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Portfolio Optimization using Forward-Looking Information

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by

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Abstract

We develop a new family of estimators of the covariance matrix that relies solely on forward-looking information. It uses only current prices of plain-vanilla options. In an out-of-sample study we show that a minimum-variance strategy based on these fully-implied estimators outperforms several benchmark strategies, including various strategies based on historical estimates, index investing, and 1/N investing. The outperformance originates in crisis periods when information flow and information asymmetry are high. Although the historical benchmark strategies improve when more recent data is used, they never outperform fully-implied strategies. Thus, our results suggest that investors are better off relying on forward-looking information.

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1 Introduction

Selecting an optimal portfolio is a classic problem in finance. Although the solution for the mean-variance investor has been well known since the seminal work by Markowitz (1952), implementation remains a challenging task. Generally, estimation errors make a simple implementation based on historical sample moments unstable (see, for example, Best and Grauer (1991), Chopra and Ziemba (1993), and Michaud (1989)), and specifically, expected returns are hard to estimate (see Merton (1980)). Facing these implementation limitations, researchers are paying growing attention to the global minimum variance portfolio (GMVP), the only efficient portfolio that doesn't depend on expected returns. The GMVP often leads to a better out-of-sample performance than a mean-variance optimized portfolio (see, for example, Ledoit and Wolf (2003) and Jagannathan and Ma (2003)).

Despite the attractiveness of the GMVP, an estimation risk with respect to the covariance matrix remains, and several recent papers suggest ways to reduce estimation errors. For example, Ledoit and Wolf (2004) impose restrictions on the covariance matrix, whereas Jagannathan and Ma (2003) as well as DeMiguel, Garlappi, Nogales, and Uppal (2009) put restrictions on the portfolio weights. Despite all the progress, the study by DeMiguel, Garlappi, and Uppal (2009) concludes that "there are still many miles to go before the gains promised by optimal portfolio selection can actually be realized out of sample." Specifically, DeMiguel, Garlappi, and Uppal (2009) base their conclusion on the finding that the GMVP is unable to beat simple benchmark strategies like investing in an equally weighted portfolio (1/N-strategy).

Echoing these concerns and the limitations raised by previous research, we suggest a new approach to estimate the covariance matrix and show that the GMVP based on the resulting estimates is able to beat the 1/N-strategy and other benchmark strategies in an out-of-sample test. The core idea of our new approach is to rely solely on current option prices when estimating the covariance matrix instead of using historical return information. Since option prices reflect the expectations of market participants about risk, our approach - unlike the backward-looking approaches used so far - is inherently forward looking.

Our paper makes two major contributions to the literature. First, we develop a new family of estimators of the covariance matrix that uses exclusively forward-looking information from a cross-section of option prices. Such estimators require implied volatilities as well as implied correlations. While implied volatilities can be easily derived from plain-vanilla options, implied correlations cannot be derived in a similar way since cross-correlation derivatives, such as exchange options and quantos, are usually not available. Therefore, we suggest a different route and develop a model that allows us to derive implied correlations from a cross-section of plain-vanilla options.

The second main contribution is to show that the GMVP based on the implied estimates of the covariance matrix performs extremely well in an out-of-sample study for US blue-chip stocks. Specifically, we show that strategies using implied estimators beat various benchmark strategies: GMVP based on historical estimates of the covariance matrix, 1/N-strategy, and index investments. The superiority of the implied approach is due to its better performance in crisis periods, while in quiet periods all strategies lead to similar results. This is highly sensible given that the information flow and the information content of option prices are high in turbulent markets. Although the historical strategies and partially-implied strategies, which use implied variances (correlations) and historical correlations (variances) at the same time, never beat the implied strategies, their disadvantage is smaller when using more recent data for the estimation. This is consistent with the view that more recent data cover the current market situation better (which is best reflected in current option prices). Overall, our empirical results suggest that relying on forward-looking information is a promising way for investors to better realize the possible gains from optimal portfolio diversification.

Our paper relates to two strands of literature. First, we extend the scarce literature on implied estimation of covariances. Skintzi and Refenes (2005) use prices of individual stock options and index options to obtain a single implied correlation measure for all stocks in the market. Hence, they assume that the correlations for all stock pairs are identical. Buss and Vilkov (2012) use cross-sectional information from option prices combined with time series information to estimate correlations. Thus, in contrast to our paper, their approach is not a fully-implied one. Chang, Christoffersen, Jacobs, and Vainberg (2012) develop a beta estimator based on implied skewness that could be combined with an implied index variance to obtain fully-implied covariances. However, positive definiteness of the resulting covariance matrix is not guaranteed. In contrast, we suggest an estimator which always leads to a positive definite matrix.

The second related strand of literature consists of the few papers that have used forward-looking information from option prices in solving portfolio problems. Kostakis, Panigirtzoglou, and Skiadopoulos (2011) show that implied distributions can be useful to solve the problem of how to allocate wealth between a market investment and a risk-free asset. However, in this problem, correlations do not matter and Kostakis, Panigirtzoglou, and Skiadopoulos (2011) consequently make no attempt to estimate implied correlations. The same holds for the portfolio allocation problem studied by Jabbour, Peña, Vera, and Zuluaga

(2008), who seek to find a portfolio's worst case Conditional Value-at-Risk. Aït-Sahalia and Brandt (2008) study the dynamic consumption and portfolio choice problem of an investor who can invest in the stock market, the bond market, and in a risk-free asset. They characterize the properties of consumption and portfolio rules using implied marginal distributions. Since they do not derive the joint implied distribution, they have to estimate the correlation between the bond and stock market from historical returns. DeMiguel, Plyakha, Uppal, and Vilkov (2012) analyze the portfolio selection problem among a large set of stocks and provide evidence on minimum-variance portfolios, but they either combine implied variances with historical correlations or historical variances with implied correlations. Thus, DeMiguel, Plyakha, Uppal, and Vilkov (2012) do not consider a fully-implied approach. This is the main difference from our paper, which is the first to present and test a fully-implied approach to find the GMVP.

The remainder of the paper is organized as follows. In Section 2 we develop the family of fully-implied estimators of the covariance matrix. In Section 3 we present our empirical study. Section 4 concludes.

2 A Family of Fully-Implied Covariance Estimators

To derive implied covariances from a cross-section of plain-vanilla options, we make two assumptions. First, we assume that the returns of a set of N assets follow a generalized version of the Sharpe (1963) market model with time-varying coefficients:

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

R_{it} and R_{mt} denote the returns of the ith asset and the market, respectively. ϵ_{it} is a zero mean idiosyncratic error term that is independent of the market return. In addition, ϵ_{it} and ϵ_{jt} are independent for all $i \neq j$. α_{it} and β_{it} are model coefficients. Note that the model is fairly general since the coefficients can change over time. In the market model the return covariances depend only on the beta coefficients and the variance of the market return:

$$Cov(R_{it}, R_{jt}) = \beta_{it}\beta_{jt}Var(R_{mt}), \qquad \forall\, i \neq j\,. \tag{2}$$

Since the variance of the market return can be derived from traded index options, we are left with the problem of identifying betas from the prices of plain-vanilla options written on the individual assets. To solve this problem, we make our second assumption, a cross-sectional restriction on one moment of the return distribution. We can derive a whole family of fully-implied covariance estimators by imposing restrictions either on the second, third, fourth, or any other higher moment, respectively. In Sections 2.1, 2.2, and 2.3 we outline estimators based on the second, third, and fourth moments, respectively, and compare the properties of these fully-implied estimators in Section 2.4.

2.1 ESTIMATOR BASED ON SECOND MOMENTS

To derive the first member of the family, we impose a cross-sectional restriction on the return variance. We assume that the same (time varying) proportion of total variance is systematic for all assets. Denote this proportion by c_t, with $0 \leq c_t < 1$. Then $\beta_{it}^2 Var(R_{mt}) = c_t Var(R_{it})$ and $Var(\epsilon_{it}) = (1 - c_t)Var(R_{it})$. Our cross-sectional restriction implies that high-beta stocks tend to have high idiosyncratic risk. Such a relation between beta and idiosyncratic risk is well documented in the literature (e.g., Fama and MacBeth (1973), Malkiel and Xu (2002), Bali and Cakici (2008), and Fu (2009)). Solving the return variance of the ith asset

$$Var(R_{it}) = \beta_{it}^2 Var(R_{mt}) + (1 - c_t)\, Var(R_{it}) \tag{3}$$

for β_{it} leads to

$$\beta_{it} = c_t^{1/2} \left(\frac{Var(R_{it})}{Var(R_{mt})} \right)^{1/2} . \tag{4}$$

Since the market beta equals one, we can use the weights w_{itm} of the different assets $i = 1, \ldots, N$ in the market portfolio to identify the parameter c_t:

$$\sum_{i=1}^{N} w_{itm}\, \beta_{it} = \sum_{i=1}^{N} w_{itm}\, c_t^{1/2} \left(\frac{Var(R_{it})}{Var(R_{mt})} \right)^{1/2} = 1. \tag{5}$$

Solving for c_t leads to

$$c_t = \frac{Var(R_{mt})}{\left(\sum_{i=1}^{N} w_{itm}\, Var(R_{it})^{1/2} \right)^2} . \tag{6}$$

The above expression shows that c_t is positive and smaller than one given that not all assets in the index are perfectly correlated. Substitution of c_t from Equation (6) into Equation (4) and substitution of the resulting betas into Equation (2) finally leads to

$$Cov(R_{it}, R_{jt}) = \frac{Var(R_{it})^{1/2}\, Var(R_{jt})^{1/2}}{\left(\sum_{i=1}^{N} w_{itm}\, Var(R_{it})^{1/2} \right)^2}\, Var(R_{mt}), \qquad \forall\, i \neq j. \tag{7}$$

Equation (7) shows that the covariances are functions of individual asset variances and the variance of the market only. No cross-moments appear. Therefore, we can use implied volatilities from plain-vanilla options written on individual assets and the market index to obtain a fully-implied covariance estimate.

2.2 ESTIMATOR BASED ON THIRD MOMENTS

To obtain the further members of the family of fully-implied estimators, we just have to replace the assumption concerning the proportion of systematic variance with a corresponding assumption about how systematic risk affects higher moments.

To derive a skewness-based estimator of covariances, we now assume that the proportion of systematic return skewness is equal for all assets.[1] Denote this proportion by c_t^{Skew}. Then, the return skewness of the ith asset is

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

and solving for β_{it} leads to

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

Again, the condition that the market beta equals one delivers the proportion c_t^{Skew}. Solving for c_t^{Skew} and substituting the solution into Equation (9) provides the beta coefficients and finally leads to the following covariances:

$$Cov(R_{it}, R_{jt}) = \frac{Skew(R_{it})^{1/3} Skew(R_{jt})^{1/3}}{\left(\sum_{i=1}^{N} w_{itm} Skew(R_{it})^{1/3} \right)^2} Var(R_{mt}), \qquad \forall\, i \neq j\,. \tag{10}$$

[1]Note that the assumption by Chang, Christoffersen, Jacobs, and Vainberg (2012) that the proportion of systematic skewness equals 100% is a special case.

Equation (10) provides the second member of our family of fully-implied estimators of covariances.

2.3 ESTIMATOR BASED ON FOURTH MOMENTS

The final example we provide is a kurtosis-based estimator of covariances. We can derive it as above, but now assume that the proportion of systematic kurtosis is equal for all N assets. We denote this proportion by c_t^{Kurt}, with $0 \leq c_t^{Kurt} < 1$, and obtain the third fully-implied covariance estimator as

$$Cov(R_{it}, R_{jt}) = \frac{Kurt(R_{it})^{1/4} Kurt(R_{jt})^{1/4}}{\left(\sum_{i=1}^{N} w_{itm} Kurt(R_{it})^{1/4}\right)^2} Var(R_{mt}), \qquad \forall\, i \neq j\,. \tag{11}$$

In a similar way, one can easily derive further estimators using restrictions on higher moments of the return distribution.

2.4 PROPERTIES OF THE ESTIMATORS

The various members of the family of covariance estimators differ with respect to their properties. Most important for our portfolio application is the fact that they have different implications for the positive definiteness of the covariance matrix and the cross-sectional variation of correlations.

A positive definite covariance matrix is a prerequisite to solve our portfolio optimization problem. The variance-based estimator of Section 2.1 guarantees a positive definite covariance matrix since $c_t < 1$.[2] In contrast, the skewness- and kurtosis-based estimators do not

[2] To guarantee positive definiteness of the covariance matrix, it is sufficient that the correlation matrix is positive definite. As we see from Equations (6) and (7), all the off-diagonal elements of the correlation

guarantee a positive definite covariance matrix. Since betas are identified from skewness or kurtosis in Sections 2.2 and 2.3, the implied beta estimates together with the implied stock and index volatilities could induce a negative estimate of the idiosyncratic variance, which would translate into an estimated covariance matrix that is not positive definite.

Based on model-free implied moments according to Bakshi, Kapadia, and Madan (2003), we empirically analyze the severity of this problem for our data set of US blue-chip stocks. Using all estimates from our empirical study in Section 3, we find that the problem appears only for the skewness-based estimator. It leads to a negative implied idiosyncratic variance in 135 cases, which affect 43 of the 169 months in our out-of-sample period. In contrast, the kurtosis-based estimator does not lead to a negative idiosyncratic variance in a single case. This finding suggests that the variance-based and kurtosis-based estimators are more promising than the skewness-based estimator in portfolio applications.[3] Therefore, we do not use the skewness-based estimator in the empirical exercise in Section 3.

With respect to the cross-sectional variation of correlations, the variance-based estimator implies a constant value of c_t across all assets, as Equations (6) and (7) show. In contrast, the kurtosis-based estimator (as well as the skewness-based estimator) does not imply such a restriction and allows for heterogeneous correlations across assets. From a theoretical point of view, the restriction to a constant correlation across all pairs of assets is undesirable. From an empirical point of view, however, the constant correlation model might lead to better out-of-sample investment results than alternative approaches (see, for example, Chan, Karceski, and Lakonishok (1999) and Elton, Gruber, and Spitzer (2006)).

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matrix equal c_t. Thus, positive definiteness is guaranteed for $c_t < 1$.

[3] Martellini and Ziemann (2010) provide complementary evidence on this issue for historical moment estimates by showing that odd moments are much more difficult to estimate than even ones.

3 Empirical Study

3.1 DATA AND PORTFOLIO STRATEGIES

Our sample consists of stocks included in the Dow Jones Industrial Average. We use daily prices (adjusted for dividends and stock splits) of all stocks included in the index during the period January 1998 to January 2012, which is our out-of-sample period. In addition, we use stock prices from January 1993 to December 1997 to estimate covariance matrices for historical benchmark strategies. The data source is Datastream. Table I provides information on the stock price data for the out-of-sample period. It shows annualized average excess log-returns, realized return volatilities, and the period for which the stocks are included in the index.[4]

[Insert Table I about here]

Table I shows that excess returns of stocks included over the whole period range from -4.7% to 11.1% p.a. and volatilities from about 19.4% to 39.7%. The Dow Jones Index itself has an average excess return of 0.5%. The index volatility is 18.1%, providing evidence for potential diversification benefits.

To estimate an implied covariance matrix we use model-free implied moments, i.e., we do not rely on a particular valuation model. The idea goes back to the seminal paper by Breeden and Litzenberger (1978), who show that the whole risk-neutral return distribution can be recovered from option prices if a continuum of strike prices is available.[5] We apply

[4]For the calculation of excess returns, we use the zero rates provided by the IvyDB data base. Interest rates provided by IvyDB are derived from BBA LIBOR rates and settlement prices of CME Eurodollar futures. We interpolate them with a cubic spline to get the appropriate yield.

[5]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 theoretical and empirical research on

the approach by Bakshi, Kapadia, and Madan (2003) to derive model-free implied moments which we then put into Equations (7) and (11) to obtain implied covariance estimates. As our data source we use the volatility surfaces provided by IvyDB. They deliver Black-Scholes implied volatilities for a variety of strike prices and maturity buckets. These surfaces are available for all individual stocks and the Dow Jones Index.

Although options provide moments under the risk-neutral measure and portfolio selection requires moments under the physical measure, we make no attempt to risk-adjust implied moments in our study. Rubinstein (1994) provides examples of how the risk-neutral and physical distributions of the market are related. He concludes that the difference lies mainly in a mean shift and that the distributions are similar in shape. Moreover, even if the shape of the distribution is changed, the GMVP remains unaffected as long as the proportional variance and covariance risk premia are the same for all assets. Thus, it is an empirical question how valuable implied moments from option prices are for investment strategies[6] – a question that we address in the sections to come.

When implementing our trading strategy, we do not allow for short sales since short-sales restrictions typically lead to a better performance in empirical studies.[7] We use a monthly rebalancing frequency for the portfolio.[8] The rebalancing data is the first trading day after the expiration day of options contracts at CBOE for rebalancing since liquid options with

model-free implied moments.

[6]A large literature shows that implied volatilities are useful to predict future realized volatilities. See Poon and Granger (2003) and Poon and Granger (2005) for surveys and Busch, Christensen, and Ørregaard Nielsen (2011) for a recent study that uses state-of-the-art benchmark predictors. For a recent survey that considers also implied correlations and betas see Christoffersen, Jacobs, and Chang (2012).

[7]See, for example, Frost and Savarino (1988), Grauer and Shen (2000), and Jagannathan and Ma (2003). This holds in our sample as well: No matter whether we use implied or historical estimators, the trading strategy delivers a better performance when short sales are not allowed.

[8]As a robustness check, we repeat the analysis using a quarterly rebalancing frequency. The results remain qualitatively the same.

a time to maturity of about 30 days exist then. For this maturity bucket, we select all out-of-the money put and call options and fit a cubic spline to obtain a smooth volatility curve for each stock and the index.[9] Outside the available range of strike prices, we assume that the volatility curve is flat. Then, we select 1000 equally spaced strike prices on the interval $[0.003 \cdot S_i, 3 \cdot S_i]$, where S_i denotes the current spot price of the ith asset. For these 1000 strike prices we convert back the implied volatilities into European option prices via the Black-Scholes formula. To do this conversion, we use the matching spot prices and the risk-free interest rates provided by IvyDB. Based on these option prices we calculate the model-free implied moments following Bakshi, Kapadia, and Madan (2003).

For every month in the out-of-sample period, we set up GMVPs that differ in the way the covariance matrices are estimated. The first group of GMVP strategies relies on the fully-implied estimators of the covariance matrix. We denote the strategy using the implied estimator based on the variance by Imp_Var and the one based on the implied kurtosis by Imp_Kurt.

As a first set of benchmarks, we consider three passive strategies for which no estimates of the covariance matrix are needed. The first benchmark follows the construction of the Dow Jones Industrial Average and applies a price weighting of the 30 stocks (Pass_DJ). The second one uses a capital weighting (Pass_CW) and the third gives equal weights to all stocks (Pass_1/N).

Our second set of benchmarks consists of three GMVP strategies using historical estimators. The first benchmark relies on the unrestricted sample estimator of the covariance matrix

[9] Using out-of-the-money options diminishes the price effect of a potential early exercise of American options, which reduces model risk with respect to the early exercise premium. Moreover, out-of-the-money options are usually much more liquid than in-the-money options.

(Hist_Sample). The other two use shrinkage estimators that attempt to find the optimal trade-off between sampling error and specification error and combine the sample covariance matrix with estimators that impose more structure. Such shrinkage estimators are successful in earlier studies, as shown by, e.g., DeMiguel, Garlappi, Nogales, and Uppal (2009). In particular, we use the estimator by Ledoit and Wolf (2004) that shrinks the sample covariance towards the estimates obtained under constant correlations (Hist_Sh_CC) and the estimator by Ledoit and Wolf (2003) that uses a one-factor market model instead of the constant-correlation model (Hist_Sh_FM). For each of the three historical estimators, we apply three different estimation windows. The first one uses monthly returns of the preceding 60 months to estimate the covariance matrix (60 Months). The second window uses weekly returns of the preceding 60 weeks (60 Weeks) and the third one employs daily returns of the preceding 60 days (60 Days). Since all estimation windows apply the same number of observations, they allow us to look at the consequences of using more or less recent information. A natural hypothesis is that the strategies using more recent historical data perform more like the strategies using implied estimators, which exploit current market information only.

For each strategy and every month in our out-of-sample period we calculate the excess log-return and the realized volatility using the daily returns within the particular month.

3.2 MAIN RESULTS

3.2.1 Base Case

Table II shows the out-of-sample average realized return volatilities ($\overline{\sigma}$) and excess returns ($\overline{R}$) of the different portfolio strategies. For ease of interpretation, we report annualized values.

[Insert Table II about here]

Panel A shows that the two implied strategies perform about the same. The out-of-sample volatility $\overline{\sigma}$ is 13.8% for both of them. These values are clearly smaller than the ones obtained from the passive benchmark strategies (shown in Panel B). The differences are statistically significant at the 1%-level in all cases as shown by the p-values of Panel B (given in brackets). The p-values refer to tests of significant differences between the respective benchmark strategy and the implied strategies. The first p-value relates to Imp_Var and the second one to Imp_Kurt. Since no statistically significant differences exist for average returns, the implied strategies clearly beat the passive benchmark strategies with respect to the risk-return trade-off. Compared to the historical benchmark strategies (shown in Panel C), the implied estimators always lead to a smaller out-of-sample volatility, irrespective of the estimation window used for the historical estimators. The difference in out-of-sample volatility is the larger the less recent data is used. For the estimation window of 60 months, the difference is significant at the 1% level for all three historical estimators and for the estimation window of 60 weeks, the significance level is 10%, at least. For an estimation window of 60 days, the significance disappears when comparing the implied estimators with the shrinkage estimators. Overall, Table II gives a clear picture. Average returns are never significantly different. Out-of-sample volatilities are smallest for the implied strategies and highest for the passive ones. Historical benchmark strategies lie in between. Within this group, we observe that the more recent the data, the better the results. Moreover, employing a shrinkage estimator instead of the sample estimator always improves the out-of-sample volatility of the GMVP strategy.

3.2.2 Information Flow and Implied Estimators

Implied moments rely on current option prices and use no historical time series. Therefore, one expects the implied strategies to perform particularly well in crisis periods for two reasons. First, the information flow is high in crisis periods. This could make historical information less valuable leading to superiority of the implied approach, which relies solely on current data. Second, informed investors can exploit their private information better in options markets than in spot markets.[10] Therefore, one expects to see a higher fraction of informed investors in the options market during periods of high information asymmetry. This would make option prices more informative, again suggesting that the implied strategy performs particularly well in crisis periods. In quiet market periods, however, when no major events occur and the information asymmetry is low, implied moments might have no advantage over historical ones. We test these hypotheses now.

Our sample period contains two major stock market crises. The first crisis is the burst of the Dot-com bubble; the second one the global financial crisis. The burst of the Dot-com bubble began in March 2000, when the NASDAQ index lost almost nine percent of its value in just six days. As the end of the Dot-com crisis we choose April 2003, the month when the stock market started its recovery. As the starting point of the global financial crisis, we use June 2007, the month when the problems of two of Bear Stearns' hedge funds became public, and we classify the whole remaining sample period until January 2012 as a crisis period. This classification leaves us with 94 observations in crisis periods and 75 observations in non-crisis periods. Table III provides the out-of-sample volatilities and excess returns of all strategies

[10] See, for example, Kumar, Sarin, and Shastri (1992), Easley, O'Hara, and Srinivas (1998), Chakravarty, Gulen, and Mayhew (2004), Cao, Chen, and Griffin (2005), and Pan and Poteshman (2006).

for crisis and non-crisis periods.

[Insert Table III about here]

Table III shows that the out-of-sample volatility is higher in the crisis periods (Panels A - C) than in the non-crisis periods (Panels D - F), which indicates that our definition of crisis periods is sensible. When looking at crisis periods, we see a similar pattern to that in Table II which is, however, more pronounced.[11] The passive strategies (Panel B) that do not use any information about the covariance matrix perform worst. They are followed by the historical strategies (Panel C). Within this group of strategies, it always pays to use a shrinkage estimator and it is always better to use more recent data to estimate the covariance matrix. This latter finding suggests that it is crucial to adapt quickly to new information in times of crisis. Consistent with this rationale, the implied strategies that rely only on contemporaneous information perform best (Panel A). Their out-of-sample volatilities are significantly smaller than the volatilities of all other strategies.

The non-crisis periods provide a different picture of the performance of various strategies: It makes no difference how one estimates the covariance matrix. Implied (Panel D) and historical (Panel F) strategies lead to almost identical out-of-sample volatilities and we do not find a single statistically significant difference. The passive strategies (Panel E) have a significantly higher volatility, but the disadvantage is much smaller than in the crisis periods. We also observe a clear pattern in average returns, although differences are not statistically significant. Optimized portfolios (GMVPs) have higher average returns than passive portfo-

[11] The p-values in brackets refer to differences between the Imp_Var strategy and the corresponding benchmark strategy. We omit the corresponding values for the Imp_Kurt strategy here and in the following tables, because they lead to the same conclusions.

lios in crisis periods and lower average returns in non-crisis periods. This finding highlights that minimum-variance portfolios are also low-beta portfolios.[12]

3.2.3 Fully- versus Partially-Implied Estimators

A main insight from the previous section is that a GMVP strategy using implied estimators for variances and correlations delivers a lower out-of-sample volatility in crisis periods than a GMVP strategy using historical estimators for variances and correlations. We now analyze GMVP strategies that use implied and historical estimates at the same time.

Table IV reports the results for such partially-implied approaches. We again use returns of the previous 60 months, 60 weeks, and 60 days, respectively, for the historical estimates. We conduct our analysis using data from the crisis periods only, since we know from Table III that the way we estimate the covariance matrix matters only in crisis periods. The p-values, reported in brackets, refer to tests of significant differences to the fully-implied approach Imp_Var, which delivers an out-of-sample volatility of 15.1% and an average return of 0.4% (see Panel A of Table III).

We present results for four partially-implied approaches. In the first approach (Panel A), we use implied correlations and historically estimated variances. In the other approaches (Panel B), we use historically estimated correlations and implied variances. The historical correlation estimates use the sample estimator, the shrinkage estimator towards constant correlations, and the shrinkage estimator based on a factor model, respectively. Since all data needed is readily available, investors can easily apply the approaches presented in Panel B. The approach of Panel A is more challenging since one has to implement our model of

[12] Clarke, De Silva, and Thorley (2010) provide analytical results on the relation between the portfolio weights of the GMVP and betas.

Section 2.1 to extract the implied correlations from a cross-section of options.

[Insert Table IV about here]

If we combine implied correlations with historical variances (Panel A of Table IV), the out-of-sample volatilities of the corresponding GMVPs are clearly higher than the ones of the fully-implied strategy (Panel A of Table III). The p-values show that the differences are significant at the 1%-level, irrespective of the estimation window. Out-of-sample volatilities resulting from a combination of implied correlations and historical variances can even be higher than those resulting from pure historical estimates based on shrinkage estimators (see Panel C of Table III). This finding suggests that it makes no sense to use our model only to estimate implied correlations. It exploits its full potential only when used to consistently estimate implied variances and correlations.

The results for the other partially-implied approaches (Panel B of Table IV) show that the use of implied variances instead of historical ones (see Panel C of Table III) always reduces out-of-sample volatilities of the portfolio strategies. Thus, using implied information about variances leads to a clear improvement. However, the resulting out-of-sample volatility of these partially-implied approaches is still significantly higher than the volatility of the fully-implied approach in most cases. Only for the shrinkage estimators implemented with recent data do we find no significant differences between fully-implied and partially-implied strategies.

To possibly get even better results for the partially-implied approach, we now use different estimation windows. Since our analysis so far shows that more recent data leads to better results, one might expect that the results get even better if we leave out older observations.

However, there is an opposite effect. Leaving out older observations reduces the number of observations and increases the estimation risk. Given that there are a recentness effect and an opposing estimation risk effect, it is not clear ex ante whether the investor is better off using fewer than 60 daily observations. She might be even better off using more observations. We test this issue by providing results for varying numbers of daily observations in Table V. We report results for 31 days, which is the shortest period we can use given that our sample consists of 30 stocks. For comparison, we also report the results for 60 days (taken from Table IV). Finally, we calculate the values for 250 days, which roughly correspond to a one-year period.

[Insert Table V about here]

Table V shows that we cannot further improve the performance of the partially-implied strategies by using the most recent estimation period possible. When using implied correlations and historical variances (Panel A) the out-of-sample volatilities remain significantly larger than the ones derived from the implied estimators. Panel B shows the results for partially implied estimators that use historical correlations and implied variances. Interestingly, it makes no big difference for the best-performing of these partially-implied strategies whether one uses 31, 60, or 250 daily observations. This finding suggests that the recentness effect and the estimation risk effect roughly cancel out. Thus, the overall conclusion of this section is that partially implied estimators do not beat the fully-implied ones despite all our efforts.

3.2.4 Combinations of Implied and Historical Estimators

A possible way to get more precise estimates is to combine different estimators. The shrinkage estimator of Ledoit and Wolf (2004) is an example of that. It consists of a linear combination of the sample covariance matrix and an estimator that imposes more structure on the covariance matrix, namely a constant correlation across assets. We now take up this idea and combine the sample covariance matrix and the implied covariance estimator. Table VI shows the out-of-sample volatilities and excess returns of GMVPs based on three different weighting schemes, that give a weight of 75% (Imp75_Hist25), 50% (Imp50_Hist50), and 25% (Imp25_Hist75), respectively, to the implied estimator. We again focus on the crisis periods only.

[Insert Table VI about here]

The results in Table VI show that none of the combined estimators leads to a significantly lower out-of-sample volatility than the pure implied one, which equals 0.151 (see Panel A of Table III). However, note that we made no attempt to determine the optimal weighting scheme. The search for "optimal" combinations of implied and historical estimators is certainly an interesting field for future research.

4 Conclusions

In this paper, we develop a family of fully-implied estimators of the covariance matrix. Our basic idea is to obtain estimates of the covariance matrix solely from current prices of plain-vanilla options. These prices reflect market expectations about the return distributions of the underlying assets. Therefore, the approach is forward looking and differs fundamentally from the backward-looking approach that uses time series of returns. The members of the family differ with respect to the moment of the implied distribution they use to obtain the covariance matrix. We implement estimators based on the second and fourth moment.

We test the quality of the new estimators by analyzing the out-of-sample performance of the corresponding global minimum variance (GMVP) strategies for the 30 stocks included in the Dow Jones Industrial Average (DJIA) and find that they work equally well. We compare their performance with several benchmark strategies and show that it makes a big difference which strategy one uses, but only in periods of high information flow. Then the investor is better off by using more recent data, in particular using only current market data as in our fully-implied approach. Historical strategies, partially-implied strategies, and strategies based on combinations of historical and implied estimators also gain from using more recent data, but never beat the fully-implied strategies.

Our empirical study delivers two main insights for an investor: First, strategies based on fully-implied estimators are a good choice because they significantly outperform the benchmark strategies in most cases and are never beaten by any other strategy. Second, if an investor nevertheless wants to use historical estimators, she should use shrinkage estimators and most recent data.

Our paper has three main limitations to be addressed in future research. First, it demonstrates a superior performance of the implied estimators only for an investment universe of 30 blue-chip stocks over a period when options data on the DJIA is available. However, the number of assets in the investment universe might have an impact on the results. Since the implied estimators impose cross-sectional restrictions that might not be adequate for a larger investment universe with more heterogeneous stocks, it is possible that the performance of the implied estimators is worse when applied to a wider investment universe.

Second, the implied estimators derived in this paper rely on a single-factor return structure. Generalizations of our fully-implied approach to multi-factor return structures are possible under two conditions. (i) We need options written on all factors to obtain implied moment estimates. (ii) We have to impose multiple cross-sectional restrictions to achieve identification of the model parameters. For example, one could assume that the proportion of systematic variance is identical for all stocks in the cross section - as for our variance-based estimator - and idiosyncratic skewness is zero as assumed by Chang, Christoffersen, Jacobs, and Vainberg (2012).

Finally, our paper focusses on GMVP strategies and, therefore, uses only forward-looking information about the covariance matrix. The natural next step would be to combine the fully-implied covariance matrix suggested in this paper with option-implied information about expected returns. This would allow us to go beyond the GMVP and possibly reach an even better out-of-sample performance. We believe that this is a promising avenue for further research since several recent papers like Ang, Bali, and Cakici (2010), Bali and Hovakimian (2009), Conrad, Dittmar, and Ghysels (2009), Cremers and Weinbaum (2010), DeMiguel, Plyakha, Uppal, and Vilkov (2012), Rehman and Vilkov (2010), and Xing, Zhang, and Zhao (2010) show that option-implied information has predictive power for expected returns.

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Table I. Excess returns and return volatilities of individual stocks and the Dow Jones Index

This table shows average excess returns and return volatilities of individual stocks and the Dow Jones Index. We calculate average excess returns and return volatilities using daily data and report annualized values. The upper part of the table lists all stocks that are in the index during the full period (January 1998 to January 2012). The lower part of the table lists all other stocks together with the periods when they have been in the index.

Tickers	$\overline{R}$	$\overline{\sigma}$	Period
CAT	0.111	0.333	01/98 - 1/12
UTX	0.097	0.272	01/98 - 1/12
MCD	0.090	0.251	01/98 - 1/12
IBM	0.071	0.264	01/98 - 1/12
XOM	0.066	0.242	01/98 - 1/12
WMT	0.057	0.254	01/98 - 1/12
MMM	0.046	0.242	01/98 - 1/12
AXP	0.038	0.354	01/98 - 1/12
JNJ	0.035	0.194	01/98 - 1/12
BA	0.028	0.313	01/98 - 1/12
PG	0.025	0.214	01/98 - 1/12
JPM	0.004	0.379	01/98 - 1/12
DD	-0.003	0.289	01/98 - 1/12
DIS	-0.003	0.314	01/98 - 1/12
KO	-0.006	0.216	01/98 - 1/12
HPQ	-0.008	0.374	01/98 - 1/12
GE	-0.022	0.289	01/98 - 1/12
MRK	-0.023	0.276	01/98 - 1/12
AA	-0.047	0.397	01/98 - 1/12
DJ Index	0.005	0.181	01/98 - 1/12
UK	0.181	0.393	01/98 - 11/99
TRV	0.161	0.215	06/09 - 1/12
MO	0.090	0.270	01/98 - 02/08
CVX	0.087	0.291	02/08 - 1/12
KFT	0.077	0.204	09/08 - 1/12
T	0.065	0.220	11/05 - 1/12
CVX	0.063	0.282	01/98 - 11/99
VZ	0.045	0.199	04/04 - 1/12
CSCO	0.041	0.281	06/09 - 1/12
HON	0.026	0.323	01/98 - 02/08
HD	-0.021	0.316	11/99 - 1/12
IP	-0.027	0.340	01/98 - 04/04
MSFT	-0.036	0.295	11/99 - 1/12
INTC	-0.043	0.379	11/99 - 1/12
PFE	-0.054	0.232	04/04 - 1/12
SBC	-0.136	0.331	11/99 - 11/05
EK	-0.144	0.333	01/98 - 04/04
C	-0.192	0.406	01/98 - 06/09
T	-0.205	0.412	01/98 - 04/04
S	-0.253	0.370	01/98 - 11/99
GM	-0.326	0.462	01/98 - 06/09
GT	-0.342	0.322	01/98 - 11/99
BAC	-0.401	0.683	02/08 - 1/12
AIG	-0.653	0.332	04/04 - 09/08

Table II. Out-of-sample volatilities and excess returns of the portfolio strategies

This table shows out-of-sample average realized return volatilities ($\overline{\sigma}$) and excess returns ($\overline{R}$) of different portfolio strategies using monthly rebalancing. We report annualized values of volatilities and returns. The out-of-sample period starts in January 1998 and ends in January 2012, i.e., the number of observations is 169. Panel A presents the results for GMVPs based on the implied estimators. We denote the strategy using the implied estimator derived in Section 2.1 by Imp_Var and the one derived in Section 2.3 by Imp_Kurt. Panel B reports the results for the following passive benchmarks strategies: passive investments using price weighting (Pass_DJ), capital weighting (Pass_CW), and equal weighting (Pass_1/N), respectively. The numbers in brackets are p-values for tests of significant differences between the implied strategies (Imp_Var, Imp_Kurt) and the benchmarks. The first p-value relates to Imp_Var and the second one to Imp_Kurt. Panel C provides the results for GMVPs based on three historical estimators for different estimation windows (60 months, 60 weeks, 60 days). The historical estimators are the sample estimator (Hist_Sample), Ledoit's and Wolf's (2004) estimator that shrinks the sample correlations towards constant correlations (Hist_Sh_CC), and Ledoit's and Wolf's (2003) estimator that shrinks the sample correlations towards those obtained from a one-factor model (Hist_Sh_FM). The numbers in brackets are again p-values for tests of significant differences between the implied strategies (Imp_Var, Imp_Kurt) and the benchmarks. The first p-value relates to Imp_Var and the second one to Imp_Kurt.

Panel A: Portfolios Based on Implied Estimators

$\overline{\sigma}$	$\overline{R}$	$\overline{\sigma}$	$\overline{R}$
Imp_Var		**Imp_Kurt**	
0.138	**0.028**	**0.138**	**0.031**

Panel B: Passive Benchmarks

$\overline{\sigma}$	$\overline{R}$	$\overline{\sigma}$	$\overline{R}$	$\overline{\sigma}$	$\overline{R}$
Pass_DJ		**Pass_CW**		**Pass_1/N**	
0.174	**0.026**	**0.181**	**0.005**	**0.187**	**0.024**
(0.000)	(0.946)	(0.000)	(0.465)	(0.000)	(0.912)
(0.000)	(0.860)	(0.000)	(0.407)	(0.000)	(0.839)

Panel C: Benchmarks Based on Historical Estimators

	$\overline{\sigma}$	$\overline{R}$	$\overline{\sigma}$	$\overline{R}$	$\overline{\sigma}$	$\overline{R}$
	Hist_Sample		**Hist_Sh_CC**		**Hist_Sh_FM**	
	0.151	**0.020**	**0.149**	**0.017**	**0.148**	**0.023**
60 Months	(0.000)	(0.724)	(0.000)	(0.565)	(0.000)	(0.821)
	(0.000)	(0.617)	(0.000)	(0.457)	(0.000)	(0.699)
	0.146	**0.026**	**0.141**	**0.025**	**0.141**	**0.018**
60 Weeks	(0.001)	(0.940)	(0.083)	(0.859)	(0.100)	(0.630)
	(0.000)	(0.221)	(0.032)	(0.897)	(0.033)	(0.440)
	0.143	**0.016**	**0.141**	**0.023**	**0.139**	**0.013**
60 Days	(0.004)	(0.540)	(0.103)	(0.755)	(0.370)	(0.404)
	(0.007)	(0.436)	(0.152)	(0.618)	(0.489)	(0.309)

Table III. Out-of-sample volatilities and excess returns of the portfolio strategies in periods of crisis and periods of no crisis

This table shows out-of-sample average realized return volatilities ($\overline{\sigma}$) and excess returns ($\overline{R}$) for the same portfolio strategies as in Table II, now separately for periods of crisis (Panels A, B, and C) and periods of no crisis (Panels D, E, and F). Crisis periods are March 2000 to April 2003 and June 2007 to January 2012 (94 observations). Non-crisis periods are January 1998 to February 2000 and May 2003 to May 2007 (75 observations). The numbers in brackets are p-values for tests of significant differences between the implied strategy Imp_Var and the benchmarks.

Panel A: Portfolios Based on Implied Estimators: Crisis

$\overline{\sigma}$	$\overline{R}$	$\overline{\sigma}$	$\overline{R}$
Imp_Var		**Imp_Kurt**	
0.151	**0.004**	**0.152**	**0.007**

Panel B: Passive Benchmarks: Crisis

$\overline{\sigma}$	$\overline{R}$	$\overline{\sigma}$	$\overline{R}$	$\overline{\sigma}$	$\overline{R}$
Pass_DJ		**Pass_CW**		**Pass_1/N**	
0.210	**-0.036**	**0.219**	**-0.065**	**0.231**	**-0.045**
(0.000)	(0.174)	(0.000)	(0.168)	(0.000)	(0.396)

Panel C: Benchmarks Based on Historical Estimators: Crisis

	$\overline{\sigma}$	$\overline{R}$	$\overline{\sigma}$	$\overline{R}$	$\overline{\sigma}$	$\overline{R}$
	Hist_Sample		**Hist_Sh_CC**		**Hist_Sh_FM**	
	0.174	**-0.018**	**0.168**	**-0.016**	**0.169**	**-0.007**
60 Months	(0.000)	(0.517)	(0.000)	(0.488)	(0.000)	(0.751)
	0.165	**-0.036**	**0.158**	**-0.017**	**0.160**	**-0.035**
60 Weeks	(0.000)	(0.196)	(0.005)	(0.387)	(0.004)	(0.168)
	0.161	**-0.015**	**0.157**	**-0.009**	**0.156**	**-0.017**
60 Days	(0.001)	(0.161)	(0.026)	(0.557)	(0.079)	(0.408)

Panel D: Portfolios Based on Implied Estimators: No Crisis

$\overline{\sigma}$	$\overline{R}$	$\overline{\sigma}$	$\overline{R}$
Imp_Var		**Imp_Kurt**	
0.120	**0.059**	**0.121**	**0.063**

Panel E: Passive Benchmarks: No Crisis

$\overline{\sigma}$	$\overline{R}$	$\overline{\sigma}$	$\overline{R}$	$\overline{\sigma}$	$\overline{R}$
Pass_DJ		**Pass_CW**		**Pass_1/N**	
0.128	**0.106**	**0.131**	**0.094**	**0.129**	**0.112**
(0.001)	(0.164)	(0.001)	(0.318)	(0.007)	(0.123)

Panel F: Benchmarks Based on Historical Estimators: No Crisis

	$\overline{\sigma}$	$\overline{R}$	$\overline{\sigma}$	$\overline{R}$	$\overline{\sigma}$	$\overline{R}$
	Hist_Sample		**Hist_Sh_CC**		**Hist_Sh_FM**	
	0.122	**0.069**	**0.124**	**0.060**	**0.121**	**0.063**
60 Months	(0.600)	(0.718)	(0.102)	(0.993)	(0.771)	(0.884)
	0.121	**0.107**	**0.119**	**0.079**	**0.118**	**0.086**
60 Weeks	(0.949)	(0.121)	(0.639)	(0.476)	(0.369)	(0.357)
	0.121	**0.055**	**0.120**	**0.063**	**0.118**	**0.051**
60 Days	(0.748)	(0.885)	(0.784)	(0.897)	(0.341)	(0.762)

Table IV. Out-of-sample volatilities and excess returns of GMVPs based on partially-implied estimators

This table shows out-of-sample average realized return volatilities ($\overline{\sigma}$) and excess returns ($\overline{R}$) of portfolio strategies based on partially-implied estimators of the covariance matrix. We again use monthly rebalancing and report annualized values of volatilities and returns. The out-of-sample period covers the crisis periods from March 2000 to April 2003 and June 2007 to January 2012 (94 observations). Historical variances and correlations use monthly returns of the preceding 60 months (60 Months), weekly returns of the preceding 60 weeks (60 Weeks), or daily returns of the preceding 60 days (60 Days). Panel A reports the results for GMVP strategies that use implied correlations and historical variances. We obtain implied correlations from our variance-based estimator derived in Section 2.1. Panel B shows the results for GMVP strategies based on historical correlations and implied variances. The historical correlation estimators are the sample estimator (Hist_Sample), Ledoit's and Wolf's (2004) estimator that shrinks the sample correlations towards constant correlations (Hist_Sh_CC), and Ledoit's and Wolf's (2003) estimator that shrinks the sample correlations towards those obtained from a one-factor model (Hist_Sh_FM). The numbers in brackets are p-values for tests of significant differences between the fully-implied strategy Imp_Var and the corresponding partially-implied strategy.

Panel A: Implied Correlations – Historical Variances

	$\overline{\sigma}$	$\overline{R}$
	0.169	**-0.011**
60 Months	(0.000)	(0.650)
	0.159	**-0.018**
60 Weeks	(0.001)	(0.354)
	0.159	**-0.002**
60 Days	(0.000)	(0.766)

Panel B: Historical Correlations – Implied Variances

	$\overline{\sigma}$	$\overline{R}$	$\overline{\sigma}$	$\overline{R}$	$\overline{\sigma}$	$\overline{R}$
	Hist_Sample		**Hist_Sh_CC**		**Hist_Sh_FM**	
	0.164	**-0.034**	**0.155**	**-0.021**	**0.160**	**-0.020**
60 Months	(0.000)	(0.187)	(0.031)	(0.134)	(0.000)	(0.309)
	0.162	**-0.024**	**0.153**	**-0.009**	**0.156**	**-0.021**
60 Weeks	(0.000)	(0.305)	(0.157)	(0.362)	(0.020)	(0.284)
	0.158	**-0.031**	**0.151**	**-0.018**	**0.152**	**-0.026**
60 Days	(0.007)	(0.172)	(0.799)	(0.167)	(0.638)	(0.187)

Table V. Out-of-Sample volatilities and excess returns of GMVPs based on partially-implied estimators: alternative estimation windows

This table shows out-of-sample average realized return volatilities ($\overline{\sigma}$) and excess returns ($\overline{R}$) for the same portfolio strategies and out-of-sample period as in Table IV, but now based on alternative estimation windows. Historical variances and correlations use daily returns of the preceding 31 days (31 Days), 60 days (60 Days), or 250 days (250 Days), respectively.

Panel A: Implied Correlations – Historical Variances

	$\overline{\sigma}$	$\overline{R}$
31 Days	**0.165** (0.000)	**0.001** (0.911)
60 Days	**0.159** (0.000)	**-0.002** (0.766)
250 Days	**0.157** (0.003)	**-0.003** (0.733)

Panel B: Historical Correlations – Implied Variances

	$\overline{\sigma}$	$\overline{R}$	$\overline{\sigma}$	$\overline{R}$	$\overline{\sigma}$	$\overline{R}$
	Hist_Sample		**Hist_Sh_CC**		**Hist_Sh_FM**	
31 Days	**0.162** (0.000)	**-0.022** (0.393)	**0.151** (0.680)	**-0.015** (0.139)	**0.153** (0.388)	**-0.020** (0.317)
60 Days	**0.158** (0.007)	**-0.031** (0.172)	**0.151** (0.799)	**-0.018** (0.167)	**0.152** (0.638)	**-0.026** (0.187)
250 Days	**0.153** (0.327)	**-0.027** (0.163)	**0.151** (0.936)	**-0.015** (0.289)	**0.152** (0.734)	**-0.021** (0.214)

Table VI. Out-of-sample volatilities and excess returns of GMVPs based on combinations of implied and historical estimators

This table shows out-of-sample average realized return volatilities ($\overline{\sigma}$) and excess returns ($\overline{R}$) of portfolio strategies based on a combination of implied and historical covariance estimators. We again use monthly rebalancing and report annualized values of volatilities and returns. The out-of-sample period covers the crisis periods from March 2000 to April 2003 and June 2007 to January 2012 (94 observations). The implied covariance estimator is the variance-based estimator Imp_Var derived in Section 2.1. The historical estimator is the sample estimator obtained from monthly returns of the preceding 60 months (60 Months), weekly returns of the preceding 60 weeks (60 Weeks), or from daily returns of the preceding 60 days (60 Days). The weight of the implied estimator is 75% (Imp75_Hist25), 50% (Imp50_Hist50), or 25% (Imp25_Hist75), respectively. The numbers in brackets are p-values for tests of significant differences between the fully-implied strategy Imp_Var and the corresponding strategy that uses a combination of implied and historical estimators.

	$\overline{\sigma}$	$\overline{R}$	$\overline{\sigma}$	$\overline{R}$	$\overline{\sigma}$	$\overline{R}$
	Imp75_Hist25		**Imp50_Hist50**		**Imp25_Hist75**	
	0.152	**-0.014**	**0.155**	**-0.021**	**0.162**	**-0.021**
60 Months	(0.762)	(0.099)	(0.019)	(0.177)	(0.000)	(0.317)
	0.150	**-0.009**	**0.153**	**-0.019**	**0.158**	**-0.028**
60 Weeks	(0.355)	(0.178)	(0.294)	(0.202)	(0.013)	(0.206)
	0.150	**-0.006**	**0.152**	**-0.011**	**0.155**	**-0.016**
60 Days	(0.228)	(0.371)	(0.838)	(0.411)	(0.070)	(0.389)

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