Jones Industrial Index with some of the highest idiosyncratic risk: General Motors (GM) and Bank of America (BAC). These two examples allow us to look at different nuances of the forecasting model.

Figure 17: General Motors Idiosyncratic Monthly Return and Its Volatility Forecast (month-end)

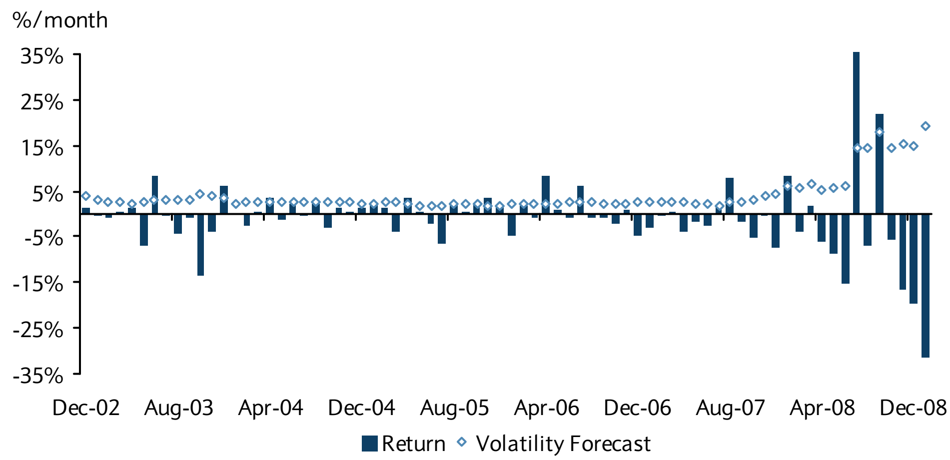


Source: Barclays Capital Portfolio Modeling

Figure 17 shows the monthly idiosyncratic return for General Motors as well as the corresponding volatility forecast – as of the end of the month – given by our forecasting model since December 2002. The figure shows that the forecast is about 3%/4% for much of the earlier period, but jumps to about 7% after the debt rating downgrade in 2005. It enters 2008 at close to that level, but more than doubles in the first eight months of the year. Note that this is the case even though the actual monthly residuals for this part of 2008 are relatively small. A forecast based on monthly observations could take some time to capture the increase in underlying volatility. The rise in our volatility forecast is consistent with a steady increase in observed daily volatilities, even if they do not always materialize at the monthly level. The last four months of 2008 were just brutal to GM, with idiosyncratic volatilities reaching 40%. During this period the idiosyncratic volatility forecast tripled.

Figure 18 shows a somewhat different story. For Bank of America, idiosyncratic risk monthly forecast was about 3% up to the first half of 2007. After the financial crisis during the summer of 2007 idiosyncratic volatility picked up to about 6%, but then doubled in one month, during July 2008, because of uncertainty coming from the acquisition of Countrywide Financial. This example clarifies how volatilities can quickly increase in our idiosyncratic model. Note that this is coherent with the fact that the nature of individual firms can vary significantly over a very short period of time.

Figure 18: Bank of America Idiosyncratic Monthly Return and Its Volatility Forecast (month-end)



Source: Barclays Capital Portfolio Modeling

5. Backtesting Our Model

In this section we present the results from the backtesting of our model. This allows us to document how our model performs for different sets of portfolios and under different periods of time.

We use the period from December 2002 to January 2009 as our backtesting period[7]. This gives us a bit more than six years covering very different market conditions – from the very high volatilities at both ends of the sample to very low during the middle period – and volatility transition periods. Given this diversity, we believe this is an interesting period for backtesting our models.

We test our model along three different dimensions: The first one tests the performance for a broad portfolio of equities. This allows us to summarize the characteristics of our volatility forecasts. For this test, we also compare the volatility estimates of our model with other standard volatility approaches, in order to better understand where the improvements lie. Moreover, our model uses 24 industry factors (GICS level 2) to reflect risk associated with the firm's line of business. Why not more or less than 24? What if the portfolio construction is done with a different aggregation level, do we capture risk accurately? We try to answer these questions with our second test. The third line of tests looks into the performance of the risk model across portfolios constructed around fundamental or technical themes, such as momentum or size. Although our model sees industries as the major drivers of volatility, we want to make sure the model performs well for portfolios constructed without any reference to them.

The general framework we use to evaluate the performance of the model is quite standard, and is generally known as the ratio test. For each period *t* and portfolio *p*, we construct a standardized return - u_p^t - that is the ratio of the actual return during that period - r_p^t - to

[7] December 2002 is the first date for which the covariance matrix is available fully integrated with the other asset classes.

the predicted volatility of that portfolio for that period - $\sigma^{t}_{p,forecast}$. Specifically:

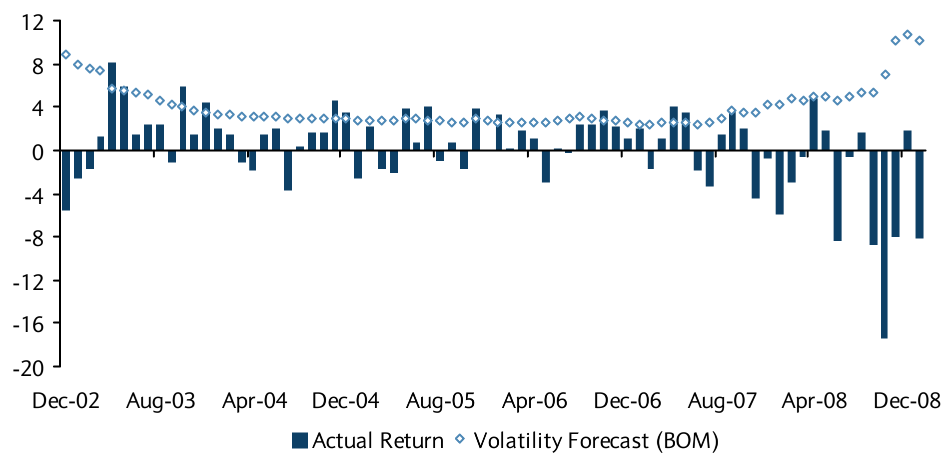
$$u_p^t = \frac{r_p^t}{\sigma^{t}_{p,forecast}}$$

If the forecast is good, the volatility of this ratio should be about 1. In what follows, we also briefly characterize the full distribution of the standardized returns. This allows us to make a better judgment regarding the behavior of the forecasting model.

Overall Market Portfolio

Our first test focuses on the forecasted volatility for the overall market portfolio. In particular, Figure 19 shows both the actual return and the forecast volatility (the two inputs used to calculate the standardized return) for the testing period.

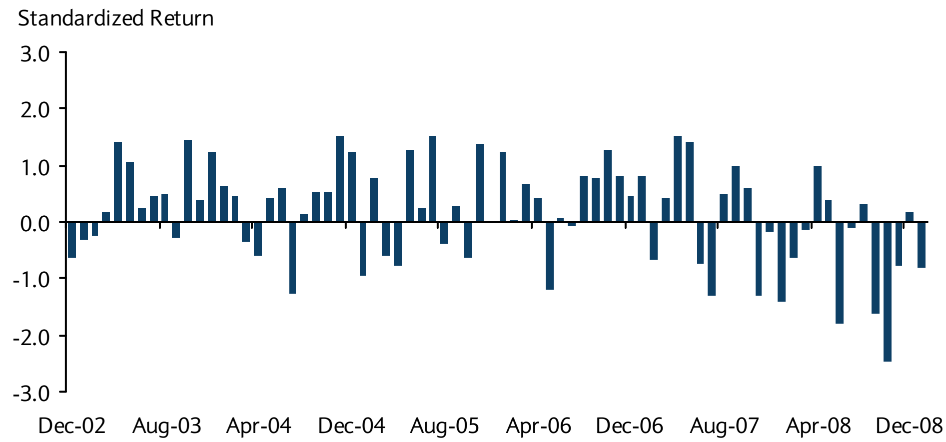
Figure 19: Actual Returns and Forecasted Volatility (BOM: Beginning of Month) for the Market Portfolio – December 2002 to January 2009



Source: Barclays Capital Portfolio Modeling

We can see that volatility forecasts respond quickly to changes in underlying conditions. For instance, in the beginning of the sample, the volatility forecast is high – at about 10% – as we come off of a recession period, but it halves in about six months, reflecting the lower volatility experienced in 2003. Volatilities remained low for much of the next four years, and start to gradually increase after the summer 2007. We entered September 2008 with volatilities at approximately 5%, but they dramatically double in the space of two months. The ability of the forecast to adjust quickly (but still in a robust way) is also documented in Figure 20, where we show the ratio of these two series – the standardized returns.

Figure 20: Standardized Returns for the Market Portfolio – December 2002 to January 2009



Source: Barclays Capital Portfolio Modeling

We can see that even under very extreme scenarios – as the one that unfolded in 2008 – standardized returns go above 2 (in absolute value) only in October 2008, when the market return was -17%! Of course, this could have been achieved by just systematically over-predicting risk. Figure 21 confirms this is not the case.

Figure 21: Summary Statistics for the Standardized Returns of the Market Portfolio – December 2002 to January 2009

	Volatility Model		
Statistic	MFVM	EWMA	EQW
Standard Deviation	0.90	1.01	0.86
Standard Deviation (JAN07 - JAN09)	1.06	1.46	1.19
Skewness	-0.53	-1.57	-1.76
Kurtosis	-0.09	4.15	5.40
5% Percentile	-1.65	-2.03	-2.07
95% Percentile	1.14	1.03	0.73

Source: Barclays Capital Portfolio Modeling

For the overall sample period, our model (MFVM) overestimated risk by about 10%, probably owing to the very low volatility environment during 2003-2006. More importantly, the model reacted very well over the past two years, underpredicting volatility by only 6%. Moreover, the distribution of the standardized returns behaves very well, with little negative skewness and almost no kurtosis. We can also see that the extreme observations are well captured by the model, although the 95% percentile (positive tail) comes below the implied by normal distributions.

These results contrast with those of two other typical volatility forecasts: Exponentially weighted moving average (EWMA, with one year half-life) and equal weighted (EQW)[8]. For the overall sample, the EWMA does a good job, slightly missing the mark (1.01). However, when we look at periods of extreme volatility (e.g., since January 2007) EWMA significantly

[8] We show the results for these other forecasts only for the market portfolio. For the other portfolios we study in this section the results are qualitatively the same.

underpredicts volatility by about 50%. This is because this forecast has some trouble catching up with the sudden higher volatility of the market, even though it has an aggressive one year half-life. Note that the EQW is always off, as it is too dependent on data prior to this period[9]. The other statistics presented in the table complete the picture. Both the EWMA and EQW forecasts have relatively fat negative tails and large kurtosis, mainly driven by the overprediction for a large number of (calmer) months. In summary, our forecast seems to be the one that delivers the most consistent results. It picks up changes in the underlying volatility, either positive or negative, quickly.

Sector, Industry, and Sub-Industry Portfolios

Another test we perform addresses the concern that the level of industry aggregation we choose in our model – GICS level 2 with 24 industries – may be inadequate for portfolio managers that set allocations using different aggregation levels, either more or less coarse. If our industry structure is very coarse, we may not capture sufficiently the diversification of a portfolio constructed based on a finer set of industries. If our structure is too thin, we may be overstating diversification. In both cases, the backtesting results should highlight this issue. To perform the test, we construct random portfolios using different industry aggregation levels and check how our model (with 24 fixed industry risk factors) performs in tracking those portfolios. Specifically, and every month, we construct 50 random portfolios of five sectors (out of 10 possible using the GICS1 classification), 50 random portfolios of 10 industries (out of 24 possible using the GICS2 classification), and 50 random portfolios of 10 sub-industries (out of 58 possible using the GICS1 classification[10]). We then compute the return of each of these portfolios as the equal weighted average of returns for each of the sector, industry, or sub-industry indices that belong to that random portfolio. Similarly, we use our model to compute the beginning-of-month volatility forecast for each portfolio. Finally, we compute the standardized returns for all these portfolios as the ratio of the two variables. Figure 22 reports the results of this experiment.

Figure 22: Summary Statistics for the Standardized Returns for Random Portfolios – December 2002 to January 2009

Statistic	Sector (10)	Industry (24)	Sub-Industry (58)
Standard Deviation	0.90	0.92	0.99
Standard Deviation [JAN07 - JAN09]	1.05	1.02	1.08
Skewness	-0.46	-0.45	-0.45
Kurtosis	0.16	-0.11	0.17
5% Percentile	-1.67	-1.70	-1.83
95% Percentile	1.30	1.28	1.39

Source: Barclays Capital Portfolio Modeling

It is clear from the exercise that whatever the level of aggregation used to construct the portfolio, our model – with the 24 industry factors – performs well in capturing the risk of these random portfolios. As in the overall market case, the model does very well during the turbulent period of 2007 and 2008, slightly underpredicting returns. The distribution of the standardized returns is close to normal, although with a slight negative skew. The tail percentiles suggest that the problem is not a strong underprediction of negative returns – note that the 5% percentile is close to normal (-1.65) – but instead owing to the fact that

[9] Our volatility estimates use data since January 1990.

[10] GICS level 3 classification has 68 sub-industries, but we narrow the universe to 58 to allow for enough members in each index.

the return distribution is itself skewed with a smaller number of large positive realizations. More importantly, the results do not differ significantly across the different levels of aggregation. Therefore, the choice of GICS level 2 seems to strike a balance between these different levels of aggregation.

Fundamental- and Technical-based Portfolios

The final test we conduct looks at whether the prominent use of industries in our risk model jeopardizes its use for portfolios constructed without any industry considerations. To test this hypothesis, we construct long-short portfolios based on variables other than industry membership. Specifically, we construct portfolios based on standard investment themes such as Momentum, Market Value (size), Book to Market, as well as our proprietary distress factor, the POINT Corporate Default Probability (CDP). The portfolios are constructed each month, by going long stocks that have loadings on the top 30% of the characteristic and going short stocks in the lower 30%. Figure 23 shows the results.

Figure 23: Summary Statistics for the Standardized Returns for Style Portfolios – December 2002 to January 2009

Statistic	Momentum	Size	Book/Price	CDP
Standard Deviation	1.16	0.94	1.20	1.02
Standard Deviation [JAN07 - JAN09]	1.06	1.11	1.02	1.16
Skewness	-0.17	-0.24	0.33	-0.34
Kurtosis	-0.18	-0.37	0.19	0.17
5% Percentile	-2.04	-1.85	-1.42	-1.93
95% Percentile	1.90	1.42	2.63	1.38

Source: Barclays Capital Portfolio Modeling

Overall, the model tends to underpredict the risk in these portfolios by about 8%. But more importantly in our view, the model performed remarkably well over the past two years. Specifically, for certain variables such as momentum and book to price, the model actually predicted the level of volatility better over this period than for the entire sample. Looking also at the other distribution statistics presented in the table, we see that the skewness and kurtosis of the standardized returns is quite small. Moreover, the tail percentiles look reasonably good, except for the book/price portfolio, where the positive tail is much higher than the value implied by a normal distribution (1.65). We will keep monitoring very closely the performance of this model along these dimensions, but we believe these numbers show how robust the model is under very different and extreme market conditions.

Overall, the evidence in this section seems to suggest that users can feel comfortable with volatilities predicted by our new equity model, independently of the portfolio construction philosophy a portfolio manager may use. For a diverse set of portfolios, the model seems to handle well scenarios of extreme volatility – as the ones we have been experiencing over the past couple of years – as well as quick changes in the underlying environment.

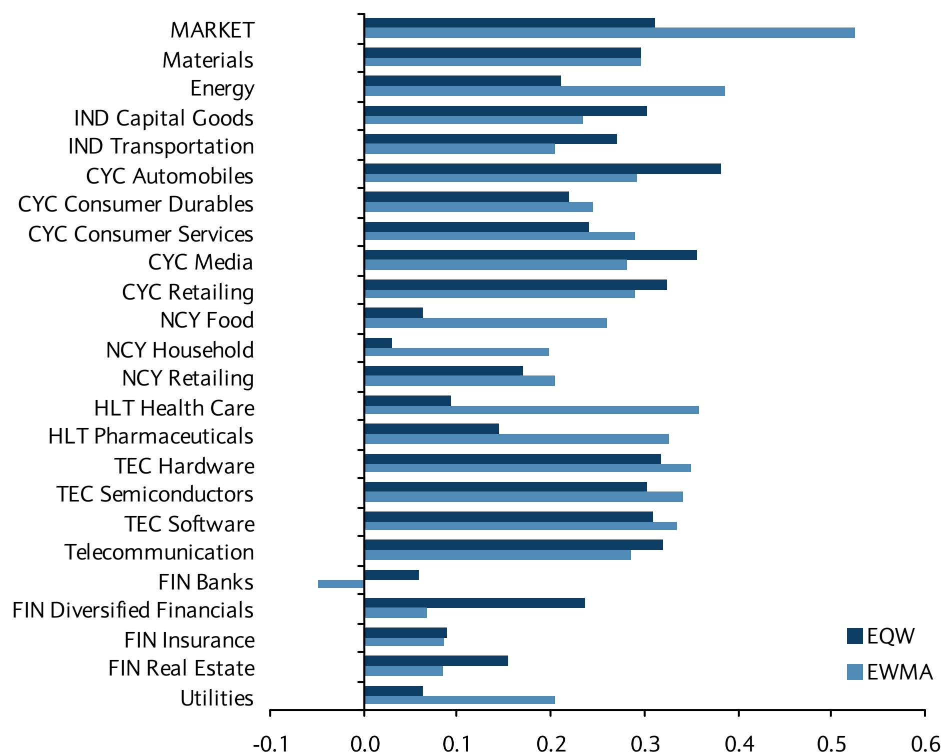
6. Integration with Credit Risk

In the Global Risk Model (GRM) in POINT, all the different asset classes are fully integrated to deliver a consistent, aggregate picture of risk exposures. The integration works with the different dimensions of risk, namely systematic and idiosyncratic. In this section, we illustrate how the new US equity model interacts with the current US credit model[11]. We first look to the interaction at the systematic risk level. Then, we shift our focus to idiosyncratic risk. We look into examples on how the GRM aggregates the different exposures to an issuer (e.g., an equity and a corporate bond from the same issuer) into a single idiosyncratic volatility forecast for that firm.

Systematic Risk

For systematic risk, we look at the correlations between the equity and credit spread industry risk factors embedded in our models. The level of these correlations drives the degree in which a systematic equity exposure may offset the risk of a systematic credit spread exposure. Figure 24 shows these correlations. In particular, the numbers are shown for both our current correlation calibrations: EQW (equal weighted), which means weighting equally all the historical data and EWMA, where we use an exponentially weighting function parametrized with a one year half-life to calculate the correlations.

Figure 24: Correlations between Equity and Fixed Income Industry Systematic Risk Factors – January 2009



Source: Barclays Capital Portfolio Modeling

It is interesting to see how diverse the correlations are, and how the dramatic events of the past couple of years have changed the picture. For the overall markets, correlations between industry spread and equity risk factors are at levels significantly higher (52%) than historical averages (30%). However, the behavior is quite asymmetrical, when we look into individual industries or sectors: For Materials, Industrials, Cyclicals, and Technology, correlations did not change significantly. For Energy, Non-Cyclicals, and Healthcare, they

[11] Even though we focus in these two asset classes, the integration goes beyond them and into other points of the capital structure (e.g. convertibles) or derivatives products like CDS, equity options, etc, and other asset classes.

increase significantly, maybe owing to increased financial distress. For Financials, correlations generally decrease. For this industry, the change in patterns may have to do with the recent government intervention and generic cash injections. This may be consistent with stock prices falling sharply on concerns of significant equity dilution while bonds rallying by a perceived implicit government guarantee. The asymmetry of behavior is a good example on how the detail in the Global Risk Model successfully captures the differentiated reactions to the changes in market environment.

Idiosyncratic Risk

We now turn to the integration of idiosyncratic risk. We want to explore the interaction between the idiosyncratic risks associated with the different parts of the capital structure for the same issuer. In particular, we illustrate this point using the following example. Suppose we hold equities in our portfolio and want to hedge their idiosyncratic risk using corporate bonds. Issuer by issuer, the idiosyncratic volatility of such portfolio can be represented as:

$$STD(IR_i^S - IR_i^B) = \sqrt{VAR(R_i^S) + VAR(IR_i^B) - 2 \times \rho \times STD(R_i^S) \times STD(IR_i^B)}$$

where *IR* stands for idiosyncratic return, *S* for stock and *B* for bond from issuer *i*. From the expression it is clear that the hedge is effective only if correlations are relatively high. In what follows, and as an example, we choose three issuers that are both active in the equity and credit markets. The particular choice of names was made for illustration purposes only. For each, we pair the stock with a corporate bond, with maturity as large as possible (usually with Option Adjusted Spread Durations of around 10 years). The three names chosen are diverse, coming from different industries and having different levels of credit spreads.

Figure 25 shows the idiosyncratic forecast volatilities coming from our GRM for the equity, the bond, and the long-short portfolio constructed by going long on the equity and short on the bond. For reference, we also show the implied idiosyncratic correlation across the two issues, calculated using the expression above. Finally, we show the Option Adjusted Spread (OAS) for the bond, so we can assess how the relative distress of the issuer impacts the success of the hedge.

Figure 25: Monthly Forecasted Volatility of Idiosyncratic Returns for some Issuers – January 2009

	Forecasted Volatility (%)				
Issuer	Stock (S)	Bond (B)	S-B	CORR(S,B)	OAS(%)
WAL-MART STORES INC	4.14	3.19	5.22	0.00	1.84
CATERPILLAR INC	11.33	4.48	10.86	0.30	3.23
BANK OF AMERICA CORP	19.23	8.02	16.28	0.55	4.44

Source: Barclays Capital Portfolio Modeling

For Wal-Mart there is absolutely no hedge, as the volatility of the equity position (4.14%) is actually smaller than that of the "hedged" portfolio (5.22%). This comes as no surprise as the implied correlation between the idiosyncratic return of the bond and the equity is zero. The low value for the OAS of the Wal-Mart bond gives us a hint. If the issuer is very safe – the credit risk embedded in the bond is small – then there is no reason for the equity and the bond to correlate. The firm's assets are much higher than those implied from the default barrier. In this case, the price of the bond is probably more related to the yield curve than to the actual asset value of Wal-Mart. Caterpillar shows a different picture. Correlations here are a bit higher. However, because the bond's volatility is still relatively small, there is only a small hedging effect (from 11.3% to 10.9%). The Bank of America example is more conclusive. Both the correlation and the volatility of the bond are higher, as the bond experiences spreads of about 4.5%. This seems to suggest that an important part of the bond's valuation comes from the bank's perceived asset values. In this case, the hedging exercise has some effect, reducing the volatility by 3 percentage points to 16.28%.

In general, we can expect the hedging performance to increase (in relative terms) as the distress level of the issuer increases.

Overall the GRM fully integrates the equity and credit components of a portfolio's exposure in an intuitive way. The integration covers both the systematic and idiosyncratic components, in order to fully reflect potential concentration risks or hedging benefits.

7. Risk Estimates and Reporting in POINT

In this section, we illustrate several dimensions of the risk reporting in POINT. We first go through some of the options available to run the reports and show how risk estimates can change accordingly. We then focus in detail on a particular risk report. This allows us to explain at length the level of detail and customization available on a typical report. In this piece, we focus on volatility estimates. We refer readers interested in tail risk statistics - also available in the regular risk report in POINT – to Meucci, Gan, Lazanas, and Phelps (2007).

To illustrate POINT's risk report, we use for this section the following parameters when running the model[12]:

Portfolio:	S&P SmallCap 600 Value Index
Benchmark:	RUSSELL 1000 index
Report as of:	January 31, 2009
Volatility Calibration:	Weighted
Risk Factor Partition:	GRM Equity Factors
Security Partition:	GICS Level 1

The options used to run the report may have material effect on the risk estimates. As an example, we run the same report for two different dates (June 30, 2008, and January 31, 2009) and under two different calibrations (weighted and unweighted). Figure 26 shows the tracking error volatility (TEV) – the predicted monthly volatility of the portfolio's return net of the benchmark - for the four different settings:

Figure 26: Risk Model Volatility Forecasts

Systematic Risk (TEV %)	June 30, 2008	January 31, 2009
Unweighted	2.3	2.5
Weighted	2.0	4.7

Source: POINT.

The figure shows that the unweighted TEV estimate is relatively flat over the period. However, the weighted calibration – that uses the MFVM described above - , shows an

[12] POINT allows you to specify a much larger set of parameters. Here we focus on the most widely used.

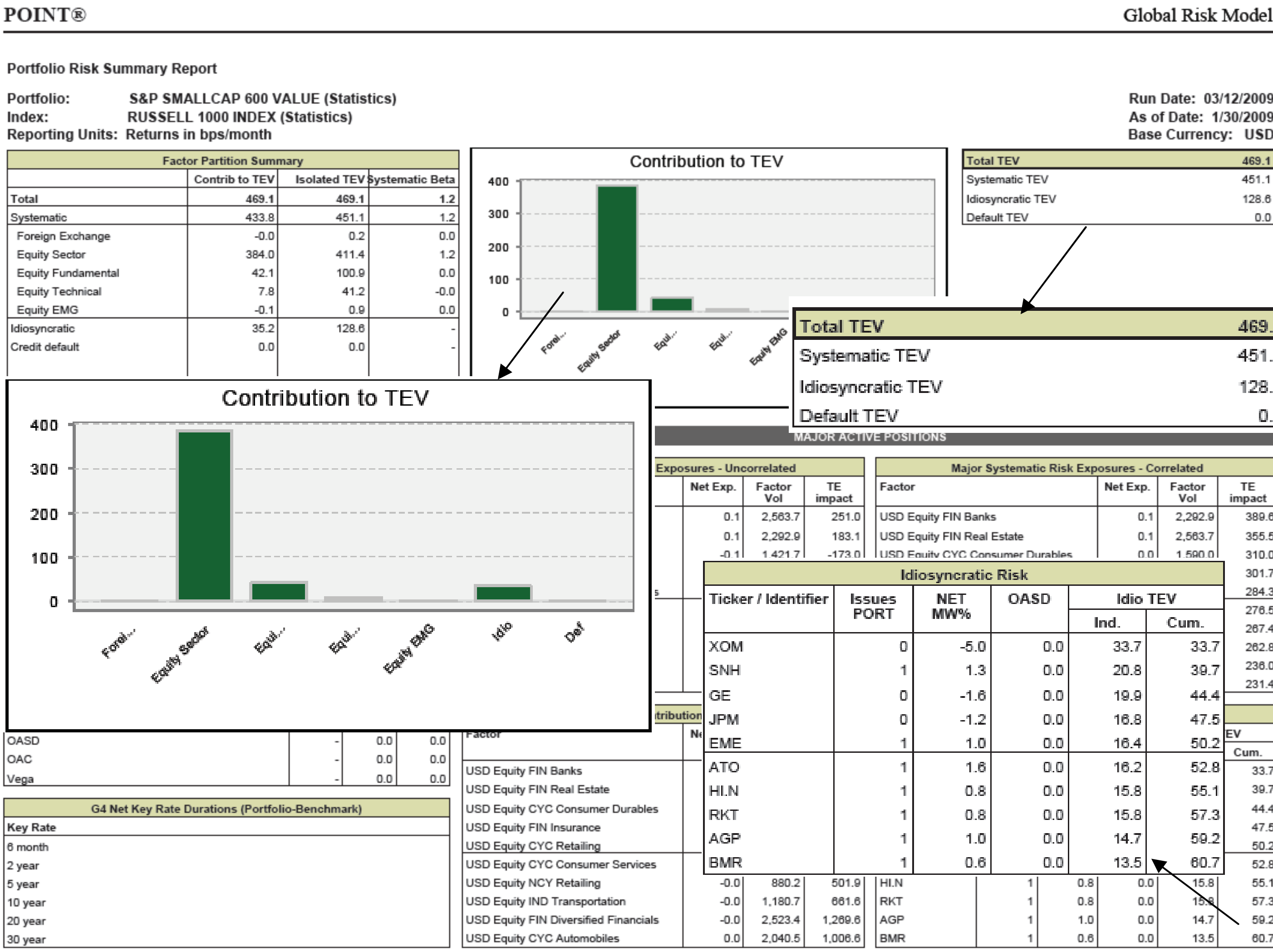
estimate for the systematic risk that more than doubled, in just 7 months. As previously described, the volatility model for the U.S. Equity model is very responsive.

We now explore in more detail the risk report available through POINT. To produce this report we used the settings described above. The overall extensive and detailed risk report is divided into four major component: (i) Summary, that encompasses the first few pages where a summary view of the portfolio, benchmark, risk and risk allocation is provided; (ii) Detail Systematic, where extensive information is given regarding all systematic risk factor exposure and sensitivities; (iii) Detail idiosyncratic, where the risk both at the issue and issuer level is detailed; and (iv) other reports, namely a systematic historical return simulation and a listing of warnings, exclusions and all options used to run the model.

Summary Reports

Figure 27 is the Portfolio Risk Summary Report in POINT. The report provides a quick snapshot of the characteristics and risk of the portfolio. For instance, we see that the total TEV of the portfolio is 4.7% per month. The chart – that uses the factor risk partition chosen by the issuer – illustrates that the major contribution to the systematic component of the TEV comes from the set of equity industry/sector factors, with about 3 percentage points of the risk. This information is also in the table to the left of the graph. The summary report also highlights the major systematic and idiosyncratic/name risk imbalances in the portfolio. On the idiosyncratic side, for instance, the largest idiosyncratic risk comes from Exxon Mobil (XOM), with 33.7bp/month. The risk comes from the fact that the portfolio does not hold any security from this issuer, while its presence in the benchmark is significant (almost 5% of the market value).

Figure 27: Portfolio Risk Summary Report



Source: POINT

The Risk Factor Partition report in Figure 28 illustrates the contribution of different risk factor groups to the TEV. Note that the items seen in this report are fully controlled by the user's choice of risk factor partition. We can see that in the systematic component, Sector and Fundamental are the major sources of risk, with 384bp and 42bp of contribution to the TEV (CTEV), respectively. The idiosyncratic risk is also non-trivial, contributing with 35bp to the overall risk of the portfolio. The report provides many other important analytics. For instance, it details the isolated TEV. This is the TEV we would get if all the other net exposures were to be set to zero. This would neutralize any correlation across factor groups given by the covariance matrix. Under this measure, the Fundamental, Technical, and Idiosyncratic factors gain relative importance. Finally, the report also shows that the portfolio has a beta if 1.19 to the benchmark, mainly coming from industry exposures.

Figure 28: Tracking Error Volatility - Risk Factor Partition Report

POINT® Global Risk Model

Tracking Error Volatility - Risk Factor Partition 1/30/2009

Portfolio: S&P SMALLCAP 600 VALUE (Statistics)
Benchmark: RUSSELL 1000 INDEX (Statistics)
Reporting Units: Returns in bps/month
Partition : GRM Equity Factors

	Contribution to TEV			TEV		Sensitivities	
Risk Factor Partition Bucket	Isolated CTEV	Correlated CTEV	Total CTEV	Isolated TEV	Liquidation Effect on TEV	TEV Elasticity (%)	Systematic Beta
Total	**469.06**	**.00**	**469.06**	**469.06**	**-469.06**	**100.00**	**1.19**
Systematic	433.83	-.00	**433.83**	451.10	-340.51	92.49	1.19
Foreign Exchange	.00	-.03	**-.03**	.22	.03	-.01	.00
FX EUR	.00	-.01	**-.01**	.07	.01	-.00	.00
FX Other	.00	-.01	**-.01**	.16	.01	-.00	.00
Equity Sector	360.78	23.18	**383.96**	411.37	-298.64	81.86	1.16
Equity Fundamental	21.71	20.44	**42.15**	100.91	-32.41	8.99	.04
Equity Technical	3.62	4.20	**7.82**	41.19	-6.05	1.67	-.01
Equity EMG	.00	-.07	**-.07**	.88	.07	-.02	.00
Idiosyncratic	35.23	.00	**35.23**	128.55	-17.96	7.51	
Credit default	**.00**	**.00**	**.00**	**.00**	**.00**	**.00**	

Source: POINT

A similar analysis is conducted in the Security Partition Report. The difference is that the partition of risk in this report is done across sets of securities, instead of across risk factors. Figure 29 shows this report.

Figure 29: Tracking Error Volatility - Security Partition Report

POINT® Global Risk Model

Tracking Error Volatility - Security Partition 1/30/2009

Portfolio: S&P SMALLCAP 600 VALUE (Statistics)
Benchmark: RUSSELL 1000 INDEX (Statistics)
Reporting Units: Returns in bps/month
Partition : GICS Level 1

		Contribution to TEV (CTEV)									TEV		Sensitivities	
		Systematic												
Security Partition Bucket	Net Market Weight (%)	Foreign Exchange	Equity Sector	Equity Fundamental	Equity Technical	Equity EMG	Systematic CTEV	Idiosyncratic CTEV	Default CTEV	Total CTEV	Isolated TEV	Liquidation Effect on TEV	TEV Elasticity (%)	Systematic Beta
Total	**-.00**	**-.03**	**383.96**	**42.15**	**7.82**	**-.07**	**433.83**	**35.23**	**.00**	**469.06**	**469.06**	**-469.06**	**100.00**	**1.19**
Energy	-12.21	-.00	41.82	.78	.41	-.02	42.99	3.53	.00	**46.52**	177.16	-13.25	9.92	1.03
Materials	1.74	.00	5.07	2.35	.83	-.03	8.22	1.79	.00	**10.01**	38.01	-8.55	2.13	1.31
Industrials	7.15	.00	48.67	7.13	.88	-.00	56.69	5.34	.00	**62.02**	144.33	-41.67	13.22	1.44
Consumer Discretionary	1.88	-.01	36.84	6.50	1.98	-.01	45.31	3.11	.00	**48.42**	70.34	-45.34	10.32	1.37
Consumer Staples	-8.69	.00	-29.91	2.53	.48	-.00	-26.91	1.57	.00	**-25.34**	59.33	28.24	-5.40	.60
Health Care	-5.50	.00	-9.32	4.57	.22	.00	-4.52	3.50	.00	**-1.02**	57.84	4.57	-.22	.80
Financials	16.42	.00	303.67	7.84	2.59	-.00	314.10	9.76	.00	**323.86**	353.98	-265.34	69.05	1.40
Information Technology	-3.85	-.01	-12.45	8.25	1.16	-.01	-3.07	4.37	.00	**1.30**	65.79	3.30	.28	1.16
Telecommunication Services	-3.30	.00	-7.52	-.00	-.12	.00	-7.64	.40	.00	**-7.24**	44.78	9.29	-1.54	1.28
Utilities	6.37	.00	7.09	2.19	-.62	.00	8.66	1.86	.00	**10.52**	55.03	-7.35	2.24	.60

Source: POINT

We note that the lines in this report are fully customizable and controlled by the chosen security partition. In our illustration, we define the partition as sector classification so that we can see the aggregate contribution of securities to TEV for each sector. The report shows the major source of risk is coming from the Financials sector (324bp of CTEV), fueled by a strong overweight versus the benchmark (16.42%). The financial role is also visible in the idiosyncratic risk, where is also the major contributor (specifically, it contributes with 10bp to the overall 35 idiosyncratic CTEV). The table also shows, for instance, that if we would hedge the financial exposure, the TEV would be less than a half (-265 out of the 469 total TEV). This table finishes the summary section of the risk report. The next section details all systematic exposures.

Systematic Report

Figure 30 shows a small part of the Factor Exposure report. This report shows, for every factor with a non-zero loading, the portfolio, benchmark and net exposures to the factor, the factor volatility as well as other statistics of interest, namely the Contributions to TEV (in bp and as percentage of the total variance – the last two columns of the report). In this figure, we show only the part of the report with the industry risk factors associated with the Financials sector. As expected factor volatilities are at historical highs, with monthly values above 20% (numbers in the figure are in bp/month). This is the result of the almost unprecedented turmoil we have been seeing in the markets and in particular in this sector. As shown, we are generally overweighting Financials in a market-value weighted beta. For example, the overweight is of 0.08 beta for the Banking industry. Among other things the figure also shows that the imbalances concerning the banking industry are responsible for 152bp of TEV per month, representing 32% of the total variance of the portfolio versus the benchmark.

This report includes other interesting insights. In the “Tracking Error Correlated Impact” column we can see that a typical movement up in these factors (let’s say a 20% movement - the average volatility) would lead to a positive portfolio net return of about 2% to 3%. This means that the empirical beta of the entire portfolio to the financials sector (as given by the risk model’s covariance matrix) is from about 0.1(2%/20%) to 0.15(3%/20%).

Figure 30: Factor Exposure - Full Detail Report (partial view)

POINT® Global Risk Model

Factor Exposure - Full Details 12/1/2008

Portfolio: S&P SMALLCAP 600 VALUE (Statistics)
Benchmark: RUSSELL 1000 INDEX (Statistics)
Reporting Units: Returns in bps/month

Factor name	Sensitivity/Exposure	Portfolio exposure	Benchmark exposure	Net exposure	Factor volatility	TE impact of an isolated 1 std. dev. up change	TE impact of a correlated 1 std. dev. up change	Marginal contribution to TEV	Percentage of tracking error variance (%)	Contribution to TEV
USD Equity FIN Banks	Empirical Beta	.105	.025	.080	2,292.90	183.07	389.61	1,904.545	32.42	152.06
USD Equity FIN Diversified Financials	Empirical Beta	.013	.049	-.036	2,523.40	-90.87	236.00	1,269.590	-9.75	-45.72
USD Equity FIN Insurance	Empirical Beta	.037	.028	.009	1,621.90	15.31	301.70	1,043.212	2.10	9.84
USD Equity FIN Real Estate	Empirical Beta	.113	.015	.098	2,563.70	250.98	355.54	1,943.238	40.56	190.24

Source: POINT

Idiosyncratic Reports

Figure 31 shows (partially) the Issue-specific Risk report. It describes some risk analytics for the portfolio’s top holdings, independently of its idiosyncratic risk. To illustrate, ATMOS Energy Group stock (ticker ATO UN) is the largest holding in the portfolio, with 1.58% of its market value. The report also shows that the idiosyncratic risk associated with that stock is 16.24bp/month. Finally, in this case, the idiosyncratic risk associated with all securities from this issuer either in the portfolio or benchmark (the “Issuer Idiosyncratic TEV”) is also 16.24bp/month. This suggests no other relevant security from this issuer is present. If that was not the case, the last two columns would report different numbers. If the portfolio or benchmark holds more than one issue from the same issuer (e.g., a stock and an option on that stock, or a CDS from that issuer), the risk of all these positions is integrated into the last column of the report.

Figure 31: Portfolio Issue – Specific Risk Report (partial view)

POINT® Global Risk Model

Portfolio Issue-Specific Risk 1/30/2009

Portfolio: S&P SMALLCAP 600 VALUE (Statistics)
Benchmark: RUSSELL 1000 INDEX (Statistics)
Reporting Units: Returns in bps/month

Identifier	Ticker	Description	Currency	Coupon (%)	Maturity	Current OAS (bps)	MV issue weight (%)	MV issue net weight (%)	MV issuer net weight (%)	Marginal systematic TEV	Systematic TEV	Idiosyncratic TEV	Issuer idiosyncratic TEV
ATO UN	ATO	ATMOS ENERGY CORP	USD			0	1.58	1.55	1.55	1.4629	11.88	16.24	16.24
SNH UN	SNH	SENIOR HOUSING PROP TRUST	USD			0	1.31	1.31	1.31	20.0333	33.43	20.84	20.84
NJR UN	NJR	NEW JERSEY RESOURCES CORP	USD			0	1.19	1.19	1.19	1.3255	10.47	10.97	10.97
OMI UN	OMI	OWENS & MINOR INC	USD			0	1.16	1.16	1.16	2.1511	8.14	12.84	12.84
AGP UN	AGP	AMERIGROUP CORP	USD			0	1.05	1.05	1.05	3.7658	12.42	14.70	14.70

Source: POINT

Figure 32 illustrates a partial view from the Ticker Report in POINT, which provides issuer-level analysis. Specifically this reports shows the list of issuers in the portfolio or benchmark in decreasing level of issuer idiosyncratic TEV. This number – as reported in the last column – is a function of the weights of each of the securities from that issuer, their idiosyncratic volatility and the correlation among all the securities of that issuer. In this case, probably not surprisingly, a lot of the top issuers in terms of contribution to risk are actually not represented in the portfolio at all (e.g., XOM). This report also shows there are significant differences between stocks in terms of the ratio of their systematic to idiosyncratic TEV. Some very large-cap stocks, such as XOM, exhibit larger systematic TEV, when compared with its idiosyncratic TEV (56 versus 34bp) whereas for other issuers, such as ATO, the opposite happens (12 versus 16).

Figure 32: Ticker Report (partial view)

POINT® Global Risk Model

Ticker Report 1/30/2009

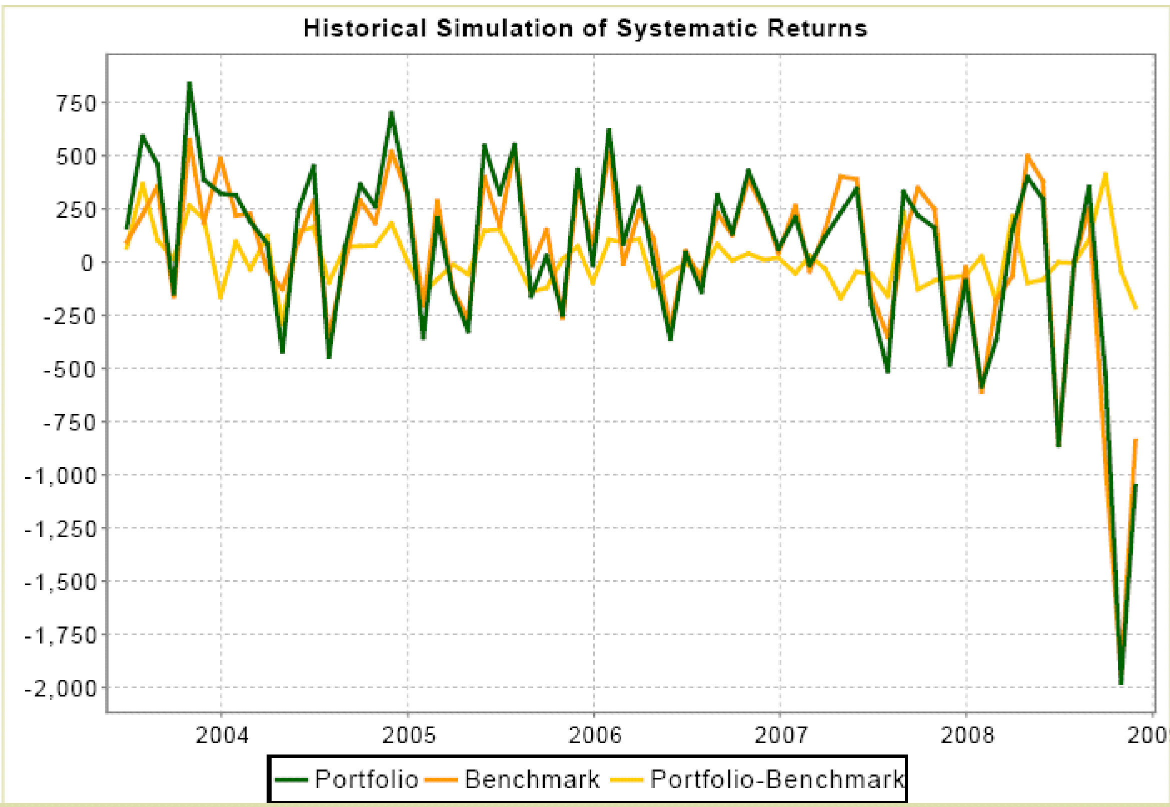
Portfolio: S&P SMALLCAP 600 VALUE (Statistics)
Benchmark: RUSSELL 1000 INDEX (Statistics)
Reporting Units: Returns in bps/month

Ticker	Name	Sector	Rating	Currency	# issues in portfolio	Portfolio weight (%)	Benchmark weight (%)	Net weight (%)	Net contribution to OASD (Yr)	Systematic TEV	Idiosyncratic TEV
XOM	EXXON MOBIL CORP	ENERGY	NR	USD	0	.00	4.98	-4.98	.000	56.32	33.74
SNH	SENIOR HOUSING PROP TRUST	REITS	NR	USD	1	1.31	.00	1.31	.000	33.43	20.84
GE	GENERAL ELECTRIC CO	DIVERSIFIED_MANUFACTURING	NR	USD	0	.00	1.57	-1.57	.000	23.22	19.92
JPM	JPMORGAN CHASE & CO	NON_CAPTIVE_DIVERSIFIED	NR	USD	0	.00	1.17	-1.17	.000	29.39	16.84
EME	EMCOR GROUP INC	CAPITAL_GOODS	NR	USD	1	.95	.00	.95	.000	16.68	16.44
ATO	ATMOS ENERGY CORP	NATURAL_GAS	NR	USD	1	1.58	.03	1.55	.000	11.88	16.24

Source: POINT

Figure 33 shows the Historical Simulation Report in POINT. The report illustrates the *historical* performance of the *current* systematic exposures of the portfolio, the benchmark and the difference between the two. Note that we call it (i) a simulation because in this exercise we keep all loadings constant across time; and (ii) systematic because only the behavior of the systematic risk factors is taken into account. Specifically, we do not report any idiosyncratic return effect. So the inputs to this simulation are the current factor loadings and the history of the systematic factor realizations. This report provides an illustration of the ability of the portfolio to follow its benchmark in different historical market conditions. As we would expect, in this case the portfolio behavior can be significantly different than that of the benchmark. For instance, in September 2008 the portfolio returned -5.5% while the benchmark returned about -9.6%.

Figure 33: Historical Simulation Report (partial view)



Legend	Axis	6/30/2003 to 11/28/2008	Last	Minimum		Maximum		Mean	Std. Dev
	Left	Portfolio Est. Return	-1,052.30	-1,976.66	10/31/2008	837.14	10/31/2003	53.69	449.09
	Left	Benchmark Est. Return	-840.49	-1,933.27	10/31/2008	572.54	10/31/2003	40.20	411.02
	Left	Difference	-211.81	-292.80	4/30/2004	411.06	9/30/2008	13.49	133.41

Source: POINT

POINT also reports the exclusions and warnings from the analysis. This report can be important to investigate why a security was excluded from the analysis or any special treatment given to it. Finally, the parameters set by the user to run the report are also shown, for reference.

8. Conclusions

The POINT US Equity Risk Model is a brand new model that was developed with no legacy issues. It includes important innovations such as proprietary factors that capture default risk and earnings manipulation, improved estimation of industry betas and fundamental factor exposures, and a new class of highly responsive models to predict both systematic and idiosyncratic risk. It is implemented in POINT – Barclays Capital portfolio analytics platform – as a part of the Global Risk Model.

Our backtesting shows that the model performs well under a variety of historical contexts and that it captures quickly changes in the underlying volatility environment. These results hold for portfolios constructed around different themes, such as industries or technical/fundamental factors.

The new US Equity Model also connects easily with the other asset classes in POINT. Specifically, POINT recognizes securities from the same issuer across the capital structure, and is able to adequately net out all the exposures into one single risk forecast for that issuer.

The US Equity Risk Model can be accessed via POINT. The risk report in POINT provides a comprehensive analysis of portfolio risk in terms of volatility and tail risk and across all asset classes. It is also highly customizable, allowing users to decompose risk along dimensions that are relevant to them.

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APPENDIX 1: UNIVARIATE QUANTILE ANALYSIS FOR THE MARKET VALUE FACTOR

Variable: Size (Log of Market Cap)
Return: Net

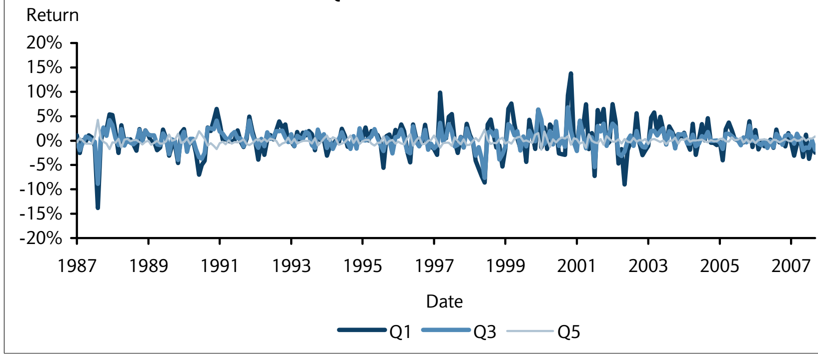
Across All Panel Data

	1-month return		
	avg(QR)	std(QR)	med(std(rit))
Q1 - low	0.38%	**3.16%**	12.42%
Q2	0.35%	**2.54%**	11.18%
Q3	0.27%	**1.94%**	10.12%
Q4	0.18%	**1.24%**	9.13%
Q5 - high	-0.05%	**0.68%**	7.80%
Q1-Q5	0.43%	**3.59%**	4.62%

Different Regimes

	Normal Vol	High Vol
Q1	2.70%	4.45%
Q2	2.24%	3.41%
Q3	1.70%	2.65%
Q4	1.06%	1.76%
Q5	0.65%	0.79%
Q1-Q5	3.20%	4.76%

Quintile Return Factors

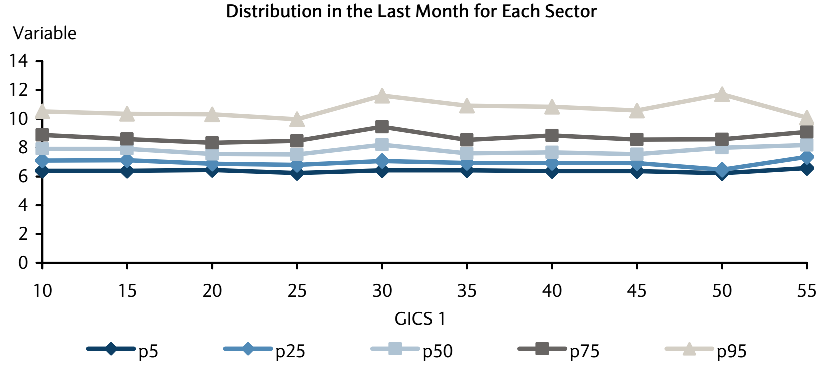


Industry Analysis

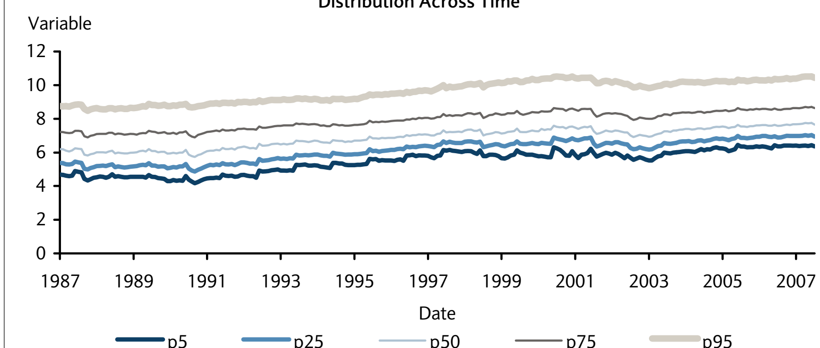
		std(TR)			
#	Name	T1	T2	T3	T1-T3
10	Energy	5.43%	4.22%	1.34%	5.24%
15	Materials	3.09%	2.07%	1.07%	3.80%
20	Industrials	3.35%	2.56%	1.21%	3.28%
25	Cons Discretionary	3.09%	2.36%	0.97%	3.74%
30	Consumer Staples	3.45%	2.43%	1.07%	3.76%
35	Health Care	4.90%	3.52%	0.94%	5.33%
40	Financials	2.62%	1.92%	0.75%	3.07%
45	Information Tech	4.84%	4.12%	1.86%	4.92%
50	Telecom Services	8.78%	5.47%	1.34%	9.35%
55	Utilities	1.83%	1.55%	0.79%	2.34%

	AVG	STD	CORR	
Q1	0.38%	3.16%		
Q3	0.27%	1.94%	0.81	
Q5	-0.05%	0.68%	-0.56	-0.59

Distribution in the Last Month for Each Sector



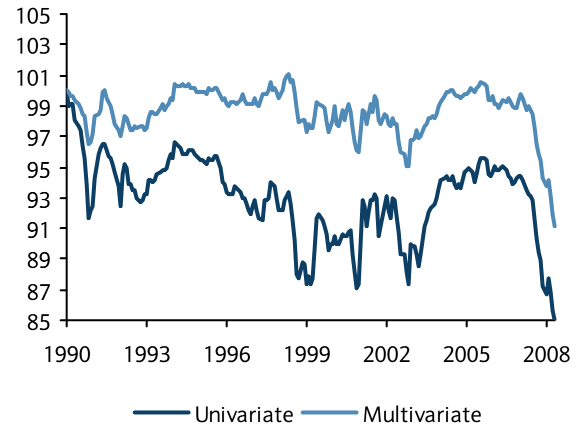
Distribution Across Time



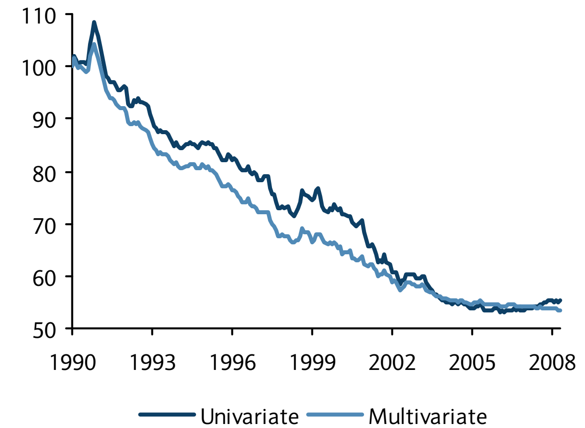
Source: Barclays Capital Portfolio Modeling

APPENDIX 2: FACTOR CHARACTERIZATIONS

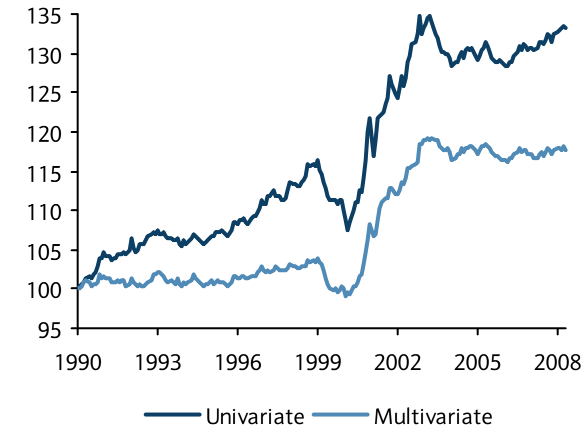
POINT Corporate Default Probability



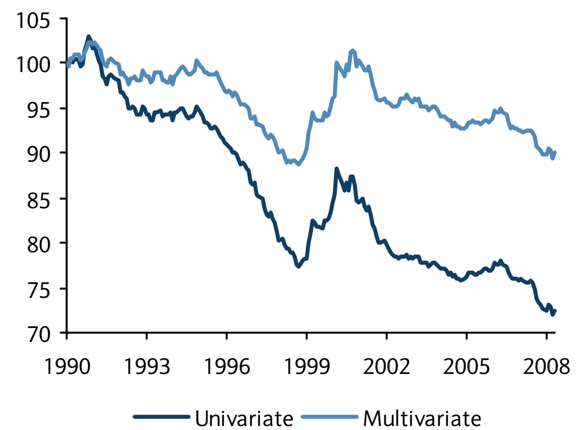
Market Value



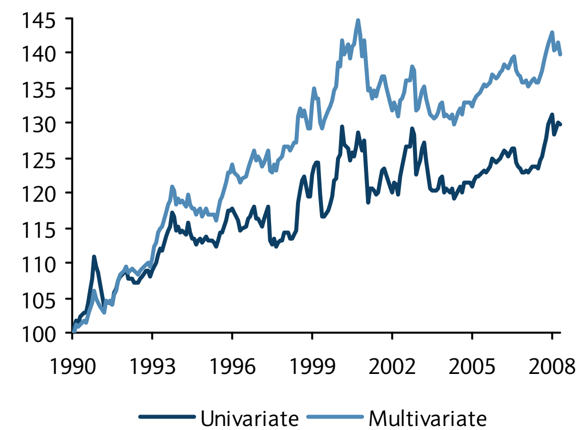
Earnings to Price



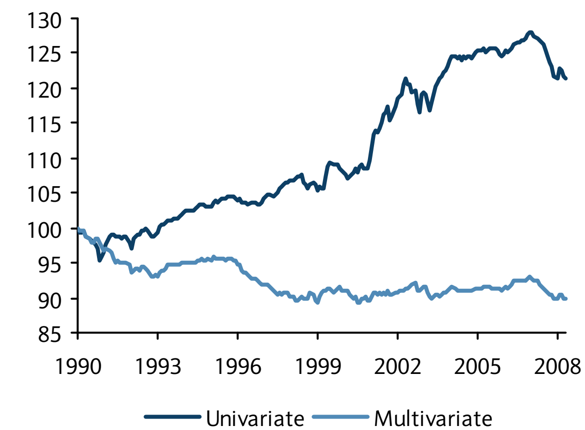
Share Turnover Rate



Momentum

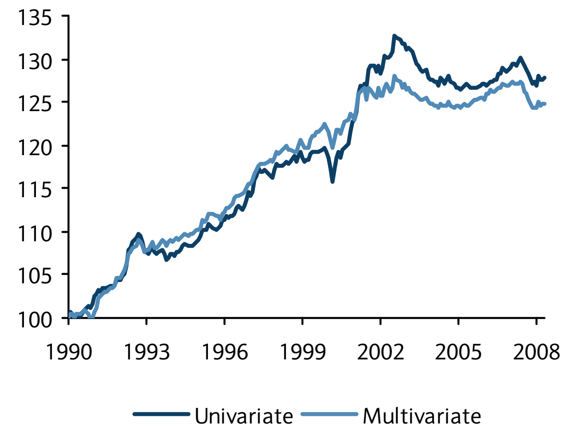


Book to Price

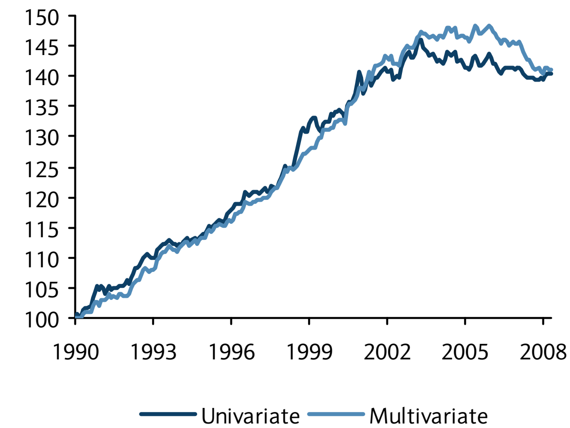


Source: Barclays Capital Portfolio Modeling

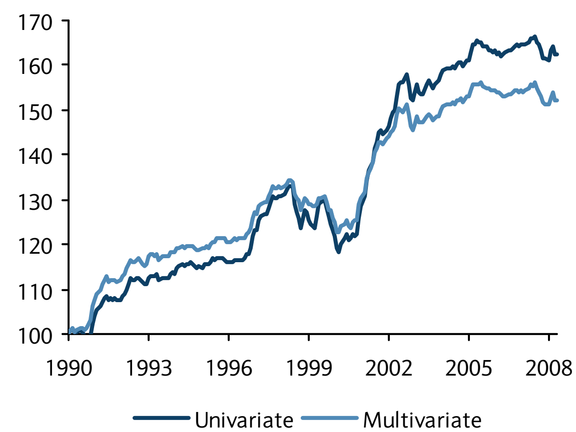
Total Yield



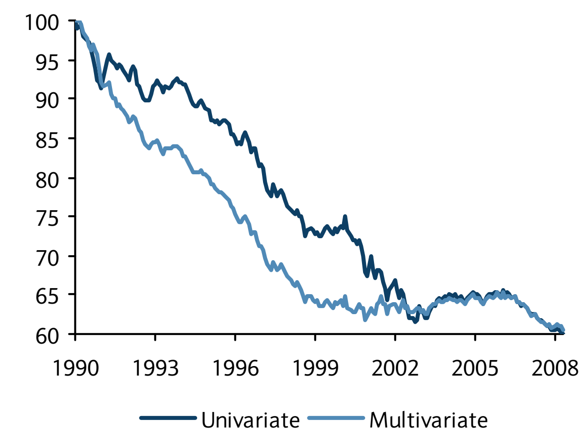
Change in Discretionary Accruals



Residualized Forward EP



Residualized Realized Volatility



Source: Barclays Capital Portfolio Modeling

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