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# On the Information Content of Option-Implied Betas [†]

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JEL Classification: G11, G12, G13, G14, G17

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## Abstract

Option-implied betas are a promising alternative to historical beta estimators, because they are inherently forward-looking and can incorporate new information immediately and fully. Recently, different implied beta estimators have been developed in previous literature, but very little is known about their properties and information content. This paper presents a first systematic comparison between six different implied beta estimators, which provides some guidance for applications and identifies directions for further improvements. The main results of the empirical study reveal that betas derived from implied variances are better predictors of realized betas than betas obtained from implied skewness, and that cross-sectional information from all stocks in the market improves beta estimation significantly. We also find that option-implied betas generally have a higher information content in periods of relatively high trading activity in options markets.



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# I Introduction

Beta coefficients play a prominent role in finance theory and practice. As measures of systematic risk, they have a variety of applications in risk management, portfolio management, and investment evaluation. In risk management, for example, individual stocks are frequently mapped on an index via beta coefficients to facilitate value-at-risk calculations. Asset managers use beta to measure and control market risk over specified re-balancing and evaluation periods, and an investment project's cost-of-capital is often based on beta as a crucial parameter.

A common, essential feature of most applications is the need for ex-ante beta coefficients. Consequently, the need for predicting betas has received much attention in recent literature. Starting with the early literature in the 1970s,[1] strong evidence revealed a time variation of beta coefficients, which led to the development of different estimation approaches.[2] Specific approaches apply multivariate GARCH models,[3] model beta as a random coefficient within a state space model,[4] or use different economic conditioning variables.[5] A major drawback of these techniques is, however, that they require stability of the assumed structures over time.

This paper investigates an alternative approach: the use of option-implied information to obtain beta coefficients. Since option prices contain information on market participants' views of the underlying stocks' return distributions, such an approach is inherently forward-looking. Moreover, no assumptions about structural stability are necessary, as this approach relies only on current market prices. Therefore, option-implied betas are a promising alternative to traditional beta estimators.

French, Groth, and Kolari (1983) were the first to use option-implied information for beta estimation by combining implied volatilities[6] with historical correlations. Buss

[1] See Blume (1971), Levy (1971), and Rosenberg and McKibben (1973).

[2] Faff, Hillier, and Hillier (2000) provide an overview and comparison of different modeling techniques.

[3] See, for example, Braun, Nelson, and Sunier (1995) and Koutmos and Knif (2002).

[4] See, for example, Jostova and Philipov (2005).

[5] Conditional betas play an important role in the asset pricing literature. See, for example, Jagannathan and Wang (1996), Lettau and Ludvigson (2001), and Ammann and Verhofen (2008).

[6] Implied volatilities are well established tools for volatility estimation and forecasting. See Poon

and Vilkov (2012) incorporate option-implied information into correlation modeling. However, their estimators still require historical correlations. Fully-implied beta estimators (i.e., estimators that do not require any time series data) were suggested by Siegel (1995) and Husmann and Stephan (2007). A drawback of these betas, however, is the need for cross-correlation derivatives between single stocks and the index, or the reliance on the validity of a very specific option pricing model.

Several fully-implied beta estimators have recently been developed in the literature. Skintzi and Refenes (2005) introduce a market's average implied correlation based on the assumption of a constant correlation between all assets. This fully-implied correlation can be combined with implied variances of individual stocks and the market index to obtain implied betas. Chang, Christoffersen, Jacobs, and Vainberg (2012) derive a fully-implied beta by starting from a market model and assuming that an individual stock's implied skewness has no idiosyncratic component.[7] They show that option-implied betas perform well compared to traditional historical betas. Finally, Kempf, Korn, and Saßning (2011) develop a family of implied betas based on the implied variance, implied skewness and implied kurtosis, respectively. Betas are identified via cross-sectional restrictions on the systematic and idiosyncratic components of individual stocks' implied moments. Kempf, Korn, and Saßning (2011) use implied betas to construct minimum variance portfolios to show that these portfolios lead to a lower out-of-sample variance than historical and passive benchmark strategies.

Because option-implied betas are very promising, it is important to gain a better understanding of their properties and information content. In particular, a comparative analysis of the different approaches of the literature is needed to guide further theoretical developments and applications. The main contribution of this paper is an empirical study that provides such an analysis. Since the major attraction of

and Granger (2003) and Poon and Granger (2005) for survey articles. The survey by Christoffersen, Jacobs, and Chang (2012) also reviews recent developments concerning higher-order implied moments and correlations.

[7] Fouque and Kollman (2011) derive a similar estimator that can be seen as a simplified version of the option-implied beta by Chang, Christoffersen, Jacobs, and Vainberg (2012).

the implied approach is to extract the most recent information about ex-ante betas from current market prices, we concentrate on fully-implied betas and their information content and do not try to find the best combination of implied and historical estimators. Besides analyzing five different implied beta estimators that have been proposed in the literature, we derive and analyze a new implied beta estimator based on kurtosis. Instead of assuming that skewness has no idiosyncratic component, like Chang, Christoffersen, Jacobs, and Vainberg (2012), this estimator is identified from the assumption of zero idiosyncratic excess kurtosis.

The main findings of the paper include: (i) Beta estimators based on implied variances provide more accurate predictions of realized betas than estimators based on implied skewness. (ii) The cross-sectional restriction that the market beta must equal one is important for the accuracy of implied betas. In this sense, implied information on all stocks in the cross section should be used to estimate an individual stock's beta. (iii) Implied betas are positively related to historical betas estimated over a short window of recent data. However, implied betas also differ significantly from historical betas as the correlation of prediction errors is far below one. (iv) Variance-based implied betas contain virtually all the information about realized betas contained in historical betas. (v) Implied betas have a higher information content in periods when options markets are more active. (vi) Implied betas perform relatively better when the time horizon is shorter, compared to historical betas.

The paper is organized as follows: Section II introduces the different fully-implied beta estimators. Section III describes the data set and the design of the empirical study. Section IV presents the results, and Section V concludes.

# II Implied Beta Estimators

All implied beta estimators studied in this paper are based on implied moments of the marginal return distributions of individual stocks and the market. The different estimators vary in terms of the used order of moments (variance, skewness, or kurtosis) and the way identification is achieved. We present the different approaches in Subsection II.A. A common prerequisite of all approaches is the estimation of the respective moments from option prices. To make a fair comparison between different betas, we use the same method for all estimators, as explained in Subsection II.B.

## A Beta Identification

We consider six different implied betas in this study. They can be grouped into variance-based betas, skewness-based betas, and kurtosis-based betas. Furthermore, an identifying assumption regarding the connection between stock and market returns is required. An initial identifying assumption is a constant correlation between all stock returns, as suggested by Skintzi and Refenes (2005) and Driessen, Maenhout, and Vilkov (2009), which leads to a variance-based beta. Another identifying assumption is a constant proportion of idiosyncratic variance (skewness, kurtosis) to total variance (skewness, kurtosis) for all stock returns. This idea, brought up by Kempf, Korn, and Saßning (2011), leads to three estimators based on the second to fourth central moments. A third identifying assumption, suggested by Chang, Christoffersen, Jacobs, and Vainberg (2012), is a zero proportion of idiosyncratic skewness; that is, the skewness of individual stocks is entirely driven by the market. A similar assumption can be made with respect to excess kurtosis (i.e., the excess kurtosis of individual stocks is solely driven by the market). The following describes the six implied betas in detail.

**(i) Variance-based betas:**

The first group of betas analyzed can be identified from the variances of individual stock returns and the market return. Assume that the market consists of $N$ assets and denote their returns in period $t$ by $R_{it}$, $i = 1, \ldots, N$. The market return is $R_{mt}$.

A first identification approach presumes that the return correlation is identical for all stocks in the cross section.[8] Under this assumption, the correlation $\rho_t$ equals

$$\rho_t = \frac{\mathrm{Var}(R_{mt}) - \sum_{i=1}^{N} w_{it}^2 \mathrm{Var}(R_{it})}{\sum_{i=1}^{N} \sum_{j \neq i} w_{it} w_{jt} \mathrm{Var}(R_{it})^{1/2} \, \mathrm{Var}(R_{jt})^{1/2}}, \tag{1}$$

where $w_{it}$ is the relative weight of stock $i$ in the market portfolio. With constant correlations, the return covariance of the $i$th asset and the market becomes $w_{it}\mathrm{Var}(R_{it}) + \sum_{j \neq i} w_{jt} \mathrm{Var}(R_{it})^{1/2} \, \mathrm{Var}(R_{jt})^{1/2} \rho_t$, leading to

$$\beta_{it}^{VarCorr} = \frac{w_{it}\mathrm{Var}(R_{it}) + \sum_{j \neq i} w_{jt} \mathrm{Var}(R_{it})^{1/2} \, \mathrm{Var}(R_{jt})^{1/2} \rho_t}{\mathrm{Var}(R_{mt})}, \tag{2}$$

with $\rho_t$ from Eq. (1).

A second way to identify beta assumes a market model with time-varying coefficients:

$$R_{it} = \alpha_{it} + \beta_{it} R_{mt} + \epsilon_{it}, \qquad i = 1, \ldots, N, \tag{3}$$

where $\epsilon_{it}$ is independent of $R_{mt}$. However, the idiosyncratic risks of different stocks are allowed to be correlated, which implies that the return correlations between stocks can be different. If one assumes that the proportion of idiosyncratic variance is identical for all stocks in the cross section,[9] the return variance of a stock equals

$$\mathrm{Var}(R_{it}) = \beta_{it}^2 \mathrm{Var}(R_{mt}) + (1 - s_t^{Var}) \, \mathrm{Var}(R_{it}), \tag{4}$$

where $s_t^{Var}$ denotes the proportion of the variance that is systematic. Solving for $\beta_{it}$ yields

$$\beta_{it} = (s_t^{Var})^{1/2} \left( \frac{\mathrm{Var}(R_{it})}{\mathrm{Var}(R_{mt})} \right)^{1/2}. \tag{5}$$

Since the market beta equals one, the weights $w_{it}$, $i = 1, \ldots, N$, of the individual

[8] See Skintzi and Refenes (2005).

[9] See Kempf, Korn, and Saßning (2011). Note also that the proportion is allowed to change over time.

assets in the market portfolio can be used to identify $s_t^{Var}$:

$$\begin{aligned} \sum_{i=1}^{N} w_{it}\,\beta_{it} = \sum_{i=1}^{N} w_{it}\,(s_t^{Var})^{1/2} \left(\frac{\mathrm{Var}(R_{it})}{\mathrm{Var}(R_{mt})}\right)^{1/2} &= 1 \\ \Leftrightarrow \quad s_t^{Var} = \frac{\mathrm{Var}(R_{mt})}{\left(\sum_{i=1}^{N} w_{it}\,\mathrm{Var}(R_{it})^{1/2}\right)^{2}} &. \end{aligned} \tag{6}$$

Substitution of $s_t^{Var}$ from Eq. (6) into Eq. (5) leads to our second beta

$$\beta_{it}^{VarProp} = \frac{\mathrm{Var}(R_{it})^{1/2}}{\sum_{j=1}^{N} w_{jt}\,\mathrm{Var}(R_{jt})^{1/2}}. \tag{7}$$

**(ii) Skewness-based betas:**

The idea to distinguish between a systematic part and an unsystematic part of the variance within the framework of a market model can also be used for the skewness. Under the assumption that the proportion of idiosyncratic skewness is identical for all stocks in the cross section, the skewness of a stock return equals

$$\mathrm{Skew}(R_{it}) \quad = \quad \beta_{it}^{3}\mathrm{Skew}(R_{mt}) + (1 - s_t^{Skew})\,\mathrm{Skew}(R_{it}), \tag{8}$$

where $s_t^{Skew}$ is the proportion of systematic skewness. Solving for $\beta_{it}$ leads to

$$\beta_{it} = (s_t^{Skew})^{1/3} \left(\frac{\mathrm{Skew}(R_{it})}{\mathrm{Skew}(R_{mt})}\right)^{1/3}. \tag{9}$$

Again, the condition that the market beta equals one can be used to identify $s_t^{Skew}$, and substitution of the implied $s_t^{Skew}$ into Eq. (9) leads to the third beta

$$\beta_{it}^{SkewProp} = \frac{\mathrm{Skew}(R_{it})^{1/3}}{\sum_{j=1}^{N} w_{jt}\,\mathrm{Skew}(R_{jt})^{1/3}}. \tag{10}$$

Chang, Christoffersen, Jacobs, and Vainberg (2012) assume that an individual asset's return skewness results only from the skewness of the market; i.e., $s_t^{Skew} = 1$.

Under this assumption, we obtain a fourth beta directly from Eq. (9):

$$\beta_{it}^{SkewSyst} = \left(\frac{\text{Skew}(R_{it})}{\text{Skew}(R_{mt})}\right)^{1/3}. \tag{11}$$

**(iii) Kurtosis-based betas:**

Under the market model (3), the kurtosis of a stock return equals

$$\text{Kurt}(R_{it}) \quad = \quad \beta_{it}^4 \text{Kurt}(R_{mt}) + 6\,\beta_{it}^2 \text{Var}(R_{mt}) \text{Var}(\epsilon_{it}) + \text{Kurt}(\epsilon_{it}). \tag{12}$$

We can again employ an assumption about the proportion of idiosyncratic kurtosis relative to total kurtosis.[10] If this proportion is identical for all stocks in the cross section, beta is identifiable in the same way as shown for the variance and the skewness. As a result, we obtain a fifth beta:

$$\beta_{it}^{KurtProp} = \frac{\text{Kurt}(R_{it})^{1/4}}{\sum_{j=1}^{N} w_{jt}\,\text{Kurt}(R_{jt})^{1/4}}. \tag{13}$$

Alternatively, similar to the idea that skewness is completely determined by the market, one could assume that excess kurtosis is systematic only. The excess kurtosis of stock $i$ equals

$$\begin{aligned} &\text{Kurt}(R_{it}) - 3\,\text{Var}(R_{it})^2 \\ &\qquad = \beta_{it}^4 \text{Kurt}(R_{mt}) + 6\,\beta_{it}^2 \text{Var}(R_{mt}) \text{Var}(\epsilon_{it}) + \text{Kurt}(\epsilon_{it}) - 3\,\text{Var}(R_{it})^2. \end{aligned} \tag{14}$$

Because of the structure of the market model, $\text{Var}(R_{it}) = \beta_{it}^2 \text{Var}(R_{mt}) + \text{Var}(\epsilon_{it})$ and $3\,\text{Var}(R_{it})^2 = 3\,[\beta_{it}^4 \text{Var}(R_{mt})^2 + 2\beta_{it}^2 \text{Var}(R_{mt}) \text{Var}(\epsilon_{it}) + \text{Var}(\epsilon_{it})^2]$. Accordingly, the excess kurtosis of stock $i$ becomes

$$\text{Kurt}(R_{it}) - 3\,\text{Var}(R_{it})^2 = \beta_{it}^4 \left[\text{Kurt}(R_{mt}) - 3\,\text{Var}(R_{mt})^2\right] + \text{Kurt}(\epsilon_{it}) - 3\,\text{Var}(\epsilon_{it})^2. \tag{15}$$

[10] See Kempf, Korn, and Saßning (2011).

Since the excess kurtosis of $\epsilon_{it}$ is zero by assumption, we obtain the following sixth beta:[11]

$$\beta_{it}^{KurtSyst} = \left( \frac{\text{Kurt}(R_{it}) - 3\,\text{Var}(R_{it})^2}{\text{Kurt}(R_{mt}) - 3\,\text{Var}(R_{mt})^2} \right)^{1/4}. \tag{16}$$

Table 1 summarizes the six different betas. Two aspects are particularly important for our research question concerning the properties and information content of implied betas. The first aspect is the moment of the return distribution employed. Two of the betas are based on the variance, two on the skewness and another two on the kurtosis. Implied variance, skewness, and kurtosis, however, might contain very different information and might be more or less reliable inputs for beta estimation. Second, four of the estimators ($\beta^{VarProp}$, $\beta^{VarCorr}$, $\beta^{SkewProp}$, and $\beta^{KurtProp}$) use information on implied moments of all assets in the market to obtain an individual asset's beta. This property is certainly a disadvantage in terms of practicability and ease of implementation in comparison with the estimators $\beta^{SkewSyst}$ and $\beta^{KurtSyst}$, which require only implied moments of the individual asset and the market as a whole. However, the additional information required by the first group of betas could also lead to a higher information content of the estimators.

[*Insert Table 1 about here*]

## B Implied moments

The various betas depend on the second to fourth moments of individual stock returns and (in case of $\beta^{VarCorr}$, $\beta^{SkewSyst}$ and $\beta^{KurtSyst}$) market returns. Once we know these moments, we also know the betas. The implied approach estimates the moments from option prices. Theoretically, given option prices for a continuum of strike prices, the complete risk-neutral return distribution can be derived without

[11] Note that beta can only be calculated if the excess kurtosis of the stock and the excess kurtosis of the market have the same sign. It is an empirical question whether this requirement causes problems for applications.

using a particular option pricing model.[12] Based on Bakshi and Madan (2000) who found that any payoff function can be spanned by explicit positions in options with different strike prices, Bakshi, Kapadia, and Madan (2003) provide pricing formulas for three specific contracts whose payoffs equal the squared return, the cubed return, and the quadrupled return of the underlying for a given time horizon $\tau$:

$$\begin{aligned} Quad &= \int_S^\infty \frac{2(1-\log(K/S))}{K^2}\, c\,(\tau,K)\,dK \\ &\quad + \int_0^S \frac{2(1+\log(S/K))}{K^2}\, p\,(\tau,K)\,dK, \end{aligned} \tag{17}$$

$$\begin{aligned} Cub &= \int_S^\infty \frac{6\log(K/S)-3(\log(K/S))^2}{K^2}\, c\,(\tau,K)\,dK \\ &\quad - \int_0^S \frac{6\log(S/K)+3(\log(S/K))^2}{K^2}\, p\,(\tau,K)\,dK, \end{aligned} \tag{18}$$

$$\begin{aligned} Quart &= \int_S^\infty \frac{12(\log(K/S))^2-4(\log(K/S))^3}{K^2}\, c\,(\tau,K)\,dK \\ &\quad + \int_0^S \frac{12(\log(S/K))^2+4(\log(S/K))^3}{K^2}\, p\,(\tau,K)\,dK, \end{aligned} \tag{19}$$

where $S$ denotes the price of the underlying and $c\,(\tau,K)$ and $p\,(\tau,K)$ denote the respective prices of a European call and put with maturity $\tau$ and strike price $K$. Based on these contracts, the implied central risk-neutral moments are given by[13]

$$\text{Var} = e^{r\tau} Quad - (E_Q[R\,])^2, \tag{20}$$

$$\text{Skew} = e^{r\tau} Cub - 3e^{r\tau}\, E_Q[R\,]\, Quad - 2(E_Q[R\,])^3, \tag{21}$$

$$\text{Kurt} = e^{r\tau} Quart - 4e^{r\tau}\, E_Q[R\,]\, Cub + 6e^{r\tau}\,(E_Q[R\,])^2\, Quad - 2(E_Q[R\,])^3. \tag{22}$$

[12] The idea of recovering underlying return distributions from option prices dates back to the seminal paper by Breeden and Litzenberger (1978). See, for example, Britten-Jones and Neuberger (2000), Carr and Madan (2001), Jiang and Tian (2005), Vanden (2008), and Shackleton, Taylor, and Yu (2010) for more recent studies on model-free implied moments.

[13] See Bakshi, Kapadia, and Madan (2003).

Here, $r$ denotes the risk-free rate, and $E_Q[R]$ is the expected log return under the risk-neutral measure, which can be calculated based on the mentioned contracts:[14]

$$E_Q[R] = e^{r\tau} - 1 - \frac{e^{r\tau}}{2} Quad - \frac{e^{r\tau}}{6} Cub - \frac{e^{r\tau}}{24} Quart. \quad (23)$$

While this approach is very appealing, its major shortcoming is that it delivers moments under the risk-neutral measure. Most applications would need betas under the physical measure, which requires the corresponding physical moments. Therefore, all implied beta estimators potentially suffer from a lacking risk adjustment of implied moments,[15] making it important do determine how this issue affects the properties of the different beta estimators. Unfortunately, the theoretical literature on the relation between risk-neutral and physical moments is scarce. Rubinstein (1994) provides examples on this relation, assuming a representative investor with constant relative risk aversion exists. He concludes that the difference lies mainly in a mean shift and the distributions are quite similar in shape.[16] Bakshi, Kapadia, and Madan (2003), also assuming constant relative risk aversion, show that the difference in the $n$-th moment of the risk-neutral and physical distribution depends on the $n+1$-st moment of the physical distribution.[17] However, since these results are limited to index options and do not consider covariances with individual stocks, we cannot easily draw conclusions about risk-adjusted implied betas from them. Therefore, we take a different route and provide some empirical evidence on how different implied beta estimators may be affected by the lacking risk adjustment of implied moments.

[14] See Bakshi, Kapadia, and Madan (2003). Terms with moments of order higher than 4 are neglected.

[15] A similar issue arises in volatility forecasting based on option-implied, i.e., risk-neutral, volatilities. Despite the lacking risk adjustment, the forecasting power of implied volatilities is very good and usually outperforms forecasts based on historical data. See Britten-Jones and Neuberger (2000) for a theoretical discussion, and, for example, Busch, Christensen, and Ørregaard Nielsen (2011) for empirical evidence. Prokopczuk and Wese Simen (2013) show that an adjustment of implied volatilities based on historical volatility risk premia further improves the forecasting performance.

[16] See Rubinstein (1994), p. 804.

[17] To be more precise, $E[R^n] - E_Q[R^n] \approx \gamma E_Q[R^{n+1}]$, where $\gamma$ is the coefficient of relative risk aversion, and terms of higher order in $\gamma$ are suppressed. See Bakshi, Kapadia, and Madan (2003), p. 138 f.

## III Empirical Study: Data and Design

The information content of option-implied betas is likely to be highest for stocks with highly liquid options markets. Therefore, blue chips from a major stock market provide a natural benchmark for the potential of option-implied betas. In our empirical study, we concentrate on the largest US stocks, represented by the Dow Jones Industrial Average (DJIA). Besides options data for the single stocks, for some betas ($\beta^{VarCorr}$, $\beta^{SkewSyst}$, and $\beta^{KurtSyst}$), we also need the data of index options. Our investigation period starts with the introduction of options on the DJIA at the Chicago Board of Options Exchange (CBOE) in January 1998[18] and ends in January 2012. Results are presented for the 19 stocks which were permanent index members over the whole investigation period.[19]

Regarding the time horizon for the estimation of option-implied betas, we consider a forward-looking period of three months as our base case. Three months is a typical horizon used in asset management for the reassessment of a strategy. As part of the robustness analysis, we also consider a shorter period (one month) and a longer period (twelve months) to gain information on the performance of the estimators for other horizons. We estimate option-implied betas on a monthly basis over the whole investigation period. Within each month, we choose the first trading day following an expiration day at the CBOE. This choice guarantees the existence of an option series close to the one-, three- and twelve-month time horizons. Option data are taken from IvyDB, and we directly use the implied volatilities IvyDB for a time horizon of 91 days (30 days and 365 days, respectively, for the robustness analysis). IvyDB calculates implied volatilities for standardized options at deltas of $0.20, 0.25, 0.30, \ldots, 0.80$ (for calls), based on closing quotes and using a kernel smoothing algorithm.[20]

[18]Actually, trading of DJIA index options at the CBOE started in October 1997. We skip the first three months to allow the price discovery process of this new market to settle.

[19]The calculations of $\beta^{VarProp}$ $\beta^{VarCorr}$, $\beta^{SkewProp}$, and $\beta^{KurtProp}$ employ information on all stocks in the index.

[20]For more details, refer to the IvyDB technical document.

For calculating the values of the *Quad*, *Cub* and *Quart* contracts according to the integrals (17)–(19), we essentially follow Chang, Christoffersen, Jacobs, and Vainberg (2012). We fit a cubic spline to interpolate between the standardized options from IvyDB. Outside the delta range $[0.20; 0.80]$, we extrapolate the implied volatility with a constant. Based on these implied volatilities, we apply the Black-Scholes formula to calculate option prices for a grid of 1000 equidistant strike prices, ranging from 0.3% to 300% of the respective underlying stock price (or index level) at the calculation date.[21] Underlying stock prices and index levels are also provided by IvyDB, so there is no problem in terms of lacking synchronicity of underlying and option prices. The same holds for the risk-free interest rate, which is also taken from IvyDB.[22] The integrals (17)–(19) are then numerically evaluated using the simple trapezoidal rule based on the 1000 calculated option prices.[23] The estimator $\beta^{KurtSyst}$ can not be calculated if the implied excess kurtosis of the market and the individual stock have different signs, which happens in about 2.5% of the cases. In these cases, we replace the missing value with a beta equal to one.[24]

Table 2 lists the 19 stocks in our study and provides some descriptive statistics of stock and option trading activity.[25] The maximum, minimum and average trading volumes over the 169months of our investigation period are given.

[*Insert Table 2 about here*]

Chakravarty, Gulen, and Mayhew (2004) show that the information share of the options market for price discovery depends on the ratio of traded option volume to traded stock volume. Because the information content of option-implied betas

[21]Note that this procedure does not assume the Black-Scholes model to hold. It is merely used to smoothly interpolate between market prices of options.

[22]IvyDB provides a zero curve of continuously-compounded zero-coupon interest rates based on BBA LIBOR rates for maturities up to 12 months and CME Eurodollar futures for longer maturities.

[23]As the option price functions are well-shaped, the accuracy of this numerical integration is quite good. See also Chang, Christoffersen, Jacobs, and Vainberg (2012) for an accuracy analysis of the procedure.

[24]For a fair comparison of the performance of different betas it would not be adequate to simply treat these cases as missing values. Applying a beta of one is a readily available alternative if the $\beta^{KurtSyst}$ estimator fails to deliver an estimate.

[25]The data source for the trading volumes is also IvyDB.

should depend on the information content of the options, the same measure could be a driver of the quality of option-implied beta estimators. As the last three columns of Table 2 show, there is a substantial variation in relative market share. In particular, a comparison between minima and maxima indicates that the variation over time can be very large. We analyze the impact of this variation on beta quality in Subsection IV.D.

One property of implied betas that we analyze is their predictive power for future realized betas. Realized betas are calculated from daily data, using the DJIA as the market index, for the forward-looking period of three months (one month and twelve months for robustness). As benchmarks, we also consider two historical beta estimators. A first historical beta estimator is based on monthly returns over a five-year time horizon (60 monthly returns). A second historical beta estimator is obtained from short-window regressions, as seen in Lewellen and Nagel (2006), using daily returns over a period equal to the forward-looking period of three months (one month and twelve months in the robustness analysis). As pointed out by Lewellen and Nagel (2006), this short-term estimator can be interpreted as a conditional beta, without explicitly using any state variables. Historical betas are calculated monthly with rolling estimation windows, parallel to each calculation of the implied betas. Historical prices for the calculation of historical benchmark betas and realized betas are taken from Datastream. Furthermore, we use a constant beta equal to one as a simple benchmark that does not require any information from current or past market prices.

# IV Empirical Study: Results

## A Distributional Properties of Implied Betas

To get a first impression of the properties of different beta estimators, we report some summary statistics. Table 3 provides the mean beta, three measures of standard deviation, the autocorrelations and a measure of stability over time. The measures of standard deviation highlight different aspects of variation. "Std. Dev. Total" is the standard deviation around the overall mean; in other words, it is a measure of total variation. "Std. Dev. Firms" measures the variation of betas between the firms in the sample. It equals the standard deviation of the 19 average betas obtained for individual firms. Finally, "Std. Dev. Time" measures the variation of betas over time. It is the average of the 19 standard deviations obtained from the beta time series of individual firms. In the same spirit, the reported autocorrelation is the average of the 19 autocorrelations obtained for individual firms. Another measure of stability over time is the mean absolute variation (MAV), defined as the average absolute difference between the beta estimates in successive months, with averages taken over time and over all 19 stocks.

[*Insert Table 3 about here*]

The summary statistics show some interesting similarities and differences between the various beta estimators. First, the VarProp, VarCorr, and KurtProp betas are very similar with respect to all measures. What clearly distinguishes them from the other implied betas is a low variation over time and a high autocorrelation, showing a high persistence. Second, the SkewSyst and KurtSyst betas have means well above one (1.173 and 1.144, respectively). In contrast, the means of the VarProp, SkewProp, KurtProp, and VarCorr estimators are close to one by construction.[26] The high mean values of the SkewSyst and KurtSyst betas cast some doubt on the identifying assumptions of zero idiosyncratic skewness (SkewSyst) and zero idiosyncratic excess kurtosis (KurtSyst). The existence of non-zero idiosyncratic skewness and excess kurtosis would result in exactly the upward bias of the SkewSyst and KurtSyst estimators that we observe.[27] Finally, the standard deviations show a remarkable difference between all implied estimators and the historical benchmarks. Whereas both historical estimators have a total standard deviation above 0.4, it is

[26]The means are not exactly one because the table reports an unweighted average over 19 stocks without taking into account other stocks that were DJIA members for a shorter time period.

[27]An upward bias results if the market skewness (excess kurtosis), the individual stock's total skewness (excess kurtosis), and its idiosyncratic skewness (excess kurtosis) all have the same sign, which is the most likely case.

below 0.27 for five out of six implied estimators (the exception being SkewSyst with a value of 0.34). So the variation of implied beta estimators is substantially lower than the variation of historical estimators (and thus realized betas, which have the same distributional properties). To determine if this is a desirable property depends on whether the variation captures information or just reflects estimation errors. We will explore this issue further by assessing the predictive performance of the different estimators.

## B Prediction of ex-post Realized Betas

An essential property of beta estimators is to provide precise predictions of future betas. Hope for improvement in this respect has certainly been a motivation for the development of the forward-looking implied estimators. Table 4 presents some measures of prediction errors. Prediction errors are defined as the difference between the beta estimate and the ex-post realized beta. The table considers the mean error (ME) as a measure of prediction bias, the standard deviation of errors (STDE) as a measure of variability, and the root mean squared error (RMSE) and the mean absolute error (MAE) as general performance measures. In addition, we include the percentage improvement in mean absolute errors over a prediction that always uses a constant beta equal to one. It serves as a measure of the informational value of a beta estimator, because a beta of one would be the natural choice of an investor with no information about market prices and firm characteristics.

[*Insert Table 4 about here*]

The mean prediction errors clearly reflect the properties of the different beta estimators, as discussed in the previous subsection. The estimators SkewSyst and KurtSyst show a strong upward prediction bias, and all other estimators are essentially unbiased on average. Even for the heavily biased SkewSyst and KurtSyst betas, the main source of prediction error is variability, which can be seen from a comparison between the standard deviation and the root mean squared error.

With respect to the overall performance measures MAE and RMSE, we can identify a leading group of implied estimators with the lowest and almost identical prediction errors. This group consists of the two variance-based betas (VarProp, VarCorr) and one of the kurtosis-based betas (KurtProp). All three estimators use information from all stocks in the index. The worst performing estimators are SkewSyst and KurtSyst, which are calculated from the implied moments of the individual stock and the market index only. They do not recognize that the market beta is known a priori and therefore do not standardize estimates in the cross section to be one on average. These estimators do not even clearly beat the simple benchmark of a constant beta.

The comparison between the KurtProp estimator and the KurtSyst estimator shows that it is not the use of implied kurtosis per se that leads to a good or bad performance, but rather the additional cross-sectional information employed by the KurtProp estimator. Out of the group of the four betas using cross-sectional information, the skewness-based estimator, SkewProp, performs worst.

The two historical benchmarks behave quite differently. The short-term historical estimator (Hist-3M) delivers very similar mean absolute prediction errors as the leading group of implied estimators, but the performance of the long-term estimator (Hist-60M) is rather bad. This finding suggests that both the first group of implied estimators and the short-term historical estimator pick up recent information that is relevant for predicting betas over the next three months. However, a comparison between the RMSE and the MAE also points to a difference between the short-term historical estimator and the implied estimators. In terms of MAE, the short-term historical estimator is closer to the first group of implied estimators than in terms of RMSE. This finding suggests that the short-term historical estimator leads to more prediction errors with large absolute values, which have a stronger impact on the RMSE than on the MAE.

Another interesting issue is the correspondence between prediction errors and the stability of beta estimates over time. We see from Tables 3 and 4 that the worst performing strategies have either a very low or a very high mean absolute variation (MAV). This finding is consistent with the long-term historical estimator adapting too slowly to information, and the implied estimators SkewSyst and KurtSyst capturing too much noise. Moreover, the implied estimators with the lowest prediction errors are much more stable (lower MAV) than the short-term historical benchmark. This result suggests that market participants in the options market do not consider all recent co-movements between a stock and the market as viable information about future betas.

In summary, we can draw two main conclusions from the results of Table 3: (i) It is important to use implied information from all stocks in the cross section to estimate individual implied betas; and (ii) Skewness-based estimators lead to relatively high prediction errors compared to variance-based and also kurtosis-based alternatives, which is in line with complementary evidence in the literature.[28]

The mean prediction errors of the VarProp, SkewProp and KurtProp estimators are close to zero by construction, if we aggregate over the universe of all stocks in the market. Nevertheless, significant mean prediction errors for individual stocks are possible. Table 5 provides some information on this issue. It reports mean prediction errors (ME), mean absolute prediction errors (MAE), and average implied betas for individual stocks. Indeed, we observe that all three implied estimators lead to significant mean prediction errors for certain stocks. Moreover, the mean prediction errors are clearly related to the size of the stocks' implied betas. As the last row of Table 5 shows, the correlations between mean prediction errors and betas are strongly negative for all three estimators, meaning that implied beta estimates for low-beta stocks tend to be too high, compared to realized betas, and implied estimates for high-beta stocks tend to be too low. Stated differently, implied betas

[28]Kempf, Korn, and Saßning (2011) find that minimum variance portfolio strategies with skewness-based implied betas perform relatively poorly compared to strategies using variance- and kurtosis-based betas. Buss and Vilkov (2012) show that their beta estimator, which incorporates the same implied correlations as the $\beta^{VarCorr}$ estimator, leads to lower errors than the skewness-based beta $\beta^{SkewSyst}$ by Chang, Christoffersen, Jacobs, and Vainberg (2012).

tend to be more centered around one than ex post realized betas.[29]

One explanation for this effect could be the assumed cross-section restrictions that are necessary to identify implied betas. Another explanation could be significant "beta risk premia" due to deviations between risk-neutral and risk-adjusted moments. If we interpret the difference between the ex-post realized beta and the ex-ante implied beta as a beta risk premium, our results accordingly show negative premia for low-beta stocks and positive premia for high beta stocks.

[*Insert Table 5 about here*]

## C Implied Betas and ex-ante Historical Betas

In this subsection, we take a closer look at the information content of implied betas. It could well be that historical price movements are the main source of information used by market participants to form expectations about future betas. In such a scenario, implied betas should have an information content very similar to historical betas. In contrast, if market participants consider historical price movements as out-dated information and then primarily use other sources, implied estimators should carry quite different information. Such a scenario does not mean, however, that implied estimators necessarily perform better than historical ones, because the alternative information set might not be superior.

To investigate exactly how much information on historical betas impacts implied betas, we regress the implied estimators on the Hist-3M estimators for all 19 stocks. The VarProp estimator serves as a representative for the implied estimators, since it belongs to the group of best-performing betas and all members of this group behave very similarly. The regression model reads

$$\beta_{it}^{VarProp} = a + b\,\beta_{it}^{Hist-3M} + \epsilon_{it}. \tag{24}$$

[29] Chang, Christoffersen, Jacobs, and Vainberg (2012) document a similar effect for the SkewSyst estimator in their empirical study.

The results presented in Table 6 show that there is a positive relation between implied betas and historical betas. The slope coefficients for all 19 stocks are positive, and we obtain an average $R^2$ of about 36%. Moreover, the coefficients are significantly different from zero (1% level) in 18 cases. Therefore, we have strong evidence that information about historical price movements does enter into implied betas. However, the relation between implied betas and historical betas is far from being one to one, as documented by an average slope coefficient of about 0.29. Moreover, the $R^2$s are much lower than one, leaving room for significant differences in information content.

*[ Insert Table 6 about here ]*

A conceptual advantage of option-implied betas is that they could in principle be based on a much broader information set than historical betas, because market participants in the options market are free to use any information they consider relevant. Our next question is therefore if this potentially larger information set completely encompasses the information contained in historical betas. To investigate this issue, we proxy the additional information contained in the Hist-3M estimator by the residuals of a regression of the Hist-3M estimator on the VarProp estimator. This incremental information content is then used as an additional regressor in the following regressions:

$$\beta_{it}^{Real} = a_1 + b_1\,\beta_{it}^{VarProp} + b_2\,Res_{it} + \epsilon_{it} \tag{25}$$

with $Res_{it}$ being the residuals of the regression

$$\beta_{it}^{Hist-3M} = a + b\,\beta_{it}^{VarProp} + u_{it}. \tag{26}$$

If Hist-3M estimators have some incremental information over VarProp estimators, it should show up in a significant slope coefficient of the additional regressor and a substantial improvement of $R^2$. Table 7 reports the corresponding results.

*[ Insert Table 7 about here ]*

There is some evidence for an additional information content of historical betas, but it is rather weak. Only two of the relevant slope coefficients are significant at the 1% level and seven at the 5% level, all with the expected positive sign. The gain in adjusted $R^2$ when compared to a regression that uses VarProp beta estimators as sole regressors, as shown in the last column of Table 7, lies on average by about 4.4%. The variation between different stocks is quite large. For four stocks we even observe a decrease in the adjusted $R^2$. Hence it would be very difficult in practice to decide if the historical beta provides useful additional information for a particular stock.

Given the weak additional information content of historical betas, using implied beta estimators without relying on historical estimators seems to be sufficient. However, an argument for using information based on both types of estimators could be a low correlation of the respective estimation errors. In such a case, a combined estimator could have a reduced estimation error even if little additional information was used. Table 8 reports linear correlation coefficients between estimation errors of the eight different implied and historical estimators.

*[ Insert Table 8 about here ]*

First, it is evident that the three implied estimators, VarCorr, VarProp, and KurtProp, move very much in line with correlations of 0.997 and larger. All three estimators use market-wide information; that is, information on all stocks contained in the index. The identifying assumptions of the two variance-based betas—homogenous correlations on the one hand, and a constant proportion of idiosyncratic variance on the other—apparently make little difference. Moreover, relying on the kurtosis instead of the variance with market-wide information doesn't seem to have a significant effect either.

The second group of implied beta estimators, SkewProp, SkewSyst, and KurtSyst, exhibits correlations in the range 0.74 to 0.86 between each other and the first group of implied estimators. These correlations are smaller than those between the first group, because the skewness-based estimators capture more uncorrelated noise than the estimators based on even central moments. Additionally, the identifying assumption of no idiosyncratic risk (in terms of skewness or kurtosis, respectively) does not cover market-wide information.

The correlation between implied and historical estimators amounts to 0.4 to 0.6, while the correlation between the Hist-3M estimator and the first group of implied estimators is about 0.58. Although the errors are far from being uncorrelated, the value is considerably smaller than 1. Thus, although historical beta estimators carry little additional information compared to historical estimators, the moderate correlation could make the former useful in reducing estimation error. As a simple example, consider a combined estimator $\beta_{it}^{comb} = 0.5\beta_{it}^{VarProp} + 0.5\beta_{it}^{Hist-3M}$. It yields a considerably reduced mean absolute error of 0.206 (compared to 0.232 of "pure" estimators, see Table 4), which demonstrates this effect.

## D Role of Options Market Activity

As implied beta estimators rely on the information content of option prices, we would expect better results in periods when option prices carry more information. Chakravarty, Gulen, and Mayhew (2004) find that the information share of options in stock price discovery tends to be higher when options trading volume is higher and stock trading volume is lower, which motivates the use of relative trading volume as a proxy of information content. We use this variable to divide our investigation period in sub-periods of relatively high and low options trading activity. A month is assigned to the sub-sample of high options activity if the average (over 19 stocks) ratio of options trading volume to stock trading volume is higher than the median value of the 169 months in our investigation period. Table 9 presents the mean absolute prediction errors of the six implied estimators and the benchmarks for both sub-samples.

*[ Insert Table 9 about here ]*

The results are clearly consistent with the hypothesis that implied betas perform better in periods with higher information content of option prices. All six implied estimators have a much lower mean prediction error in the sub-sample of high options trading activity.[30] As the last two columns of the table indicate, differences between the two sub-samples are not only economically significant, but also statistically significant at a 1% level. The results for the historical estimators show no significant differences between the sub-samples at a 1% level. This finding is further evidence that the documented differences for the implied strategies result from a differential information content of options and are not merely a coincidence of the sample selection.

## E Alternative Time Horizons

Because applications that require ex-ante betas differ in terms of the relevant time horizon, it is important to investigate the robustness of our results with respect to changing horizons. Hence we repeat our analysis for time horizons of one month and twelve months. The results for the mean prediction errors (ME) and the mean absolute predictions errors (MAE) are presented in Table 10.

*[ Insert Table 10 about here ]*

We can see that MAEs are generally higher for shorter time horizons than for longer ones, irrespective of the estimator employed. The main reason should be that realized short-horizon betas simply vary more strongly than long-horizon betas. The major findings about different implied estimators obtained for the base case remain stable for the one-month horizon and the twelve-month horizon. The leading group of best performing estimators (VarProp, VarCorr, KurtProp) exhibit very similar

[30]If we use a different sorting and build a first sub-sample that contains all stocks with above median average (over 169 months) options trading activity ratios and a second sub-sample with all other stocks, we obtain similar results. The group of stocks with higher average options trading activity shows lower absolute prediction errors for the implied estimators than the group with lower activity. However, the differences are smaller than for the other sorting. This finding is not surprising because the variation of options trading activity is much stronger over time than between different stocks.

prediction errors. The SkewProp estimator always performs worse than the estimators of the first group, and the SkewSyst and KurtSyst estimators generally lead to very bad results. We can therefore conclude that the use of implied skewness as the basis for a beta estimator is not advisable, and the use of cross-sectional information to standardize estimators brings important advantages.

The analysis of different time horizons reveals another interesting point. The short-term historical beta estimator leads to clearly higher prediction errors than the first group of implied estimators for the one-month horizon, and similar errors for the three-month and twelve-month horizons. This finding suggests that the shorter the forward-looking period, the more important the use of most recent information, which is reflected in implied estimators. If the horizon gets longer and shocks level out over time, however, most recent information might lose relative importance compared to the "usual" co-movement between the stock and the index observed over the previous year.

An additional explanation for the comparatively good results of the implied estimators for shorter time horizons is that statistical estimation errors affect historical and implied estimators differently. Whereas the Hist-1M estimator is subject to a larger statistical estimation error than the Hist-3M estimator due to the smaller number of observations, the implied estimators are not. On the contrary, the higher liquidity of short-term options should reduce errors for shorter time horizons.

# V Conclusions

We have analyzed the properties of different implied beta estimators based on higher moments extracted from options data. Implied beta estimators can be categorized by the order of the moment they use and by their identifying assumption. For a good performance, even moments (variance or kurtosis) should be used, and the identifying assumption should cover market-wide data of single stocks instead of only using data of the one stock under estimation together with the market index.

This requirement holds for the identifying assumptions of homogenous correlations and of a homogenous proportion of systematic risk across all single stocks. The three estimators that fulfill both criteria are very similar, as their prediction errors are correlated with coefficients above 0.99.

Compared to the benchmarks of historical beta estimators, the predictive performance of this leading group of implied beta estimators is clearly superior if the time horizon is short (one month), or options market activity is high. This property makes them an attractive alternative to traditional short-window regressions with historical data, which are used in asset pricing studies to obtain conditional betas.

As we concentrated on fully-implied approaches in this paper, a field of future research emerges from the identification of optimal combinations of historical and implied strategies; for example, the hybrid estimator suggested by Buss and Vilkov (2012). Our correlation analysis, having found moderate correlations between prediction errors of implied and historical betas, provides arguments for convex combinations of both types of betas. Moreover, we find some indication for beta risk premia in our study. A better understanding of such premia and the development of appropriate risk adjustments for option-implied betas are further challenges that need to be addressed in the future.

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**Table 1:** Overview of Implied Beta Estimators.

| Beta | Moment | Identifying Assumption | Reference |
|---|---|---|---|
| **VarProp** | variance | constant proportion of systematic variance | Kempf, Korn, and Saßning (2011) |
| **VarCorr** | variance | constant correlation | Skintzi and Refenes (2005) |
| **SkewProp** | skewness | constant proportion of systematic skewness | Kempf, Korn, and Saßning (2011) |
| **SkewSyst** | skewness | no idiosyncratic skewness | Chang, Christoffersen, Jacobs, and Vainberg (2012) |
| **KurtProp** | kurtosis | constant proportion of systematic kurtosis | Kempf, Korn, and Saßning (2011) |
| **KurtSyst** | kurtosis | no idiosyncratic excess kurtosis | this paper |

**Table 2:** Stocks and Options Trading Volume.

| Ticker | Company | Stock Trading | | | Option Trading | | | Ratio | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Min | Max | Avg | Min | Max | Avg | Min | Max | Avg |
| **AA** | Alcoa | 545 | 79777 | 10973 | .2 | 167.1 | 24.8 | 0.03 | 0.91 | 0.20 |
| **AXP** | American Express | 640 | 40438 | 6911 | .7 | 127.6 | 16.2 | 0.06 | 0.84 | 0.22 |
| **BA** | Boeing | 1246 | 14106 | 4489 | 1.2 | 36.0 | 10.8 | 0.03 | 0.76 | 0.24 |
| **CAT** | Caterpillar | 429 | 22128 | 5004 | .4 | 170.4 | 21.5 | 0.04 | 1.12 | 0.33 |
| **DD** | Du Pont | 885 | 16851 | 4674 | .6 | 47.5 | 8.2 | 0.02 | 0.72 | 0.18 |
| **DIS** | Walt Disney | 1336 | 39966 | 8593 | 1.4 | 58.2 | 11.2 | 0.04 | 0.48 | 0.14 |
| **GE** | General Electric | 3240 | 223996 | 3505 | 4.0 | 555.1 | 77.7 | 0.11 | 0.44 | 0.22 |
| **HPQ** | Hewlett Packard | 1979 | 61128 | 12050 | 2.8 | 204.0 | 25.3 | 0.04 | 0.61 | 0.20 |
| **IBM** | IBM | 1654 | 15133 | 6874 | 7.1 | 125.6 | 36.1 | 0.17 | 1.42 | 0.53 |
| **JNJ** | Johnson & Johnson | 1179 | 32807 | 8337 | 1.3 | 75.7 | 17.4 | 0.07 | 0.53 | 0.21 |
| **JPM** | JP Morgan Chase | 1028 | 146841 | 20339 | 2.2 | 366.2 | 49.6 | 0.07 | 1.06 | 0.24 |
| **KO** | Coca-Cola | 2208 | 18685 | 6667 | 1.4 | 57.8 | 14.8 | 0.05 | 0.75 | 0.21 |
| **MCD** | McDonald's | 1281 | 16888 | 5612 | .8 | 51.0 | 1.7 | 0.02 | 1.02 | 0.20 |
| **MMM** | 3M | 465 | 14470 | 3122 | .3 | 39.8 | 8.6 | 0.04 | 0.89 | 0.26 |
| **MRK** | Merck & Co | 1556 | 56311 | 10717 | 2.9 | 149.3 | 20.9 | 0.04 | 1.43 | 0.21 |
| **PG** | Procter & Gamble | 1089 | 26077 | 6779 | 1.3 | 313.4 | 16.0 | 0.06 | 2.71 | 0.23 |
| **UTX** | United Technologies | 316 | 11280 | 3237 | .1 | 22.8 | 5.0 | 0.02 | 0.52 | 0.15 |
| **WMT** | Wal Mart | 1885 | 53102 | 11314 | .9 | 160.0 | 29.0 | 0.05 | 0.68 | 0.23 |
| **XOM** | Exxon Mobil | 2219 | 74998 | 15559 | 1.1 | 156.2 | 35.4 | 0.03 | 0.47 | 0.20 |

The table reports minimum, maximum, and average daily trading volume in stocks and options for the 19 stocks included in the study. Averages were taken over all days between January 1998 through January 2012 when betas were calculated. The figures refer to thousands of traded contracts. The last three columns show the ratios of traded options to traded stocks in percent.

**Table 3:** Summary Statistics of Different Beta Estimators.

| | Mean | Std. Dev. Total | Std. Dev. Firms | Std. Dev. Time | Autocorr. | MAV |
|---|---|---|---|---|---|---|
| **VarProp** | **1.010** | **0.240** | **0.178** | **0.152** | **0.845** | **0.056** |
| **VarCorr** | **1.001** | **0.242** | **0.177** | **0.156** | **0.846** | **0.057** |
| **SkewProp** | **0.998** | **0.261** | **0.141** | **0.213** | **0.551** | **0.105** |
| **SkewSyst** | **1.173** | **0.341** | **0.168** | **0.290** | **0.694** | **0.146** |
| **KurtProp** | **1.008** | **0.230** | **0.170** | **0.147** | **0.845** | **0.054** |
| **KurtSyst** | **1.144** | **0.258** | **0.116** | **0.228** | **0.667** | **0.131** |
| **Hist-3M** | **1.020** | **0.413** | **0.274** | **0.308** | **0.820** | **0.129** |
| **Hist-60M** | **1.034** | **0.430** | **0.347** | **0.251** | **0.965** | **0.033** |
| **Const** | **1.000** | **0.000** | **0.000** | **0.000** | — | **0.000** |

The table reports summary statistics of six implied beta estimators and historical benchmark estimators. All results are calculated from the 19 stocks that have been permanently included in the DJIA Index over the investigation period from January 1998 to January 2012 (3211 observation for each estimator). The table contains the mean beta (Mean), the standard deviation around the overall mean (Std. Dev. Total), the standard deviation of the 19 average betas obtained for individual stocks (Std. Dev. Firms), the average of the 19 standard deviations obtained from the beta time series of individual stocks (Std. Dev. Time), the average (over the 19 stocks) autocorrelation, and the average (over the 19 stocks) absolute difference between the beta estimates in successive months (MAV).

**Table 4:** Prediction Errors of Different Beta Estimators.

| | ME | STDE | RMSE | MAE | % Impr. of MAE over Const |
|---|---|---|---|---|---|
| **VarProp** | **-0.012** | **0.304** | **0.304** | **0.232** | **27.9** |
| **VarCorr** | **-0.016** | **0.301** | **0.302** | **0.230** | **28.3** |
| **SkewProp** | **-0.023** | **0.342** | **0.343** | **0.255** | **20.7** |
| **SkewSyst** | **0.151** | **0.385** | **0.414** | **0.313** | **2.7** |
| **KurtProp** | **-0.013** | **0.306** | **0.306** | **0.234** | **27.2** |
| **KurtSyst** | **0.122** | **0.413** | **0.431** | **0.327** | **-1.7** |
| **Hist-3M** | **-0.001** | **0.320** | **0.320** | **0.232** | **27.8** |
| **Hist-60M** | **0.012** | **0.382** | **0.382** | **0.293** | **9.0** |
| **Const** | **-0.021** | **0.417** | **0.418** | **0.321** | **0.0** |

The table reports the mean prediction error (ME), the standard deviation of the prediction error (STDE), the root mean squared prediction error (RMSE), the mean absolute prediction error (MAE), and the percentage reduction in MAE over a constant beta of one of six implied beta estimators and historical benchmark estimators. Prediction errors are defined as the difference between the beta estimate and the ex post realized beta. All results are calculated from the 19 stocks that have been permanently included in the DJIA Index over the investigation period from January 1998 to January 2012 (3211 observations for each estimator).

**Table 5:** Prediction Errors and Betas for Individual Stocks.

| | VarProp | | | SkewProp | | | KurtProp | | |
|---|---|---|---|---|---|---|---|---|---|
| **Ticker** | **ME** | **MAE** | **Beta** | **ME** | **MAE** | **Beta** | **ME** | **MAE** | **Beta** |
| **AA** | **-0.031** | **0.273** | **1.354** | **-0.252** | **0.403** | **1.133** | **-0.052** | **0.282** | **1.334** |
| **AXP** | **-0.243** | **0.312** | **1.189** | **-0.225** | **0.309** | **1.207** | **-0.253** | **0.316** | **1.179** |
| **BA** | **0.029** | **0.199** | **1.117** | **-0.032** | **0.217** | **1.056** | **0.022** | **0.200** | **1.110** |
| **CAT** | **-0.147** | **0.227** | **1.185** | **-0.261** | **0.308** | **1.071** | **-0.161** | **0.236** | **1.172** |
| **DD** | **-0.133** | **0.204** | **0.988** | **-0.138** | **0.206** | **0.983** | **-0.134** | **0.205** | **0.987** |
| **DIS** | **0.019** | **0.231** | **1.089** | **-0.021** | **0.249** | **1.049** | **0.015** | **0.233** | **1.085** |
| **GE** | **-0.184** | **0.233** | **1.008** | **-0.138** | **0.222** | **1.054** | **-0.179** | **0.229** | **1.013** |
| **HPQ** | **0.072** | **0.276** | **1.287** | **-0.028** | **0.279** | **1.188** | **0.056** | **0.272** | **1.272** |
| **IBM** | **-0.038** | **0.198** | **0.951** | **-0.009** | **0.211** | **0.979** | **-0.035** | **0.199** | **0.954** |
| **JNJ** | **0.151** | **0.214** | **0.741** | **0.220** | **0.261** | **0.810** | **0.163** | **0.220** | **0.753** |
| **JPM** | **-0.270** | **0.325** | **1.210** | **-0.189** | **0.293** | **1.291** | **-0.272** | **0.328** | **1.209** |
| **KO** | **0.151** | **0.205** | **0.774** | **0.182** | **0.231** | **0.805** | **0.156** | **0.208** | **0.779** |
| **MCD** | **0.225** | **0.283** | **0.941** | **0.211** | **0.293** | **0.926** | **0.227** | **0.286** | **0.942** |
| **MMM** | **-0.054** | **0.166** | **0.886** | **-0.034** | **0.181** | **0.906** | **-0.053** | **0.166** | **0.887** |
| **MRK** | **0.183** | **0.247** | **0.985** | **0.195** | **0,266** | **0.996** | **0.185** | **0.247** | **0.986** |
| **PG** | **0.127** | **0.209** | **0.755** | **0.159** | **0.248** | **0.787** | **0.137** | **0.216** | **0.765** |
| **UTX** | **-0.147** | **0.184** | **0.959** | **-0.156** | **0.209** | **0.950** | **-0.148** | **0.184** | **0.959** |
| **WMT** | **0.035** | **0.204** | **0.907** | **0.036** | **0.219** | **0.907** | **0.038** | **0.207** | **0.909** |
| **XOM** | **0.036** | **0.215** | **0.857** | **0.043** | **0.240** | **0.865** | **0.039** | **0.213** | **0.860** |
| **average** | **-0.012** | **0.232** | **1.010** | **-0.023** | **0.255** | **0.998** | **-0.013** | **0.234** | **1.008** |
| **std. dev.** | **0.146** | **0.043** | **0.178** | **0.161** | **0.052** | **0.141** | **0.149** | **0.044** | **0.170** |
| **min** | **-0.270** | **0.166** | **0.741** | **-0.261** | **0.181** | **0.787** | **-0.272** | **0.166** | **0.753** |
| **max** | **0.225** | **0.325** | **1.354** | **0.220** | **0.403** | **1.291** | **0.227** | **0.328** | **1.334** |
| **Corr(ME, Beta)** | | **-0.49** | | | **-0.72** | | | **-0.53** | |

The table reports the mean prediction error (ME), the mean absolute prediction error (MAE) and the average beta (Beta) of three implied beta estimators (VarProp, SkewProp, KurtProp). Prediction errors are defined as the difference between the beta estimate and the ex post realized beta. Results are calculated separately for each of the 19 stocks that have been permanently included in the DJIA Index over the investigation period from January 1998 to January 2012.

**Table 6:** Historical Information and Implied Beta Estimators.

| **Ticker** | **Intercept** *(p-value)* | **Slope** *(p-value)* | **Adj.** $R^2$ |
|---|---|---|---|
| **AA** | **0.7565** | **0.4369** | **0.4793** |
| | *(0.000)* | *(0.000)* | |
| **AXP** | **0.5384** | **0.4553** | **0.4883** |
| | *(0.000)* | *(0.000)* | |
| **BA** | **0.8088** | **0.2832** | **0.5103** |
| | *(0.000)* | *(0.000)* | |
| **CAT** | **0.6648** | **0.3939** | **0.5883** |
| | *(0.000)* | *(0.000)* | |
| **DD** | **0.6467** | **0.3047** | **0.4762** |
| | *(0.000)* | *(0.000)* | |
| **DIS** | **0.9071** | **0.1715** | **0.2830** |
| | *(0.000)* | *(0.000)* | |
| **GE** | **0.2130** | **0.6672** | **0.4556** |
| | *(0.180)* | *(0.030)* | |
| **HPQ** | **0.9672** | **0.2640** | **0.3013** |
| | *(0.000)* | *(0.000)* | |
| **IBM** | **0.7224** | **0.2305** | **0.3355** |
| | *(0.000)* | *(0.000)* | |
| **JNJ** | **0.6235** | **0.1974** | **0.2293** |
| | *(0.000)* | *(0.000)* | |
| **JPM** | **0.5333** | **0.4600** | **0.4968** |
| | *(0.000)* | *(0.000)* | |
| **KO** | **0.7009** | **0.1162** | **0.0583** |
| | *(0.000)* | *(0.000)* | |
| **MCD** | **0.6759** | **0.3675** | **0.4168** |
| | *(0.000)* | *(0.000)* | |
| **MMM** | **0.7187** | **0.1792** | **0.2758** |
| | *(0.000)* | *(0.000)* | |
| **MRK** | **0.8346** | **0.1850** | **0.1553** |
| | *(0.000)* | *(0.000)* | |
| **PG** | **0.6725** | **0.1284** | **0.1309** |
| | *(0.000)* | *(0.000)* | |
| **UTX** | **0.8154** | **0.1306** | **0.1469** |
| | *(0.000)* | *(0.000)* | |
| **WMT** | **0.6059** | **0.3412** | **0.6608** |
| | *(0.000)* | *(0.000)* | |
| **XOM** | **0.6558** | **0.2472** | **0.3900** |
| | *(0.000)* | *(0.000)* | |
| **mean** | **0.6874** | **0.2926** | **0.3620** |
| *std. dev.* | *0.1576* | *0.1402* | *0.1632* |

The table reports the results of univariate regressions $\beta_{it}^{VarProp} = a + b\,\beta_{it}^{Hist-3M} + \epsilon_{it}$ for the 19 stocks that have been permanently in the DJIA Index over the investigation period January 1998 to January 2012. The values in parentheses are the p-values of significance tests for the null hypotheses that the intercept equals zero and the slope coefficient equals one. The p-values are based on the heteroscedasticity and autocorrelation consistent estimator by Newey and West (1987) with two lags, which accounts for the autocorrelation caused by the overlapping intervals. In addition, the table reports the summary statistics mean and standard deviation for the regression coefficients and the adjusted $R^2$.

**Table 7:** Incremental Information of Historical Beta Estimators.

| Ticker | Intercept *(p-value)* | $b_1$ *(p-value)* | $b_2$ *(p-value)* | Adj. $R^2$ | Incr. Adj. $R^2$ |
|---|---|---|---|---|---|
| **AA** | **-0.0194** | **1.0374** | **0.3845** | **0.4840** | **0.0720** |
| | *(0.916)* | *(0.783)* | *(0.016)* | | |
| **AXP** | **0.1644** | **1.0663** | **0.3694** | **0.5458** | **0.0674** |
| | *(0.624)* | *(0.823)* | *(0.043)* | | |
| **BA** | **-0.4113** | **1.3420** | **0.1889** | **0.2930** | **0.0134** |
| | *(0.336)* | *(0.325)* | *(0.175)* | | |
| **CAT** | **-0.2539** | **1.3386** | **0.1537** | **0.4601** | **0.0062** |
| | *(0.287)* | *(0.095)* | *(0.280)* | | |
| **DD** | **0.0063** | **1.1281** | **0.1069** | **0.2356** | **0.0012** |
| | *(0.981)* | *(0.660)* | *(0.615)* | | |
| **DIS** | **0.0402** | **0.9458** | **0.3884** | **0.1962** | **0.1070** |
| | *(0.886)* | *(0.840)* | *(0.000)* | | |
| **GE** | **0.5382** | **0.6487** | **0.0662** | **0.4042** | **-0.0011** |
| | *(0.000)* | *(0.003)* | *(0.611)* | | |
| **HPQ** | **0.0487** | **0.9063** | **0.2092** | **0.2052** | **0.0254** |
| | *(0.865)* | *(0.712)* | *(0.256)* | | |
| **IBM** | **0.2561** | **0.7702** | **0.2689** | **0.1356** | **0.0447** |
| | *(0.476)* | *(0.558)* | *(0.163)* | | |
| **JNJ** | **0.0922** | **0.6715** | **0.3487** | **0.1599** | **0.0896** |
| | *(0.627)* | *(0.245)* | *(0.049)* | | |
| **JPM** | **0.1620** | **1.0896** | **-0.0128** | **0.4810** | **-0.0030** |
| | *(0.364)* | *(0.510)* | *(0.936)* | | |
| **KO** | **0.4104** | **0.2749** | **0.2921** | **0.0840** | **0.0741** |
| | *(0.120)* | *(0.045)* | *(0.013)* | | |
| **MCD** | **-0.1648** | **0.9358** | **0.0053** | **0.2713** | **-0.0043** |
| | *(0.639)* | *(0.875)* | *(0.977)* | | |
| **MMM** | **0.0454** | **1.0100** | **0.1504** | **0.1268** | **0.0116** |
| | *(0.864)* | *(0.972)* | *(0.372)* | | |
| **MRK** | **0.1658** | **0.6454** | **0.2152** | **0.1240** | **0.0359** |
| | *(0.670)* | *(0.349)* | *(0.269)* | | |
| **PG** | **0.2889** | **0.4488** | **0.4306** | **0.1755** | **0.1568** |
| | *(0.421)* | *(0.284)* | *(0.115)* | | |
| **UTX** | **0.2751** | **0.8668** | **0.0417** | **0.0700** | **-0.0042** |
| | *(0.159)* | *(0.503)* | *(0.306)* | | |
| **WMT** | **-0.7415** | **1.7795** | **0.3062** | **0.5733** | **0.0287** |
| | *(0.000)* | *(0.000)* | *(0.033)* | | |
| **XOM** | **-0.3426** | **1.3579** | **0.4314** | **0.3817** | **0.1069** |
| | *(0.268)* | *(0.325)* | *(0.002)* | | |
| **mean** | **0.0295** | **0.9612** | **0.2287** | **0.2846** | **0.0436** |
| *std. dev.* | *0.2982* | *0.3435* | *0.1407* | *0.1602* | *0.0458* |

The table reports the results of the bivariate regression $\beta_{it}^{Real} = a_1 + b_1\,\beta_{it}^{VarProp} + b_2\,Res_{it} + \epsilon_{it}$, with $Res_{it}$ being the residuals of the regression $\beta_{it}^{Hist-3M} = a + b\,\beta_{it}^{VarProp} + u_{it}$ for an estimation horizon of 3 months. The values for the intercept, both coefficients, and the adjusted $R^2$s are reported. The final column reports the increase in adjusted $R^2$ with respect to a univariate regression without the incremental historical information. The values in parentheses are the p-values for the significance tests for the null hypotheses that the intercept $a$ and the slope coefficient $b_2$ for the historical incremental information equals zero, respectively, and the slope coefficient $b_1$ for the implied beta equals one. The p-values are based on the heteroscedasticity and autocorrelation consistent estimator by Newey and West (1987) with two lags, which accounts for the autocorrelation caused by the overlapping intervals. In addition, the table reports the summary statistics mean and standard deviation for the regression coefficients across the 19 stocks.

**Table 8:** Correlation Between Prediction Errors of Different Beta Estimators.

| | Implied Estimators | | | | | | Historical Estimators | |
|---|---|---|---|---|---|---|---|---|
| | **VarProp** | **VarCorr** | **SkewProp** | **SkewSyst** | **KurtProp** | **KurtSyst** | **Hist-3M** | **Hist-60M** |
| **VarProp** | 1.000 | | | | | | | |
| **VarCorr** | 0.997 | 1.000 | | | | | | |
| **SkewProp** | 0.849 | 0.850 | 1.000 | | | | | |
| **SkewSyst** | 0.736 | 0.735 | 0.854 | 1.000 | | | | |
| **KurtProp** | 0.999 | 0.996 | 0.858 | 0.742 | 1.000 | | | |
| **KurtSyst** | 0.806 | 0.800 | 0.748 | 0.832 | 0.821 | 1.000 | | |
| **Hist-3M** | 0.582 | 0.586 | 0.482 | 0.429 | 0.579 | 0.446 | 1.000 | |
| **Hist-60M** | 0.612 | 0.607 | 0.504 | 0.439 | 0.605 | 0.492 | 0.458 | 1.000 |

The table reports linear correlations between the prediction errors of six implied beta estimators and two historical benchmark estimators over the period January 1998 and January 2012.

**Table 9:** Prediction Errors for Periods with High and Low Options Trading Activity.

| | **Low Option Ratio** | **High Option Ratio** | **Difference** | *(p-value)* |
|---|---|---|---|---|
| | **MAE** | **MAE** | | |
| **VarProp** | **0.261** | **0.202** | **0.059** | *(0.000)* |
| **VarCorr** | **0.259** | **0.202** | **0.057** | *(0.000)* |
| **SkewProp** | **0.290** | **0.219** | **0.071** | *(0.000)* |
| **SkewSyst** | **0.355** | **0.269** | **0.086** | *(0.000)* |
| **KurtProp** | **0.263** | **0.205** | **0.058** | *(0.000)* |
| **KurtSyst** | **0.362** | **0.291** | **0.071** | *(0.000)* |
| **Hist-3M** | **0.249** | **0.215** | **0.034** | *(0.011)* |
| **Hist-60M** | **0.301** | **0.284** | **0.017** | *(0.444)* |
| **Const** | **0.335** | **0.308** | **0.027** | *(0.336)* |

The table shows the mean absolute prediction error (MAE) of six implied beta estimators and historical benchmark estimators for periods of high and low options trading activity. A period is classified as showing "high options trading activity" if the ratio of average (over all 19 stocks) monthly options trading volume over stock trading volume is above the median of all periods. A period is classified as showing "low options trading activity" if the ratio is below the median. The full investigation period is January 1998 to January 2012. The final column of the table reports p-values for a t-test of the null hypothesis that the MAE is identical in both subsamples.

**Table 10:** Predictive Performance of Beta Estimators Over Different Time Horizons.

| | 1M | | 3M | | 12M | |
|---|---|---|---|---|---|---|
| | **ME** | **MAE** | **ME** | **MAE** | **ME** | **MAE** |
| **Imp-VarProp** | -0.005 | 0.312 | -0.012 | 0.232 | -0.021 | 0.197 |
| **Imp-VarCorr** | -0.010 | 0.312 | -0.016 | 0.230 | -0.024 | 0.197 |
| **Imp-SkewProp** | -0.032 | 0.409 | -0.023 | 0.255 | -0.031 | 0.247 |
| **Imp-SkewSyst** | 0.140 | 0.481 | 0.151 | 0.313 | 0.087 | 0.279 |
| **Imp-KurtProp** | -0.007 | 0.315 | -0.013 | 0.234 | -0.022 | 0.200 |
| **Imp-KurtSyst** | 0.291 | 0.457 | 0.122 | 0.327 | 0.001 | 0.315 |
| **Hist-xM** | 0.002 | 0.368 | -0.001 | 0.232 | -0.007 | 0.195 |
| **Hist-60M** | 0.015 | 0.361 | 0.012 | 0.293 | 0.006 | 0.255 |
| **Const** | -0.018 | 0.387 | -0.021 | 0.321 | -0.027 | 0.281 |

The table reports the mean prediction error (ME) and the mean absolute prediction error (MAE) of six implied beta estimators and historical benchmark estimators for different estimation horizons (one month 1M, three months 3M, and twelve months 12M). As with the base case of three months, all results are calculated from the 19 stocks that have been permanently includes in the DJIA Index over the investigation period from January 1998 to January 2012. The results for 3M are thus identical with Table 4. The benchmark estimator Hist-xM is consistent with the estimation period, that is, for 1M, one month of daily historical data is applied, for 3M three months, and for 12M twelve months.

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