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In this paper we compute long-term stock return expectations (across the business cycle) for individual firms using information backed out from the credit derivatives market. Our methodology builds on previous theoretical results in the literature on stock return expectations and, empirically, we demonstrate a close relationship between credit-implied stock return expectations and future realized stock returns. We also find stock portfolios selected based on credit-implied stock return forecasts to beat equally- and value-weighted portfolios of the same stocks out-of-sample. Contrary to many other studies, our expectations/predictions are made at the individual stock level rather than at the portfolio level, and no parameter estimations using historical stock price- or credit spread observations are needed.

Keywords: stock market; credit default swap; implied volatility; CreditGrades; return expectations
JEL classification codes: G10; G01

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The goal of this paper is to demonstrate how one can compute, or explain, long-term stock return expectations (across the business cycle) using information from the credit derivatives market. We also show how stock portfolios formed based on these expectations outperform simple benchmark stock portfolios.

We build our approach on a model suggested by Martin and Wagner (2016) that links stock return expectations and risk-neutral idiosyncratic (or rather individual) stock return variances (SVIX indexes). While Martin and Wagner (2016) uses option-implied variances we instead use credit default swap (CDS) implied variances backed out using the methodology described in Byström (2015, 2016). In addition to reflecting stock market expectations among the market participants in the credit market rather than those in the equity market, our approach has the advantage of allowing for a much longer-term focus than the equity market. If one uses ordinary call- and put-options, like Martin and Wagner (2016), the available option maturities limit the horizon of the expectation or forecast to a maximum of twelve, or perhaps twenty-four, months. Martin and Wagner (2016), indeed, looks at horizons between one and twelve months. If one instead uses credit default swaps to back out the implied stock return variances then the available horizons are much longer. In most markets there are credit default swaps with maturities between one year and ten years and this allows us to back out stock market expectations at the same time horizons. Such long-term expectations and forecasts are obviously relevant for the strategic asset allocation of asset managers with long investment horizons such as pension funds and insurance companies. However, hedge funds and family offices also need to form long-term expectations on individual stocks. The literature on long-term expectations of individual stock returns is very limited though and the volume does not reflect the practical relevance and importance that real-life investors attribute to reliable long-term stock market forecasts.

Since our approach builds directly on the theoretical results in Martin and Wagner (2016) it shares the nice feature of not relying on parameter estimations. No historical stock price- or credit spread observations are needed. Moreover, the expectations can be updated in real-time and apply to individual stocks rather than portfolios. In Martin and Wagner (2016), the risk-neutral equity-implied variances are linked to return expectations through indexes labeled SVIX indexes. In this paper the risk-neutral implied variances come from the credit market, and to emphasize the different origins of the expectations we label our variance indexes ^{C}SVIX indexes.

According to standard financial theory it is systematic risk, rather than firm-specific or idiosyncratic risk, that is of interest to stock market investors. The insight that only systemic risk is priced has been challenged in the recent literature, however. Goyal and Santa-Clara (2003), for instance, claims that idiosyncratic volatility can positively predict excess market returns. Fu (2009) also finds a positive relationship between expected returns and (conditional) idiosyncratic volatility. Ang et al. (2006) instead finds that stocks with high idiosyncratic volatility (and high firm-specific volatility) have low average returns, a finding that is subsequently rebutted by Fu (2009). Adding to the conflicting empirical evidence, in a recent paper Begin et al. (2016) also uses options data and shows that it is tail risk, rather than diffusion risk, that plays a central role in the pricing of idiosyncratic risk.

Martin and Wagner (2016) looks at the variance of individual stocks and suggests a positive link between the options-implied variance of a stock and the expected (excess) return of the stock. They go on to show that their theoretical relationship holds empirically for horizons between one and twelve months. In this paper we confirm that the theoretical relationship in Martin and Wagner (2016) holds also when we replace equity options (SVIX) with credit default swaps (^{C}SVIX). We find a strong link between risk-neutral variances and realized returns at the much longer horizon of five years. And when we pick stocks based on our credit-implied ^{C}SVIX indexes the stock-portfolios beat both equally- and value-weighted portfolios out-of-sample. While we only forecast stock returns over a five-year horizon in this paper, in theory, the methodology lends itself equally well to any forecasting horizon between one- and ten years.

In the next section we review the Martin and Wagner (2016) methodology and introduce the ^{C}SVIX indexes. Section two describes our method of backing out risk-neutral stock return variances from the credit derivatives market and section three presents the data and the empirical results. Section four contains some robustness checks and section five concludes the paper.

1. ^{C}SVIX-Indexes and the Expected Return of a Stock

Martin and Wagner (2016) shows theoretically how the expected return on an individual stock can be expressed in terms of the risk-neutral variance of the market (SVIX), the risk-neutral variance of the individual stock (SVIX_i), and a value-weighted average of individual stocks' risk-neutral variances ($\mathrm{SVIX}_{\mathrm{average}}$). Assuming constant fixed effects across stocks, Martin and Wagner (2016) ends up with the following formula for the expected excess return of a stock

$$\frac{E_t R_{i,t+1} - R_{f,t+1}}{R_{f,t+1}} = SVIX_t^2 + \frac{1}{2}\left(SVIX_{i,t}^2 - SVIX_{average,t}^2\right) \quad (1)$$

where the SVIX variance indexes are defined as

$$SVIX_t^2 = \mathrm{var}_t^*\left(\frac{R_{m,t+1}}{R_{f,t+1}}\right)$$

$$SVIX_{i,t}^2 = \mathrm{var}_t^*\left(\frac{R_{i,t+1}}{R_{f,t+1}}\right)$$

$$SVIX_{average,t}^2 = \sum_i w_{i,t} SVIX_{i,t}^2$$

and $R_{i,t+1}$ is the (gross) return of the individual stock i, $R_{m,t+1}$ is the (gross) return of the market, $R_{f,t+1}$ is the (gross) risk-free return and w_i is the market weight of stock i.

Martin and Wagner (2016) computes the various SVIX variance indexes using stock return variances implied by equity options. In this paper we instead use stock return variances implied by credit derivatives. Our approach of backing out variances from credit default swap spreads will be described in the next section and in order to highlight the different origin of the variance we name the resulting volatility indexes $^{C}SVIX$, $^{C}SVIX_{i}$, and $^{C}SVIX_{average}$. The only difference compared to the original SVIX indexes of Martin and Wagner (2016) is the source of the implied variance and the resulting formula for the expected return of a stock is therefore

$$\frac{E_t R_{i,t+1} - R_{f,t+1}}{R_{f,t+1}} = {}^{C}SVIX_t^2 + \frac{1}{2}\left({}^{C}SVIX_{i,t}^2 - {}^{C}SVIX_{average,t}^2\right) \tag{2}$$

Like in Martin and Wagner (2016), our implementation of the relationship between expected stock returns and risk-neutral stock return variances requires no parameter estimation using historical stock prices or CDS spreads.

2. Stock Market Volatility According to the Credit Derivatives Market

Implied stock return volatilities (variances) are typically backed out from equity options. Martin and Wagner (2016) follows this path and computes implied (risk-neutral) stock return variances using call- and put options on individual stocks. The maturities of the options employed by Martin and Wagner (2016) range from one month to one year. In this paper, we turn to the credit derivatives market, rather than the equity derivatives market, to back out stock market variances. We follow Byström (2015, 2016) and compute implied stock volatilities by inverting the CreditGrades (2002) model. The process is similar to how ordinary implied volatilities are backed out using the Black-Scholes model, but with the equity options market replaced by the credit default swap market. Compared to Martin and Wagner (2016) our expected stock returns are therefore the expectations of credit- rather than equity investors. Another important difference is the maturity of the forecast. As a result of the long maturities in the CDS market, the expectations generated using our approach are expectations over the coming years, i.e. very long-term expectations, while the expectations in Martin and Wagner (2016) are expectations over the coming months. In this paper we have chosen a five-year forecasting horizon but we could equally well had chosen any other horizon between one and ten years, i.e. the available maturities of the credit default swaps in the market.

CreditGrades is normally used to compute stock-market implied CDS spreads and it relies on stock prices, stock return volatilities, debt levels and model assumptions similar to those in Merton (1974) to do so. The asset value is assumed to follow a standard geometric Brownian motion but, in a generalization of the Merton model, CreditGrades also allows the recovery rate to fluctuate. In the CreditGrades model the credit default swap spread for a certain maturity, T, is

$$CDS_{spread} = r(1-R)\frac{1-P(0)+e^{r\xi}(G(T+\xi)-G(\xi))}{P(0)-P(T)e^{-rT}-e^{r\xi}(G(T+\xi)-G(\xi))} \tag{3}$$

where $P(t)$ is the survival probability

$$P(t) = N(-\frac{A_t}{2}+\frac{\ln(d)}{A_t}) - dN(-\frac{A_t}{2}-\frac{\ln(d)}{A_t})$$

and where

$$d = \frac{V_0}{L_{mean}D}e^{\lambda^2},$$

$$A_t^{\,2} = \sigma^2 t + \lambda^2,$$

$$G(t) = d^{z+\frac{1}{2}}N(-\frac{\ln(d)}{\sigma\sqrt{t}} - z\sigma\sqrt{t}) + d^{-z+\frac{1}{2}}N(-\frac{\ln(d)}{\sigma\sqrt{t}} + z\sigma\sqrt{t}),$$

$$\xi = \frac{\lambda^2}{\sigma^2},$$

$$z = \sqrt{\frac{1}{4} + \frac{2r}{\sigma^2}}.$$

L_{mean} and λ is the mean and standard deviation, respectively, of the global recovery rate while R is the issue-specific recovery rate. r is the risk-free interest rate and σ, the asset volatility, is normally calculated from the equity volatility, σ_E, since asset values are non-observable. CreditGrades uses the linear approximation $V = E + L_{mean}D$, where E and D is the firm's equity and debt, respectively, and this implies that $\sigma = (\sigma_E E) / (E + L_{mean}D)$. For a more detailed description of the CreditGrades model we refer to the CreditGrades™ Technical Document (CreditGrades (2002)).

Now, in this paper we follow Byström (2015, 2016) and invert the CreditGrades model (numerically) in order to get stock return volatilities, σ_E, implied by the observed credit default swap spreads in the market. These volatilities are then used to compute the ^{C}SVIX indexes that we use to estimate the expected stock returns. The CreditGrades model requires estimates of the mean global recovery rate, L_{mean}, the standard deviation of the global recovery rate, λ, as well as the issue-specific recovery rate, R. We follow the CreditGrades Technical Document (CreditGrades, 2002) when choosing the global recovery rate; i.e. we let $L_{mean} = 0.5$. We then let the issue-specific recovery rate R be equal to the global recovery rate for all firms. When it comes to λ, however, we treat non-financial and financial firms differently. As discussed in Byström (2015), the CreditGrades Technical Document acknowledges that λ is likely to be lower for financial firms than for non-financial firms. We therefore follow Byström (2015) and let λ=0.3 for non-financial firms and λ=0.03 for financial firms. In other words, the CreditGrades benchmark λ-value is used for non-financial firms while a λ-value one tenth the size of the benchmark value is used for financial firms. This choice is based on the difference in leverage between non-financial firms and financial firms.

We also follow Byström (2015) in treating financial firms' debt different from non-financial firms'. In the light of the discussion on government bank support and "effective leverage ratios" in the CreditGrades Technical Document, Byström (2015) adjusts financial firm debt by multiplying the actual debt levels by one half to better reflect the actual default risk. In this paper, we also calculate effective debt levels for financial firms in this way.

3. Data and Empirical Results

In this section, we empirically examine the performance of the credit default swap market in predicting future stock returns using the theoretical relationship derived by Martin and Wagner (2016) between a stock's expected return and the risk-neutral variance of the market, the individual stock's risk-neutral variance, and the value-weighted average risk-neutral variance across all individual stocks. We have chosen to focus on the expected stock returns of the 125 firms in the iTraxx Europe CDS index (Series 25). The European CDS market is one of the most mature CDS markets and the credit default swaps included in the iTraxx index are among the most liquid CDS contracts around. The 125 European firms come from five industry sectors (Autos & Industrials, Consumers, Energy, Financials and TMT). Due to missing observations, firms not having publicly traded stocks or (a few) non-converging numerical volatility estimations (when keeping the L_{mean} and λ values unchanged) the final sample consists of 91 firms, among which 68 are non-financial firms and 23 are financial firms.

The overall time-period of the study, December 14, 2007 to December 31, 2015, is determined by data availability. We are focusing on long-term (five-year) stock return expectations and forecasts, and our credit-implied expected stock returns are consequently only computed from December 14, 2007 to December 31, 2010, since a five-year long out-of-sample period is needed for forecast evaluation purposes. The maturity of the (Euro-denominated) CDS contracts is five years and all data, except the leverage ratios, is available on a daily basis and downloaded from Datastream. The leverage ratios are available on a yearly basis and are from the web page of Professor Damodaran at New York University. They are transformed to daily debt levels using a linear interpolation between year-end observations. All values are denominated in Euro and as a proxy for the risk-free interest rate we use the Euro 3M deposit rate.

The expected five-year excess returns computed from equation (2) are plotted in Figure 1 (averaged across firms). The expectations are based on five-year credit default swap spreads and therefore correspond to long-term (five-year) forecasts. As shown in Figure 1, and in line with the short-term expectations in Martin and Wagner (2016), our long-term expectations are both high and volatile. At the beginning of the sample, the credit market expects European stock returns over the coming five years (2007-2012) to be around 10% annually. During the crisis, the expectations steadily rise until the expectations of future five-year returns (2009-2014) reach a maximum of 30% around the time of the stock market bottom in March 2009. From then on, the expectations fluctuate between 20% and 35% with an all-time-maximum for the average firm of 36% in May 2010. Among the various industry sectors, the only sector that stands out is the financial sector where, from the start of the financial crisis in October 2008 onwards, the expectations are much lower than in the other industry sectors. This is probably as expected considering that the crisis had its epicenter in the financial industry, and it is also consistent with the, ex post, much lower observed stock returns from 2008 to 2010 in the financial sector, compared to in the other non-financial sectors.

3.1 Correlation Results

Before we turn to regressions between expected excess returns and (subsequent) realized excess returns we look at simple pair-wise correlations between the two. We calculate *average* correlations in two ways; (i) the time-series *average* of daily *cross-sectional correlations* among the firms in the sample (for a given day, how similar are the distributions of expected and realized returns among the firms) and (ii) the cross-sectional *average* across the firms of (firm by firm) *time-series correlations* between expected and realized returns (for a given firm, how similar are the time-series movements for expected and realized returns). High correlations of the type labelled *cross-sectional correlation* opens up for stock picking while high correlations of the type labelled *time-series correlation* opens up for market timing.

Now, for our particular sample of firms, and for our choice of time-period, the average *cross-sectional* correlation is found to be quite high at 0.41 and the average *time-series correlation* is found to be even higher at 0.75. I.e. the numbers are high enough to imply a strong link between ^{C}SVIX-implied expected returns and subsequent realized returns. The high correlations also indicate that ^{C}SVIX indexes possibly could be used both for stock picking and for market timing.

3.2 Regression Results

We will now test, more formally, whether equation (2) holds or not, empirically, when we replace the SVIX indexes of Martin and Wagner (2016) with our ^{C}SVIX indexes, i.e. when we replace equity-derivatives implied variances with credit-derivatives implied ones.

Like Martin and Wagner (2016) we start with a preliminary analysis of whether time-series averages of stocks' excess returns line up with ^{C}SVIX, ^{C}SVIX$_{i}$ and ^{C}SVIX$_{average}$ as postulated by equation (2). Since we rely on five-year credit default swaps, all the ^{C}SVIX indexes represent the credit derivatives market's forecasts of stock return variances over the next five years. Equation (2) predicts that for each percentage point change in ^{C}SVIX$^{2}_{i}$ - ^{C}SVIX$^{2}_{average}$ the expected excess stock return should change half a percentage point. In the empirical analysis we replace the expected excess return with the realized excess return and in OLS regressions of excess returns on 0.5•(^{C}SVIX$^{2}_{i}$ - ^{C}SVIX$^{2}_{average}$), averaged across the time-period Dec. 14, 2007 to Dec. 31, 2010, the estimated slope value is 1.14 (t-value = 4.67 and R^2 = 0.20). This is close to the value predicted by theory (1.0) and close to the value of 1.12 in Martin and Wagner (2016) for their longest maturity (one year). The estimate of the intercept is not significantly different from zero and the relationship between excess returns and risk-neutral variances suggested by Martin and Wagner (2016) holds up well, at least when we look at time-series averages, when equity-option implied variances are replaced by credit default swap implied variances (like Martin and Wagner (2016) we require full-sample period coverage of all firms).

The next step is to perform a conditional analysis, using monthly data, where we test if the relationship in (2) holds by pooling all our panel observations and run the regression

$$\frac{R_{i,t+1} - R_{f,t+1}}{R_{f,t+1}} = \alpha + \beta \cdot {}^{C}\ SVIX_{t}^{2} + \gamma \cdot \left({}^{C}\ SVIX_{i,t}^{2} - {}^{C}\ SVIX_{average,t}^{2} \right) + \varepsilon_{i,t+1} \tag{4}$$

We expect α = 0, β = 1 and γ = 0.5, and the results for the full sample of firms are found in Table I. We find α = -0.16, β = 0.94 and γ = 0.38 and all the regression coefficients are statistically significant (R^2 = 0.26). The two slope coefficients β and γ are close to the theoretically expected values but the intercept term α is different from zero (negative). The interpretation of this is that while there indeed is a strong positive relationship between stocks' risk-neutral variances and excess returns, as postulated by theory, the constant term α shifts the entire relationship downwards. This negative shift is most likely caused by our particular choice of time-period, with the large negative (realized) returns during the time of the financial crisis dominating the picture. In fact, this is confirmed in section 4 below when we perform our analysis on a year-by-year basis. In sum, however, the theoretical relationship in Martin and Wagner (2016) seems to hold also when we replace short-term (<1Y) equity options-implied variances with long-term (5Y) credit default swap-implied ones.

3.3 Portfolio Selection and Simple Trading Schemes

The statistically significant relationship between current risk-neutral variances and future excess returns in the previous sub-section opens up for the possibility of using credit default swaps when making long-term predictions in the stock market. We will now look into the economic significance of this opportunity using a simple investment (portfolio selection) scheme based on the predictive ability of the ^{C}SVIX indexes. Forecasts of individual firms' excess stock returns are made using contemporaneous data. Neither future- nor historical data is used and the resulting out-of-sample portfolio selection scheme closely resembles a real-life trading exercise.

Our investment strategy is essentially the same as that in Martin and Wagner (2016) and, like them, we construct stock portfolios with weights based on the model-implied expected returns and then compare these portfolios with naïve equally-weighted and value-weighted portfolios of the same stocks. Like Martin and Wagner (2016) we build on Asness et al. (2013) and choose weights in our model-implied portfolios based on the ranks of the firms' expected five-year excess returns at time *t*

$$w_{i,t}^{rank} = \frac{rank\left[E_t R_{i,t+1}\right]^{\theta}}{\sum_i rank\left[E_t R_{i,t+1}\right]^{\theta}} \tag{5}$$

where $\theta > 0$ is a measure of the aggressiveness of the strategy. This portfolio selection strategy ensures that the weights allocated to the stocks are all positive, that they increase with the stocks' expected returns and that they sum to one, i.e. our hypothetical investor behaves like a fully invested long-only investor with equally- and value-weighted portfolios of the same stocks as natural benchmarks. Like Martin and Wagner (2016) we vary the aggressiveness in the stock selection by setting $\theta = 1$ or $\theta = 2$ in our empirical analysis. The higher the θ-value the more emphasis is put on the model's ranking of stocks' expected returns when choosing the portfolio weights. With $\theta = 1$ or $\theta = 2$ we avoid extreme over- or under-weighting of stocks and ensure that the model-implied portfolio is always well diversified. We either let the investor form a buy-and-hold portfolio on the first day of the sample, Dec. 31, 2007, or rebalance the portfolio once a year (on Dec 31), i.e. four times over the 2007 - 2010 period covered by our ^{C}SVIX indexes. We do not allow for more frequent (daily or monthly) rebalancing for the simple reason that it would be inconsistent with our forecasts being long-term five-year forecasts rather than one-day or one-month forecasts.

Table II presents mean returns, standard deviations, skewness, kurtosis and Sharpe ratios for the four portfolio strategies: *(i)* the model-implied portfolio with $\theta = 1$, *(ii)* the model-implied portfolio with $\theta = 2$, *(iii)* an equally weighted portfolio and *(iv)* a value-weighted portfolio. The two model portfolios clearly perform better than the two naïve portfolios. While both the equally weighted- and the value weighted portfolios lose money, each of the two model-implied portfolios make a profit, regardless of whether we rebalance or not. The annualized excess returns of the model portfolios vary between 1.09% and 2.10% while the annualized excess returns of the equally weighted and the value weighted portfolio is -1.07% and -2.38%, respectively. The more aggressive model strategy dominates the less aggressive strategy but rebalancing the portfolio once a year does not improve the performance significantly. The latter finding is in accordance with what one would expect, considering that the forecasts are very long-term (five years) and that they (in theory) should not change too much from one year to the next. Finally, it should be added that there are (essentially) no transaction costs to consider for our investment strategies since even the rebalanced portfolio is traded only once a year. The day-to-day movements of the cumulative portfolio value, with and without rebalancing, is plotted in Figures 2 and 3 and it is clear that the out-performance by the model portfolios is not caused by a single significant event but is building up quite steadily over the eight-year long time-period.

As an additional example of how information from the credit derivatives market (the ^{C}SVIX indexes) could be used to outperform the overall stock market Figures 2 and 3 also show the performance of two small equally-weighted portfolios containing the three highest- and the three lowest ranked stocks, again ranked according to their expected future five-year excess return as of Dec. 31, 2007. The significant difference in performance of these two portfolios adds some evidence to the predictive abilities of the credit market; while a portfolio made up of the bottom-three stocks loses more than 30% across the sample period the portfolio made up of the top-three stocks gains more than 25%. Further evidence of this predictive ability of the credit-implied expected returns is shown in Table III where we show the cumulative portfolio performance of the top-*n* as well as the bottom-*n* portfolios for *n* = 1 to 10 (without rebalancing). For most *n*, the portfolios containing the *n* stocks with the *n* highest *expected* returns perform very well over the eight-year long sample period while the portfolios with the *n* lowest ranked stocks perform much worse. In fact, a simple long/short strategy going long the top-10 ranked stocks and shorting the bottom-10 stocks, as of Dec. 31, 2007, in this sample of 91 European stocks across the time-period 2007 to 2015, a period that is dominated by the financial crisis, would generate a return of around 55%. Again, this indicates how gains could be made from using credit derivatives market information when predicting stock returns.

4. Robustness Checks

The results in the previous section indicate a strong relationship between individual stocks' risk-neutral volatility and subsequent excess stock returns. The results are all averaged-out results across the entire sample, however, and it is possible that a few extreme episodes, perhaps linked to the stock market correction around the collapse of Lehman Brothers, drive the results. It is also possible that the results differ among the industries in the sample. For robustness, and to investigate the stability of the results over time and across firm-type, we therefore present the correlation, regression- and trading results above for sub-periods as well. We look at each year from 2008 to 2015 individually to get some indications on the stability of the results and to tell whether the crisis years 2008 and 2009 differ from the other years. In addition to this year-by-year treatment we will also treat stocks from each of the five industries separately.

The correlations in Table IV show that, regardless of how we compute the correlation between expected- and realized returns, the link between the two is strong also when we divide the sample into one-year long sub-periods. The cross-sectional correlation measure is very stable over time and the correlation coefficient is essentially the same every year (around 0.40) while the time-series correlation measure is somewhat higher in 2008 (0.80) than in 2009 and 2010 (0.36 and 0.50, respectively).

As for the regressions, in Table V we show the regression results year-by-year and the results for 2008 and 2009 are essentially the same as those for the entire sample; all the regression coefficients are statistically significant and the slope coefficients β and γ are close to the theoretically expected values while the intercept term α is negative. The year 2010 differs from 2008 and 2009, however, with the relationship between returns and volatilities being somewhat weakened but with slopes that are still statistically significant and a constant term that, in correspondence with theory, is not significantly different from zero. This partly supports our hypothesis that the negative α estimate found for the full sample could be due to the Lehman Brothers crash and its dramatic and long-lasting effect on the stock market not only in 2008 but in 2009 as well.

As for the portfolio strategies, we present year-by-year mean returns, standard deviations and Sharpe ratios for the four portfolio strategies in Table VI. Except for the two years 2008 and 2014, the model portfolios perform better than the naïve portfolios every year (and even in 2008 and 2014 the worst strategy is one of the two naïve strategies). The results do not seem to be driven by one or two "freak events" and our simple investment strategy based on information from the CDS market seems to work in turbulent years (perhaps to a slightly lesser degree) as well as in less turbulent years.

Overall, the support of the theoretical relationship in Martin and Wagner (2016) between expected long-term stock returns and long-term variances found in the previous section seems to hold also when we look at each year separately. To further investigate the robustness of our results we also look at each industry separately. The number of firms in each industry is quite low (between 14 and 26 firms), however, and we therefore focus solely on correlations. Each industry is treated separately, with all analysis redone on an industry-by-industry basis and with the firms in the particular industry making up the "market" in the computation of expected returns of individual stocks. Table VII shows that the correlation results above, indeed, are robust across industries. All the correlations are positive, statistically significant and of similar size, except for the small negative, and statistically insignificant, cross-sectional correlation among the firms in the consumers industry.

5. Conclusions

In this paper we have demonstrated how one can compute stock return expectations using information from the credit derivatives market. Our methodology builds on work by Martin and Wagner (2016) but instead of using ordinary call- and put options to impute risk-neutral stock variances we use credit default swaps. One advantage of this approach is that very long-term forecasts of stock returns can be made (across the entire business cycle if needed).

In the empirical part of the paper we show that the theoretical relationship between expected excess returns and risk-neutral variances in Martin and Wagner (2016) holds also when we replace short-term (<1Y) equity options-implied variances with long-term (5Y) credit default swap-implied variances. We also examine the performance of the credit default swap market in making long-term (5Y) stock market predictions and, out-of-sample, we find stock portfolios selected based on credit-implied stock return forecasts to beat both equally- and value-weighted benchmark portfolios. The empirical results in the paper are robust across years, across industries and to varying sample-sizes.

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Table I
Pooled Regression Results

In this Table we present results from OLS regressions, using monthly data, between realized five-year excess returns and five-year risk-neutral variances pooled across all 91 firms. Values in square brackets are *p*-values and the regressions are based on 3367 monthly observations from December 31, 2007 to December 31, 2010.

α	β	γ	F	$\hat{R}^2$
-0.160	0.941	0.380	602.1	0.264
[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Table II
Portfolio Performance

In this Table we present the performance of our model portfolios for two different levels of aggressiveness (θ) compared to naïve equally-weighted and value-weighted portfolios with and without yearly portfolio rebalancing. The portfolio holding period is from December 31, 2007 to December 31, 2015 and the portfolios are made up of long positions in all the 91 firms in the sample. The returns and standard deviations are annualized.

Buy-and-Hold

	Model (θ=1)	*Model (θ=2)*	*Equally weighted*	*Value weighted*
Mean return (%)	1.12	1.94	-1.07	-2.38
Standard deviation (%)	22.14	22.23	23.03	21.61
Skewness	-0.13	-0.13	-0.10	-0.07
Kurtosis	5.55	5.63	5.27	5.38
Sharpe ratio	0.051	0.087	-0.047	-0.110

Yearly Rebalancing

	Model (θ=1)	*Model (θ=2)*	*Equally weighted*	*Value weighted*
Mean return (%)	1.09	2.10	-1.07	-2.38
Standard deviation (%)	22.48	22.94	23.03	21.61
Skewness	-0.12	-0.11	-0.10	-0.07
Kurtosis	5.26	5.07	5.27	5.38
Sharpe ratio	0.049	0.091	-0.047	-0.110

Table III
Portfolio Performance – Highest and Lowest Ranked Stocks

In this Table we present the cumulative performance of equally-weighted portfolios of the top-*n* and bottom-*n* ranked stocks without yearly portfolio rebalancing. The portfolio holding period is from December 31, 2007 to December 31, 2015 and the numbers are cumulative percentage returns.

n	top-*n*	bottom-*n*
1	+11.9	+9.4
2	+18.3	-22.2
3	+25.3	-31.2
4	+12.3	-23.4
5	-0.6	-24.2
6	-1.1	-28.8
7	+25.4	-32.1
8	+31.3	-39.4
9	+27.8	-42.9
10	+28.2	-45.5

Table IV
Robustness: Year-by-Year Correlation Results

In this Table we present average correlations between expected five-year excess returns and subsequent realized five-year excess returns for two different ways of calculating average correlations on a year-by-year basis; (i) the time-series average of daily *cross-sectional correlations* among the firms in the sample and (ii) the cross-sectional average across the firms of *time-series correlations* between expected and realized returns. The correlations are computed using 91 firms and daily return observations from 2008, 2009 and 2010, respectively.

	2008-2010	2008	2009	2010
Cross-sectional correlation	0.41	0.41	0.44	0.38
Time-series correlation	0.75	0.80	0.36	0.50

Table V
Robustness: Year-by-Year Pooled Regression Results

In this Table we present results from OLS regressions between realized monthly excess returns and monthly risk-neutral variances pooled across all 91 firms on a year-by-year basis. Values in square brackets are *p*-values and all regressions are based on 1092 monthly observations from, respectively, 2008, 2009 and 2010.

2008

α	β	γ	F	$\hat{R}^2$
-0.187	1.113	0.508	129.6	0.192
[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

2009

α	β	γ	F	$\hat{R}^2$
-0.191	1.178	0.339	76.7	0.123
[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

2010

α	β	γ	F	$\hat{R}^2$
-0.005	0.424	0.323	48.6	0.082
[0.174]	[0.002]	[0.000]	[0.000]	[0.000]

Table VI
Robustness: Year-by-Year Portfolio Performance

In this Table we present the performance of our model portfolios for two different levels of aggressiveness (θ) compared to naïve equally-weighted and value-weighted portfolios with yearly portfolio rebalancing on a year-by-year basis. The portfolio holding period is always one year and the portfolios are made up of long positions in all the 91 firms in the sample. The returns and standard deviations are annualized.

	Model (θ=1)	*Model (θ=2)*	*Equally weighted*	*Value weighted*
2008				
Mean return (%)	-60.73	-59.45	-65.96	-51.63
Standard deviation (%)	36.36	36.73	37.07	34.64
Sharpe ratio	-1.67	-1.62	-1.78	-1.49
2009				
Mean return (%)	26.77	27.32	26.02	16.02
Standard deviation (%)	27.02	28.18	27.89	25.19
Sharpe ratio	0.99	0.97	0.93	0.64
2010				
Mean return (%)	14.37	16.58	9.70	4.65
Standard deviation (%)	18.56	19.09	19.08	17.62
Sharpe ratio	0.77	0.87	0.51	0.26
2011				
Mean return (%)	-12.35	-11.29	-17.10	-11.29
Standard deviation (%)	24.79	25.31	25.54	23.38
Sharpe ratio	-0.50	-0.45	-0.67	-0.48
2012				
Mean return (%)	15.96	16.72	15.27	9.94
Standard deviation (%)	16.73	17.21	17.49	15.84
Sharpe ratio	0.95	0.97	0.87	0.63
2013				
Mean return (%)	17.84	18.86	17.20	14.24
Standard deviation (%)	12.68	13.03	12.93	12.58
Sharpe ratio	1.41	1.45	1.33	1.13
2014				
Mean return (%)	1.60	1.65	1.80	0.09
Standard deviation (%)	13.77	13.98	13.93	14.18
Sharpe ratio	0.12	0.12	0.13	0.01
2015				
Mean return (%)	5.41	6.53	4.64	-0.97
Standard deviation (%)	19.60	19.58	19.73	20.59
Sharpe ratio	0.28	0.33	0.24	-0.05

Table VII
Robustness: Industry-by-Industry Correlation Results

In this Table we present average correlations between expected five-year excess returns and subsequent realized five-year excess returns for two different ways of calculating average correlations on an industry-by-industry basis; (i) the time-series average of daily *cross-sectional correlations* among the firms in the sample and (ii) the cross-sectional average across the firms of *time-series correlations* between expected and realized returns. The *cross-sectional correlations* are computed using 91 firms (or less, for the industries) and the *time-series correlations* are computed using 796 daily return observations from December 14, 2007 to December 31, 2010.

	All Firms	*Auto. & Ind.*	*Consumers*	*Energy*	*Financials*	*TMT*
Cross-sectional correlation	0.41	0.38	-0.14	0.54	0.37	0.39
Time-series correlation	0.75	0.76	0.65	0.53	0.74	0.72

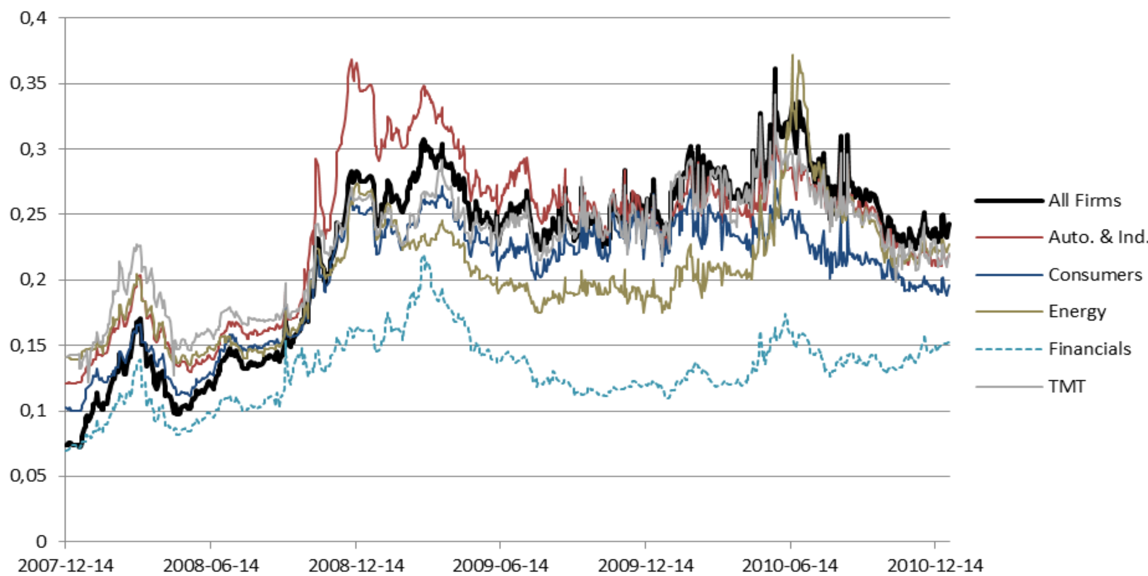

Figure 1. Average Expected Excess Returns. This graph shows the average daily expected five-year excess return (annualized) for the firms in the sample, divided into industries, across the time period December 14, 2007 to December 31, 2010.

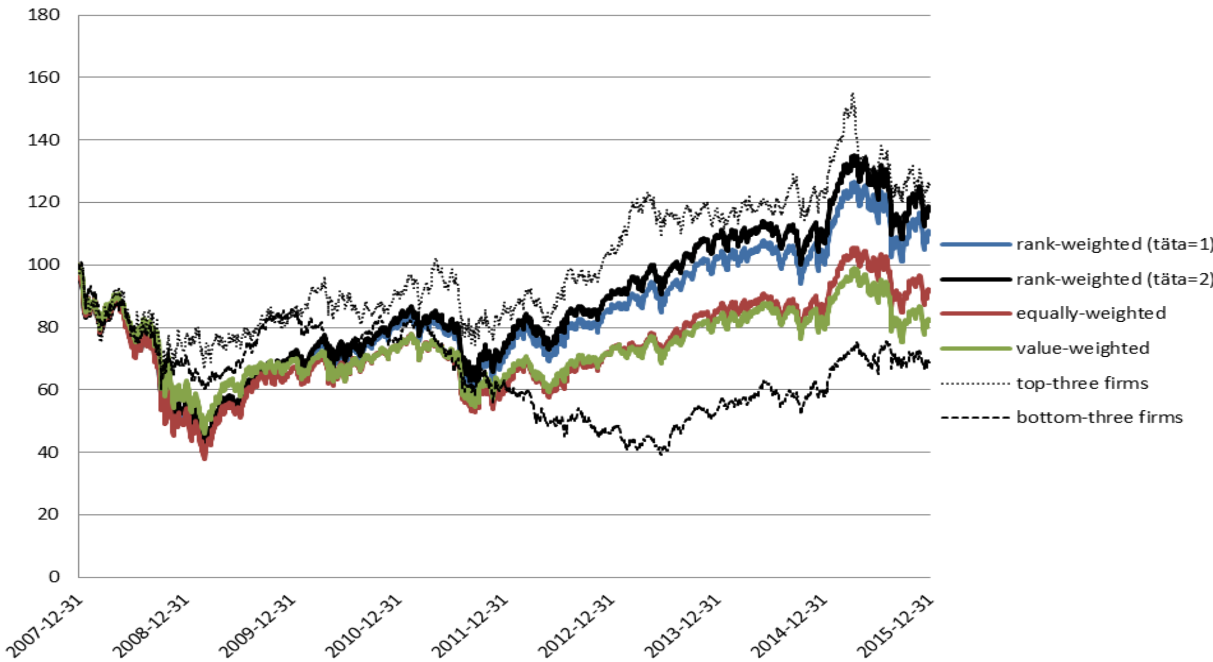

Figure 2. Portfolio Performance: Buy-and-Hold. This graph shows the cumulative portfolio performance of our model portfolios for two different levels of aggressiveness (θ) without yearly portfolio rebalancing compared to naïve equally-weighted and value-weighted portfolios and two equally-weighted portfolios containing the three highest- and the three lowest ranked stocks, respectively. The portfolio holding period is from December 31, 2007 to December 31, 2015 and the portfolios are made up of long positions in all the 91 firms in the sample.

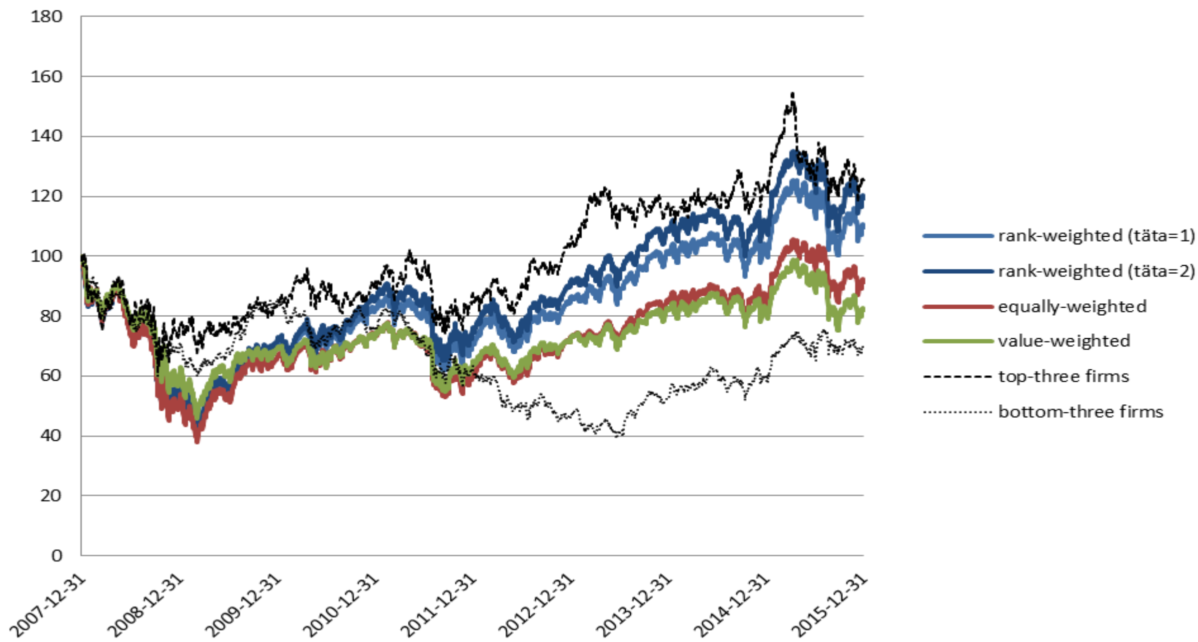

Figure 3. Portfolio Performance: Yearly Rebalancing. This graph shows the cumulative portfolio performance of our model portfolios for two different levels of aggressiveness (θ) with yearly portfolio rebalancing compared to naïve equally-weighted and value-weighted portfolios and two equally-weighted portfolios containing the three highest- and the three lowest ranked stocks, respectively. The portfolio holding period is from December 31, 2007 to December 31, 2015 and the portfolios are made up of long positions in all the 91 firms in the sample.